An investigation of the proof-of-concept for a perceptual control approach to inform robotic rehabilitation

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Maximilian G. Parker

Division of Psychology and Mental Health

School of Health Sciences

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List of Abbreviations

AcS	Acute Stroke
ABILHAND-K	ABILHAND-Kids
ADL	Activities of Daily Living
AI	Active Inference
ANOVA	Analysis of Variance
ARAT	Action Research Arm Test
AS	Ashworth Scale
BBT	Box and Blocks Test
BI	Barthel Index
BRTP	Bilateral Robotic Training Protocol
CI	Confidence Interval
CM	Chedoke McMaster Test
CNS	Central Nervous System
COPM	Canadian Occupational Performance Measure
CP	Cerebral Palsy
CS	Chronic Stroke
CT	Control Therapy
DoF	Degrees of Freedom
EEG	Electroencephalography
EMG	Electromyography
FIM	Functional Independence Measure
FMA	Fugl-Mayer Test for the Upper Extremity

FTI	Full-time Intervention
FTHUE	Functional Test of the Hemiparetic Upper Extremity
HCM	Hierarchical Control Model
HEM	Hierarchical Extrapolation Model
HIRT	High Intensity Robot Therapy
HTI	Half-time Intervention
ICF	International Classification of Functioning
JTHT	Jebsen Taylor Hand Test
LIRT	Low Intensity Robot Therapy
MAL	Motor Activity Log
MAM	Manual Ability Measure
MAS	Modified Ashworth Scale
MI	Motricity Index
MPS `	Motor Power Score
MRC	Medical Research Council test of muscle strength
MS	Multiple Sclerosis
ms	Milliseconds
MSS	Motor Status Score
MST	Medial Superior Temporal
MT	Middle Temporal
NHPT	Nine Hole Peg Test
NIHSS	National Institutes of Health Stroke Score
OFCT	Optimal Feedback Control Theory

OT	Occupational Therapy
PCT	Perceptual Control Theory
PCM	Position Control Model
PD	Parkinson’s Disease
PEM	Position Extrapolation Model
PPC	Posterior Parietal Cortex
PT	Physical Therapy
RCT	Randomised Control Trial
RMSE	Root Mean Square Error
RMA	Rivermead Motor Assessment
RMI	Rivermead Mobility Index
RT	Robotic Training/Therapy
SA	Subacute Stroke
SIS	Stroke Impact Scale
SMA	Supplementary Motor Area
TBI	Traumatic Brain Injury
TEMPA	Test Evaluant les Membres Superieurs des Personnes Agees
UCM	Uncontrolled Manifold Hypothesis
UK	United Kingdom
UL	Upper Limb
URTP	Uni-manual Robotic Training Protocol
WHO	World Health Organization
WMFT	Wolf Motor Function Test

Abstract

Neurological damage often results in motor impairments and reductions in individuals' functional abilities, particularly when the upper limbs are affected. Many individuals fail to achieve potential recovery of hand function due to insufficient volume of arm-hand training. Robotic rehabilitation has been proposed as an adjunct to physical therapy to meet this shortfall. However, it may be the case that functional recovery is also limited by practice. It has been observed that advances in motor control theory, mostly arising from computational modelling of behavioural data, have not been integrated in rehabilitation practice. The relatively new field of rehabilitation robotics presents a perfect application and testbed for principles of motor theory. Moreover, one specific motor theory, perceptual control theory (Powers, 1973, 2008), has been identified as architecture for designing robotic control architectures (Young, 2018).

In this thesis, we commence a research agenda that aims to test the proof-of-principle of PCT to inform robotic motor rehabilitation. The thesis consists of five original research reports. Two systematic reviews were conducted. The first aims to establish whether end-effector devices for arm and hand rehabilitation are efficacious in reducing impairment and improving functional outcomes. Findings suggested that device training may be efficacious for acute, subacute and chronic stroke patients. Thus it was determined that a research agenda which aimed to inform device development through motor theory was justified. A second systematic review evaluated the research literature regarding PCT models of manual tracking performance, in order to determine the extent to which PCT can account for motor performance in the task. Several key limitations in the PCT modelling literature were found. These limitations were investigated in a series of tracking experiments in which PCT models were optimised to, and simulated individual performance.

In the first experiment, we developed a test for model individual-specificity. This was applied to PCT models and it was found that optimised PCT models simulated performance at validation (one-week later) with a higher degree of accuracy than a general PCT model. This demonstrates that the PCT model can discriminate between individual control characteristics. In the second experiment, we aimed to establish the effect of delay on model performance as it was not clear whether PCT models could compensate for long feedback delays that are present in the central nervous system. Four PCT model

architectures were compared. The standard PCT position control model showed a reduction in model fit to anticipatory tracking behaviour at increasing delays. Conversely, models that controlled a novel perceptual variable (integrated motion representations) showed no such cost to performance at longer delays. Thus, given the appropriate controlled perceptual variable, PCT models can compensate for sensorimotor delays in motor performance. In the final experiment we aimed to investigate the generalisability of the model to a different task conditions. We evaluated whether the most superior model from the previous experiment could make individual-specific predictions (as per the first experiment), when individuals tracked sinusoidal and pseudorandom targets at different speeds with a new apparatus (steering wheel). The model was found to generalise well across task constraints.

In sum, the thesis develops a control model that can characterise and simulate individual performance over a range of task constraints. In the process, we addressed several important limitations in the evidence base for PCT. The implications of these advancements for the fields of motor control, and rehabilitation, are discussed in the concluding chapter. The aim of future work will be to implement the novel PCT architecture within the control algorithm for a robotic device for motor rehabilitation.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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Rationale for submitting the thesis in an alternative format

This thesis produced five original research manuscripts. One is published (Chapter 5). Three are in preparation for submission to journals (Chapters 4, 6, and 7).

Preface

The author holds an undergraduate degree in Psychology from the University of Manchester, which he gained in 2014. Throughout undergraduate studies he worked as research assistant. He began the current PhD programme in October 2014. This was funded by the Faculty of Biology, Medicine and Health of the University of Manchester, and a President's Doctoral Scholar Award.

Publications and conferences arising from this thesis

Based on Chapter 5

Parker, M. G., Tyson, S. F., Weightman, A. P., Abbott, B., Emsley, R., & Mansell, W. (2017). Perceptual control models of pursuit manual tracking demonstrate individual specificity and parameter consistency. Attention, Perception, & Psychophysics, 79(8), 2523-2537. (Research Article)

Parker, M. G., Tyson, S.F., Weightman, A.P, Abbott, B., Emsley, R., & Mansell, W. (2017). *"Can computational models be optimised to individual's tracking movements and accurately simulate their performance after one week?"*. Poster at the Human Action Control Winter School, University of Tübingen

Parker, M. G., & Mansell, W. (2017). *"Evaluating Perceptual Control Theory: Computational Models of Pursuit Tracking"*. Invited oral presentation, Sheffield Robotics

Parker, M. G., Tyson, S.F, Weightman, A.P, & Mansell, W (2017). *"Modelling individual differences in A Manual Pursuit Tracking Task"*. Invited research lecture for a Psychology MSc. course, Manchester Metropolitan University

Based on Chapters 5 & 6

Parker, M. G., Tyson, S.F, Weightman, A.P, Abbott, B., Emsley, R., & Mansell, W. (2017). *"Perceptual control models of pursuit manual tracking demonstrate temporal stability in parameters and simulate individual performance"*. Poster at the European Society for Cognitive Psychology (ESCoP), University of Potsdam

Based on Chapters 5, 6 & 7

Parker, M. G., Tyson, S.F, Weightman, A.P, & Mansell, W. (2018) "*From Measurement to Models to Movements: Reproducing Human Tracking Performance with a Model Driven Steering Wheel"*. Oral presentation at the Measuring behavior Conference, Manchester Metropolitan University

Chapter 1: Introduction

1.1 Chapter outline

This thesis aims to investigate the proof-of-principle for perceptual control applications to robotic rehabilitation. This chapter sets out the rationale for the aim and objectives of the thesis. First, I discuss motor control problems in neurological conditions (1.2). Following this, in section 1.3, neuroplasticity, cortical reorganisation, and the scope for functional recovery are examined. Neurorehabilitation is reviewed within the context of motor control (1.4). The case for robotic rehabilitation for motor relearning is made in the following section (1.5). Subsequently, principles from motor control theory are presented (1.6). The argument is made that specific challenges within rehabilitation robotics may be addressed by considering insights from motor control theory, and in particular, perceptual control theory (1.7). In the last section a research agenda is outlined which aims to apply this theory to robotic rehabilitation. This section also sets out the objectives of the current thesis, which aims to begin investigation within this research agenda (1.8).

1.2 Neurological problems that affect action control

1.2.1 Neurological Issues

Disorders of the Central Nervous System (CNS) can result in severe and persistent physical disability. Stroke is the most prevalent neurological disorder: over 100,000 individuals have a stroke per year in the UK alone (Stroke Association, 2018). The estimated burden in cost of stroke to society in the UK is £23 billion (Patel et al., 2017). Spinal Cord Injury, Traumatic Brain Injury (TBI), Cerebral Palsy (CP), Parkinson’s Disease (PD) and Multiple Sclerosis (MS) are several other common neurological causes of physical disability. Neurological damage that results in the loss of functional use of a limb, or limbs can be particularly disabling because it can affect an individual’s ability to complete Activities of Daily Living (ADL) such as dressing or washing. Due to the higher prevalence of stroke than other neurological conditions, much research in motor impairment and rehabilitation is focused on this group.

Physical disability is a loss of functional ability and independence (World Health Organization, 2001). Following neurological damage, common motor impairments include paresis (weakness or partial loss of movement), plegia (total loss of movement), hyper-reflexia and contracture (causes of muscle stiffness), tremor (involuntary oscillatory muscle contraction), and apraxia (difficulties with motor planning and preparation). These are often associated with focal or distributed neurological damage affecting motor areas. The size and topography of CNS lesions are related to the severity of impairment (Cheung et al., 2015). Sensation and control of the body parts in the brain hemispheres are contra-lateralised, thus a focal lesion to one hemisphere, as is usually the case in stroke, typically results in asymmetric impairment (Feydy et al., 2002). In stroke, three quarters of affected individuals report upper limb paresis (Stroke Association, 2018). Impairments may be further compounded by deconditioning from inactivity during hospitalisation (Rabadi, 2007), as well as to learned non-use of the affected limb (reliance on the unaffected limb) during recovery (Edward Taub, Uswatte, & Pidikiti, 1999). In addition to motor impairments, neurological damage often results in cognitive and sensory impairments. Sensory and perceptual impairments may interact with motor impairments and contribute significantly to physical disability (Tecchio et al., 2006).

Sensory impairments may be observed in multiple modalities, and are estimated to affect between 40 and 65% of individuals with stroke (Carey, Matyas, & Oke, 1993; Connell, Lincoln, & Radford, 2008). For example, tactile and proprioceptive impairments are common and may be associated with stroke severity and paresis (Mary et al., 2015; Tyson, Hanley, Chillala, Selley, & Tallis, 2008). Impairments in vision (Pollock et al., 2011) and balance (Tyson, Hanley, Chillala, Selley, & Tallis, 2006) are also common. Some studies have found correlations between the presences of sensory deficits in multiple modalities (Mary et al., 2015; Vallar, Antonucci, Guariglia, & Pizzamiglio, 1993); indeed, lesions to secondary sensory and associative areas may result in impairments in integrated perception such as apraxia, visuospatial neglect, and balance disorders (Mary et al., 2015; Smania, Picelli, Gandolfi, Fiaschi, & Tinazzi, 2008). Sensory and perceptual impairments have been shown to have a detrimental effect on motor learning (Vidoni & Boyd, 2009). Critically, individuals with comorbid perceptual and motor impairments experience slower and more limited functional recovery than those with no perceptual impairments (Carey et al., 1993; Mary et al., 2015; Smania et al., 2008; Tyson et al., 2008).

Groups of individuals with the same neurological diagnosis, lesion site or severity may still have heterogeneous symptoms, impairments, and abilities (Kwakkel, Kollen, & Wagenaar, 1999). This may be due to differences in latent functional localization, age-related reductions in neural plasticity (the capacity for cortical reorganisation), and a range of other person-specific factors (Öneş, Yalçinkaya, Toklu, & Çağlar, 2009).

1.2.2 Plasticity, cortical reorganisation, and the scope for functional recovery

Spontaneous full functional recovery is possible only for a small minority of individuals (Ekusheva & Damulin, 2015). Like impairments, recovery outcomes are heterogeneous and difficult to predict (Kwakkel et al., 1999). The potential for recovery may depend on many factors, including those stated in the previous section (1.2.1) but hinges on the propensity of the brain to undergo cortical reorganisation. Cortical reorganisation is the process of structural alteration of brain matter via deafferention of existing neural pathways, and generation of new interneural pathways via Hebbian processes (Ekusheva & Damulin, 2015). Neuroplasticity refers to the extent to which a brain is able to tolerate changes in cortical structure due to cortical reorganisation. Neuroplasticity decreases across the life span (Kleim & Jones, 2008).

Cortical reorganisation is proposed to underpin learning (Bütefisch, Kleiser, & Seitz, 2006). Sensory and motor cortices in adults are somato-topically organised (Carey et al., 1993; Rossini et al., 2007). This means that afferent and efferent signals from body units project to specific regions of the sensorimotor cortex, and functions are localised there (Pizzella, Tecchio, Romani, & Rossini, 1999). As a result of functional localisation, focal lesions may impair sensation or movement at specific body sites (Bütefisch et al., 2006; Grefkes & Fink, 2014). Cortical reorganisation in regions adjacent to the lesioned site may facilitate localisation of the function to spared cortical regions which may not have previously been involved (Bütefisch et al., 2006; Chen, Cohen, & Hallett, 2002; Rossini et al., 2007); promoting functional recovery.

There is substantial evidence for cortical reorganisation following neurological infarct from neuroimaging studies (Grefkes & Fink, 2014; Ward, 2006). Following focal brain lesions such as in stroke or TBI, spikes in neural activity are observed in the cortical regions surrounding the damaged site during motor task performance (Calautti, Leroy, Guincestre, & Baron, 2003; Chen et al., 2002). These activations tend to reduce during recovery, presumably as the individual localizes function to spared cortical regions (Kwakkel et al., 1999). In chronic stroke patients (six months or more post-stroke) with a secondary motor area lesion, activation in non-lesioned secondary motor areas was inversely correlated with functional recovery of the hand (Rossini et al., 2007; Ward & Frackowiak, 2006). This indicates that large-scale cortical reorganisation may be a short-term adaptive mechanism following neurologic injury. The pattern of spontaneous recovery following stroke supports this conclusion as functional recovery tends to plateau between 6 months to a year post stroke onset, with most recovery occurring in the first 3 months (Dobkin, 2018). Recovery of hand function plateaus around one year (Andrews, Brocklehurst, Richards, & Laycock, 1981). Whilst studies of motor impaired individuals tend to focus on cortical reorganisation in motor areas and the cerebellum, reorganisation is not limited to these areas (Bütefisch et al., 2006; Ward & Frackowiak, 2006).

Sensory cortical areas also undergo cortical reorganisation in parallel to motor cortical reorganisation following lesions to motor areas (Suminski, Tkach, Fagg, & Hatsopoulos, 2010; Tecchio et al., 2006). This is not surprising given the dependence of motor skills on perceptual input (and vice versa), the degree of cortical connectivity between motor and sensory areas (Bütefisch et al., 2006; Ward & Frackowiak, 2006), and the likelihood of sensory impairment following neurologic injury (Carey et al., 1993; Connell et al., 2008; Smania et al., 2008; Tyson et al., 2008). Therefore it has been proposed that sensory cortical reorganisation is fundamental to motor relearning (Ekusheva & Damulin, 2015). This conclusion is supported by evidence of poorer functional motor outcomes of those with sensory and perceptual impairments (Greenhalgh, Long, Flynn, & Tyson, 2008; Tyson et al., 2008). This understanding of the neural mechanism of motor learning underpins methods of rehabilitation of motor impairment and functional abilities. Use of an affected limb will stimulate increased activation in both sensory and motor areas (Rossini et al., 2007). These areas will consequently undergo cortical reorganisation which may facilitate recovery of limb function (Sun et al., 2013). Neurorehabilitation is used to promote neuroplasticity and cortical reorganisation by practice and training.

1.3 Neurorehabilitation

1.3.1 Principles

Neurorehabilitation is typically a multidisciplinary approach that aims to promote recovery following neurological damage (Kwakkel et al., 1999; Langhorne, Coupar, & Pollock, 2009). It may involve motor rehabilitation, cognitive and memory work, speech and language therapy, occupational therapy (OT) and a host of other approaches (Turner-Stokes, Nair, Sedki, Disler, & Wade, 2005). Physical therapy (PT) and OT are used to reduce motor impairment and improve functional use of the affected limb(s) (Langhorne et al., 2009). Three core principles of training have consistently been demonstrated to promote positive outcomes in motor rehabilitation: repetition, intensity, and specificity (Kwakkel et al., 1999).

Task-specificity refers to the benefit of training motor skills rather than mere use of the affected limb. In healthy humans, movements are executed to achieve perceptual goals. Therefore motor learning may be facilitated by training goal-directed movements rather than ambiguous movements (Kleim & Jones, 2008). However this is not easy to achieve. Many approaches improve muscular activation patterns and other impairments but do not result in functional improvements in ADL performance (Kwakkel et al., 1999). Whereas the literature indicates practice of *a specific ADL activity* results in improvements in ability to complete that task but rarely generalises to other activities and tasks (Kwakkel, Kollen, & Krebs, 2008; Kwakkel et al., 1999; Langhorne, Bernhardt, & Kwakkel, 2011; Langhorne et al., 2009). On a cortical level, repetition of skilled movement synergies leads to increased corticospinal plasticity-related activation relative to repetition of unskilled movements (Kleim & Jones, 2008; Ward, 2006). However, training in one task does not improve abilities in other tasks, even if they share similar movements (Kwakkel et al., 1999). Practice should also be repetitive and of high intensity (Kwakkel et al., 1999; Kwakkel, Kollen, & Lindeman, 2004; Langhorne et al., 2011, 2009). Activity in the cortical regions surrounding the infarct will result from movement of the affected limb. During movement repetition, co-activation of neural circuitry will increase the number and strength of connections between cortical motor and sensory regions (Ekusheva & Damulin, 2015). Importantly, repetition must not be replicative (Kwakkel et al., 1999). For instance, picking a glass up from different random locations, or using a variety of glasses and cups, is preferable to repeating exactly the same movement. Altering the constraints of a task should improve generalised ability across exemplars of the same task. Intensity of training ensures that cortical reorganisation is sustained. Thus high intensity, repetitive, and task-specific practice should promote cortical reorganisation of sensorimotor networks that will support lasting improvements in performance of a specific functional task.

Typically early training is encouraged as it tends to lead to better functional outcomes than later onset rehabilitative training, with most improvements occurring in the acute phase (Hayward & Brauer, 2015). This may stem from the increased neuroplasticity immediately following stroke onset (Calautti, Leroy, Guincestre, & Baron, 2003; Chen et al., 2002). It must be considered that in alongside the importance of promoting reorganisation to relearn lost skills, non-use may further impair performance as muscle tone may be reduced with inactivity (Lambercy, 2009), and because non-use exacerbates loss of function by repurposing of neural networks to other functional tasks via cortical reorganisation (Kleim & Jones, 2008). Therefore training may not just promote relearning but also attenuate degradation of existing neural networks.

Despite the application of the above principles in rehabilitation, treatment effects over and above those that result from spontaneous recovery are relatively small (Kwakkel, Kollen, & Twisk, 2006). It is likely that recovery is highly dependent on the extent of cerebral damage and the ability of the brain to spontaneously recover. However, it may also be the case that current rehabilitation practice falls short of meeting individuals' functional potential. A number of factors that may contribute to this shortfall are considered in the next section.

1.3.2 Challenges

Trends in rehabilitation practice tend to be informed by 'what works', rather than by theoretical principles in motor control and learning (Carr & Shepherd, 1989). Rehabilitation methods tend to focus on movement practice under the assumption that reproducing movements will lead to neurological change in favour of increased functionality (Rossini et al., 2007). However, there is limited evidence to suggest what exactly is learned in a given task, and how movements are coordinated in the moment to meet these goals (Kwakkel et al., 2004). Theory and findings in motor control may elucidate mechanisms of change and inform practice. Indeed it has been proposed that "*a better theoretical understanding of the underlying mechanisms of disordered movement co-ordination, and perception and action in general, could ultimately lead to the development of new therapies and more effective rehabilitation strategies*" (page 385, Kwakkel et al., 1999). Given that action is oriented toward perceptual goals, and the evidence that sensory and perceptual impairments play a role in maintaining motor impairments and disability (Meyer, Karttunen, Thijs, Feys, & Verheyden, 2014), perceptual aspects of motor control and impairment appear important. Indeed, visual perception training for individuals with neglect may be one training approach in rehabilitation results in transfer across multiple tasks (Webster et al., 1984). However, there is insufficient evidence that visual perception training is efficacious for visual field deficits in general, or improves ADL performance (Pollock et al., 2014).

In the UK, an ageing population is contributing to an increased demand or requirement for rehabilitation (Truelsen et al., 2006). Consequently, primary rehabilitation programmes are becoming shorter (Richards, Hanson, Wellborn, & Sethi, 2008). In the inpatient setting, individuals may be in receipt of several different types of rehabilitation; with a focus on restoring walking abilities to improve their mobility (Hayward & Brauer, 2015). In the UK, typically very little time is spent on arm-hand practice (Connell, McMahon, Eng, & Watkins, 2014). A high dose of arm-hand practice is recommended but this dosage is rarely met (Hayward & Brauer, 2015). The current dosage has been described as low intensity, and may not be sufficient to meet optimal potential outcomes (Connell et al., 2014). In outpatient settings, patients are encouraged to practice arm-hand skills in their own time, although instructions and support are often insufficient (Connell et al., 2014). In addition, adherence to home training programmes is not well quantified and may be negatively affected by low motivation (Jurkiewicz, Marzolini, & Oh, 2011). Individuals may prefer to use their unaffected arm to complete tasks (Edward Taub et al., 1999), or use their affected arm in a way that they would not have prior to stroke onset (Langhorne et al., 2011). This may be less effortful or frustrating than practicing and failing at tasks with the affected limb. However, as mentioned previously, learned non-use may compound this issue and reduce the ability to recover function in the affected limb (Edward Taub et al., 1999). A second problem for outpatients is access. Individuals may need to visit their treatment centre several times per week but may be unable to drive or have limited mobility (Hayward & Brauer, 2015; Turner-Stokes et al., 2005). This presents an obstacle for accessing therapies and may further reduce the total amount of time individuals receive therapy, and thus the volume of practice they receive. Again, this may limit the extent of functional recovery.

Alternative rehabilitation methods, such as Robotic Training (RT), may be used as an adjunct to occupational and physical therapy to address these shortfalls.

1.4 Robotic neurorehabilitation

1.4.1 Rationale and methods

Robotic neurorehabilitation devices have been proposed as an adjunct to PT and OT to enable patients to attain the massed practice necessary for neuroplasticity and recovery (Hsieh et al., 2011; Krebs, Dipietro, Volpe, & Hogan, 2003; Krebs, Hogan, Aisen, & Volpe, 1998; Kutner, Zhang, Butler, Wolf, & Alberts, 2010; Weightman et al., 2011). Such devices can precisely apply assistive or resistive forces to individuals whilst they complete a motor task (Maciejasz, Eschweiler, Gerlach-Hahn, Jansen-Troy, & Leonhardt, 2014). It has therefore been proposed that robotic devices could be used within the home for intensive task practice (without direct therapist supervision), or within the clinic where a therapist might supervise multiple patients interacting with the robots (Linder, Reiss, et al., 2013; Linder, Rosenfeldt, et al., 2013; Reinkensmeyer, Pang, Nessler, & Painter, 2002; Sivan et al., 2014; Standen et al., 2011; Weightman et al., 2011). Thus robotic devices may present a platform to improve access to physical therapy. Robots typically use virtual environments and games which are thought to increase attention and motivation, and may promote adherence to home-based training programmes (Nijenhuis et al., 2015). Robotic devices enable patients with little or no ability to produce movements to practice high-intensity therapy. An additional advantage is that kinematic measurements relating to movement parameters and task performance can be collected during training (Babaiasl, Mahdioun, Jaryani, & Yazdani, 2015; Reinkensmeyer et al., 2002; Timmermans, Seelen, Willmann, & Kingma, 2009; van Delden, Peper, Kwakkel, & Beek, 2012; Wu et al., 2012). Some robots and tasks can also provide enhanced sensory feedback, such as tactile sensory information via haptics or visual/auditory feedback via the computer interface, or apply forces that therapists could not (Maciejasz et al., 2014).

Robotic devices are typically connected to a computer (Maciejasz et al., 2014). Control algorithms in computer software define the training schedule of assistive and resistive forces applied to the limb (Marchal-Crespo & Reinkensmeyer, 2009). Usually device training is accompanied by a virtual game which trains discrete or continuous movements. For instance, a discrete task could involve separate reaching movements to move a virtual hand to grasp apples and return them to a basket. An example of a continuous task might be sustained tracking movements such those used when driving. Virtual environments give a task-specific context and serves to make the training more enjoyable and may promote attention and engagement (Huang & Krakauer, 2009; Maciejasz et al., 2014; Patton & Mussa-Ivaldi, 2004; Takahashi, Der-Yeghiaian, Le, Motiwala, & Cramer, 2008). The parameters of games can be adapted to make the task more or less challenging; as can the magnitude of assistive force or resistive force supplied by the device. These changes allow the training to be catered to the individual such that the optimum level of challenge is achieved (Marchal-Crespo & Reinkensmeyer, 2009).

Devices can be split into two broad categories: exoskeletons and end-effectors (Maciejasz et al., 2014). Exoskeletons are devices with motors that are mechanically aligned with the joints of the body, such that the motors produce torque (rotational force) at these joints to assist movement. These devices typically support many Degrees of Freedom (DoF) in movement. These may be controlled simultaneously to allow users to practice complex synergistic task movements. Exoskeletons may even be controlled by electromyographic (EMG) signals derived from measurement by dermal electrodes (Hu et al., 2008; Li, Hu, Tong, & Member, 2008; Takaiwa, Noritsugu, Ito, & Sasaki, 2011). Whereas end-effector devices have a single point of contact, usually with the most distal section of the user's limb, such as a joystick setup where the hand holds the handle. End-effector devices are typically simpler than exoskeletons, comprising fewer motors and supporting fewer DoF (Maciejasz et al., 2014). Additionally, because exoskeletons provide torque at joints, they can constrain the individual's movement to biomechanically optimal and safe trajectories (Lo & Xie, 2012). However, this constraint may impede learning because trajectories may be replicated during repetitive practice. Furthermore, these constraints are not present without the exoskeleton and this may mean learnt skills are not easily executed without the device. End-effectors do not constrain movements, therefore individuals must find their own solution in a task, and may develop compensatory movements that can translate to use after training. There is some evidence that end-effector devices lead to better functional outcomes than exoskeletons in lower limb rehabilitation (Chua, Culpan, & Menon, 2016).

1.4.2 Evidence

Several systematic reviews have been conducted with the aim of establishing whether rehabilitation devices are efficacious in reducing impairment and promoting functional recovery. For upper limb rehabilitation, reviews found that RT reduced impairment in the hemiparetic limb in stroke patients (Kwakkel et al., 2008; Prange, Jannink, Groothuis-Oudshoorn, Catharina Hermens, & Ijzerman, 2006). A similar pattern was found in a review of upper limb RT for children with CP (Chen & Howard, 2014). However, evidence for translation to functional recovery or ADL performance was more limited, often by low quality evidence (Mehrholz, Pohl, Platz, Kugler, & Elsner, 2015). These reviews included many devices that trained only the proximal upper limb (shoulder and elbow), and included both exoskeleton and end-effector devices. One review of distal upper limb RT found both reductions in impairment and improvements in functional abilities with some devices (Balasubramanian, Klein, & Burdet, 2010). It may be the case the distal upper limb training promotes recovery to a greater extent than proximal training. RT, particularly of the distal upper limb, may be a promising adjunct to therapist-based rehabilitation methods. The efficacy of end-effector devices for hand rehabilitation will be reviewed and discussed in Chapter 3.

1.4.3 Challenges

Despite the evidence that devices may be efficacious as an adjunct to therapist-based rehabilitation, robotic devices have rarely been used outside of research studies. One simple explanation is that their development only began over the last decade, there are currently very few commercially available devices (Babaiasl et al., 2015; Lo & Xie, 2012; van Delden et al., 2012). However it may also be the case that health service providers have concerns about cost, safety, training and maintenance. Cost analyses tend to report very small benefits to robotic therapy over conventional therapies when long-term care is considered (Wagner et al., 2011). Moreover, commercial production should bring down the unit price and maintenance cost, making devices more affordable for health services (Maciejasz et al., 2014). As end-effector devices tend to be mechanically simpler than exoskeletons, end-effectors are typically smaller, easier to set up and significantly cheaper, with simpler control algorithms. End-effectors are likely more suitable for home-based rehabilitation and implementation in health services than exoskeletons (Balasubramanian et al., 2010). These devices may present a solution to the shortfall in practice of functional arm-hand movements noted in the previous section (1.4), particularly if they can be set up in service users' homes (Balasubramanian et al., 2010; Kwakkel et al., 2008). Not only would this increase access to the therapy but also the volume of practice that could be achieved.

In addition to pragmatic considerations, the previously considered challenges in neurorehabilitation also apply with robotic devices. Yet robotic devices may present an opportunity to address these challenges. It was previously mentioned that rehabilitation outcomes may be improved by better understanding the mechanism of action control in both healthy and impaired populations. Robotic platforms with computer peripherals have been used to test these mechanisms within the motor control literature (Gollee, Gawthrop, Lakie, & Loram, 2017; Inoue & Sakaguchi, 2014; Khoramshahi, Shukla, & Billard, 2014; Poulton, 1952a; Schlesinger, Porter, & Russell, 2013; Stepp & Turvey, 2017; Yu, Gillespie, Freudenberg, & Cook, 2014). As these systems enable accurate measurement of kinematic data and task performance they can also be useful tools for deriving models of what and how individuals control in these tasks, and elucidating the mechanism of motor learning. These insights may be applied to the rehabilitation setting. Firstly, this knowledge could inform the design of robotic devices and peripherals (Kwakkel et al., 2008). Moreover, in impaired individuals, task performance and kinematic data could be used for assessment purposes offline by therapists to quantify disordered movement and inform their prognosis via predictive statistical models (Allen et al., 2007; Au, Lei, Oishi, & McKeown, 2010; Oishi, Ashoori, & McKeown, 2010; Oishi, Talebifard, & McKeown, 2011). Behavioural data may be used to track the progress of individuals on-line and adapt the amount of assistance or resistance to best suit the individual at that point in time, via adaptive control algorithms (Marchal-Crespo & Reinkensmeyer, 2009).

In the next section, the motor control literature is reviewed through a rehabilitation lens, with a view to reconcile accounts of motor behaviour and learning across these fields. Specifically, this section aims to identify the principles that underpin currently efficacious practices, and identify those that might advance understanding and practice in rehabilitation.

1.5 Insights from motor control

1.5.1 Motor redundancy and the Uncontrolled Manifold

Motor control is the study of how the CNS and body produce movement. The human body comprises many joints and muscles, and therefore a very large number of biomechanical Degrees of Freedom (DoF) (Scholz & Schöner, 1999). Consequently, actions for any motor task are completed differently on each repetition, as a near-infinite number of different combinations of muscle forces and joint angles are possible. This was first observed by Nikolai Bernstein in the 1920s in his cyclographic studies of repetition of a practiced motor task (Carpenter, 1968): hitting a chisel with a hammer. The movement trajectory of the arm segments and hammer varied with every strike, yet the hammer reliably hit the chisel. Bernstein termed this ‘repetition without repetition’, to describe how the pattern of joint angles, muscle forces and trajectories differ whilst the task goal is consistently achieved.

These numerous DoF have been both described as redundant and abundant. ‘Redundant DoF’ recognises the inherent challenge of action selection in the face of many options (motor redundancy). ‘Abundant DoF’ instead recognises the flexibility that this affords the motor system in completing task-oriented action. These two perspectives remain relevant to contemporary motor theories, which must propose a solution for how the CNS selects action whilst preserving this flexibility. Numerous findings suggest that the CNS restricts certain DoF whilst others can vary freely (Hogan & Flash, 1987; Morasso, 1981; Soechting & Lacquaniti, 1981). For example, during reaching movements to different points, hand trajectories were found to be regular, quasilinear, and had bell-shaped velocity profiles, whereas the observed trajectories at other joints varied in irregular patterns (Morasso, 1981). This has led authors to propose the Uncontrolled Manifold hypothesis (UCM; Scholz & Schöner, 1999). The UCM states that the CNS selects a combination of elements that achieves stability in a performance variable (the variable characterising the goal), while allowing other kinematic or anatomical DoF to vary (M. Latash, Scholz, & Schoner, 2002). This would reduce the complexity of action selection as fewer DoF must be specified by the CNS. Optimal Feedback Control Theory (OFCT; Todorov, 2004; Todorov & Jordan, 2002) proposes that elemental solutions are estimated on-line during trajectory execution through statistical optimisation of a cost function. A cost function specifies a time-integral value that is minimised during optimisation. For example, minimum jerk describes optimisation of trajectory control by minimising the rate of change of acceleration (Todorov, 2004). Under the OFCT proposal, action planning and execution are not separate processes, and this further reduces the complexity of determining trajectory control.

The fundamental insight that individuals control task-relevant variables may qualify principles of neurorehabilitation. Firstly, practice of unskilled movements may not result in transfer to improved task performance because the required movements for a given task vary based on the initial conditions. Instead, training is required to adaptively coordinate different movements to achieve this goal. Consequently, the principle that task-specific practice should be repetitive, but not replicative, is explained by the fact that humans do not replicate the same movements exactly even when the goal and task conditions are the same. Importantly, the focus on goals or task-invariances in movement suggests a perceptual basis of action control. A group of theories divert from action selection completely by proposing that actions (outputs) are not controlled at all; instead, individuals control (or predict) inputs. This is presented as an alternate solution to the problem of action selection. These theories will be described in the next section (1.6.2.) but also conform to a task-centred view of action control.

1.5.2 A shared representation of perception and action

Emerging from the concept of goal-oriented action is the proposal that action and perception share a common representation within the CNS. This is the basis of the ideomotor principle, first proposed by William James in 1890, and advanced in a contemporary form by Prinz and Hommel (Hommel, 2009; Prinz, 1997). Indeed this is supported by reciprocal connections between motor and sensory areas (Friston, Mattout, & Kilner, 2011). According to the ideomotor principle, actions are coded in terms of action effects (perceptual results) and thus the two share a common neural substrate (Prinz, 1990). This is proposed to enable humans to learn to produce action based on associations between previous actions and action effects (Hommel, 2009). The opposite is also proposed; that actions are motivated by recalling action effects. However, the ideomotor interpretation is limited because actions vary to achieve the same action effect - the problem of motor redundancy (see section 1.6.1). Moreover, there can be no strict association between an action and its effect as the latter will vary depending on initial conditions and disturbances including those caused by muscle interactions (Feldman, Goussev, Sangole, & Levin, 2007).

Perceptual control theory (PCT; Powers, 1973, 2008; Powers, Clark, & McFarland, 1960; Powers, Clark, & McFarland, 1960) proposes instead that actions are varied control perceptions. The theory proposes a hierarchy of perceptual control units that operates as a two-way cascade (Powers et al., 1960). Perceptual signals flow up the hierarchy via bottom-up projections. Superordinate units provide top-down projections which convey reference signals to units below: desired perceptual states. At each unit, this reference signal is compared to incoming perceptual signals (Powers, 1973). This comparison yields an error term that results in the specification of a top-down reference value for the unit below. Each unit possesses an input function and an output function. The input function integrates perceptions from lower units into the input perceptual signal to be controlled at the current level. The output function transforms the error term into the reference signal to the unit below, and therefore defines the magnitude of output relative to a change in input. Units at the lowest level produce action and thus, output functions at this level transform perceptual error into output. Action is the method used to reduce perceptual error, rather than a controlled quantity itself (Powers, 1973, 2008). The challenge of motor redundancy is avoided because the DoF are not controlled; rather perceptions are controlled by varying these DoF.

Active Inference (AI; Adams, Shipp, & Friston, 2013; Brown, Friston, & Bestmann, 2011; Friston et al., 2011; Perrinet, Adams, & Friston, 2014), also proposes a shared representation of action in perceptual coordinates. The theory is rooted in Hermann von Helmholtz's unconscious inference: the idea that rather than a bottom-up receiver of sensory information, the CNS makes inferences (predictions) about the cause of sensory information (top-down). This concept is formalized in predictive coding (see Clark, 2013), for a review). In predictive coding, the primary function of the CNS is to optimise top-down hypotheses about its sensory input using bottom-up prediction errors in a multi-layer hierarchy (Clark, 2013). The AI theory attempts to integrate action control within this framework. In this conception, action is driven by the motivation to reduce error in predictions of future sensory inputs. Top-down signals in the AI account are predictions of proprioceptive input (sensations regarding body parts in the spatial frame). Bottom-up projections are prediction errors, propagated upward to alter priors in order to improve future predictions of proprioceptive input. Action is conceived as the use of reflex arcs to resample sensory information to minimise prediction errors. Thus the key difference between PCT and AI is the locus and function of error correction. In PCT, error correction occurs at each level to reduce the error between the controlled perception and the perceptual goal. In AI, the error correction is proposed to update the prediction of sensory input or 'internal model', and thus operates between levels.

In both PCT and AI, error can be reduced either by changing the way in which the environment is sampled (action), or changing top-down signals (references or predictions). It should be noted that, as in PCT and AI the downward projections are specifications of sensory inputs and not motor commands, these are context-independent (Adams et al., 2013). That is, they do not take account of contextual factors such as muscle length or external load. Therefore, these signals must be converted to context-dependent motor commands by corticospinal neurons to produce torque at joints. Because of this, descending signals are predictions of sensory effects; there is no action selection per se.

These perspectives highlight the perceptual nature of action control and therefore the need to quantify perceptual intentions or goals within a given task. All three theories break down the classical distinction between perception and action. The implications of these proposals for motor rehabilitation are wide-ranging. One implication is that the long-perceived functional differentiation of the motor and sensory cortices may be in question (Friston, Daunizeau, Kilner, & Kiebel, 2010). By extension, the distinction between sensory and motor impairment becomes less clear. Within a given task it may be necessary to establish which perceptual variables are controlled (or predicted, in AI) rather than characterising the movement pattern itself. Critically, it is these perceptions that are learnt, rather than the actions that produce it; thus motor learning might be reframed as *perceptual learning*.

1.5.3 Referent Control

Goal attainment is dependent on quantifying the value of the goal to be achieved, in addition to having the means to achieve it. Central to the definition of the reference signal in PCT is that it represents individuals' intentions (Marken, 2013a). PCT recognises that in any task there are many different perceptions that may be controlled (Powers, 1978, 1989). Consequently, an individual may control many different perceptual variables simultaneously, and switch control from one variable to another (Powers, 1978). It should be recognised therefore that two individuals may approach the same task by controlling different perceptions or similar perceptions but at different reference values (Bourbon, Copeland, Dyer, Harman, & Mosley, 1990; Powers, 1989). This idea underpins heterogeneity in performance and learning. Consequently, PCT proposes the functional modelling methodology (Mansell & Huddy, 2018; Runkel, 2007). The aim of this methodology is to determine which perceptions an individual is controlling in a given task (Runkel, 1990), and model their individual performance (Mansell & Huddy, 2018). This may be a useful methodology to apply within rehabilitation as it explicitly attempts to quantify the inherent heterogeneity of control. Models may be applied to elucidate individual learning. Moreover, PCT proposes that perceptual control operates at all levels of individual functioning, not simply perception and action (Powers, 1973). For example, PCT has been applied to mental health and wellbeing in the form of Method of Levels psychotherapy (Carey, 2006; Carey, 2008; Powers et al., 2011). Given the impact of neurological damage on cognitive and emotional functioning, as well as physical functioning, such a holistic theoretical approach may be valuable. Therefore the theory may be a useful framework for understanding and approaching multidisciplinary aspects of neurological recovery.

1.5.4 The role of negative feedback

Negative feedback describes the process of keeping a system in an equilibrium state by dynamically reducing error between a set point (reference) and the current state. It is ubiquitous in engineering control applications such as servo control, thermostats, and cruise control systems. In living organisms, negative feedback operates throughout the body in regulatory functions such as homeostasis (Turrigiano, 2007). The cybernetics movement first applied these principles to purposeful behaviour (Rosenblueth, Wiener, & Bigelow, 1943). In action control, perception guides action, which in turn, alters sensory inputs and perceptions. Thus sensory information regarding the results of action is a feedback arc (Wiener, 1948). Contemporary theoretical accounts of action control incorporate some aspect of negative feedback control for error minimisation.

In PCT, negative feedback control is the fundamental operation of controlling perceptual input. Within each control unit, negative feedback control is applied to maintain perceptual input at the reference value (Powers, 1973). Error at the lowest level motivates action, which does not cease until error is reduced to a stable minimum. Error in superordinate levels motivates change in the value of the reference signal to the unit below. In other motor control theories, such as AI and OFCT, negative feedback is used in conjunction with prediction as a mechanism of error minimisation (Friston et al., 2011; Todorov & Jordan, 2002b; Wolpert, 2007). Bottom-up prediction error in AI forms a sort of 'internal' feedback on the accuracy of top-down predictions. These prediction errors encode the extent to which input differs from its expected value. If the input matches the prediction, no prediction error signal is sent up the hierarchy (Adams et al., 2013). This is in contrast to PCT in which integrated perceptual inputs are consistently projected up the hierarchy (Powers, 1973). OFCT builds on classical control theory by proposing that a cost function is used to derive the optimal feedback control law for a given task through inverse predictive models (Todorov, 2004).

Feedback is thus a critical component of action execution. Feedback control has a unique role in altering action on-line as a result of sensory error, and enables compensation for disturbances that occur during movement execution. However, receiving and processing sensory feedback for coordinating action takes time (Keele & Posner, 1968), which necessitates that action produced in relation to incoming sensory information is delayed (Scott, 2008). Additionally the interval of the delay at each hierarchical level may differ (Marken, Mansell, & Khatib, 2013), and so timing in complex motor actions must account for these irregularities (Rohde & Ernst, 2016). This presents a challenge for feedback control approaches because delays in processing feedback information must be compensated within the CNS, so that executed movements are appropriate for *current* sensory inputs (Hollerbach, 1982). AI and OFCT propose that prediction provides this compensation mechanism. In PCT the effect of sensorimotor delays on action may be mitigated by hierarchical perceptual processing (Powers, 1973). At each ascending hierarchical level, units control more complex, long-term, and integrated perceptual variables (Powers et al., 1960). Descending reference signals may specify future-oriented reference values. Mechanisms of prediction will be considered in the following section (1.6.5).

1.5.5 Motor (perceptual) learning, prediction and optimisation

Prediction in OFCT and AI use a similar Bayesian statistical computation to optimise predictions (Wolpert, 1997, 2007). However, in AI predictions are solely ‘feedforward’, whilst OFCT also implements ‘inverse’ predictions. Feedforward refers to the prediction of sensory outcomes. For example, corollary discharge (a copy of the outgoing motor command) may be used to estimate of the future position of the limb (Grush, 2004; Wolpert, 2007). This prediction may be compared to the resulting sensory input, which produces a prediction error term. This error term serves two functions. Firstly, the subtraction of prediction error from predictions may enable disambiguation of the cause of changes in sensory input (external or movement driven). Second, the error term can be used to update the accuracy of predictions in the future (perceptual learning) (Friston et al., 2011).

OFCT also utilises prediction and prediction error. However, rather than feedforward predictions of future sensory input, an inverse model is proposed to compute the required motor commands to achieve a desired sensory result (action effect), effectively formalising the ideomotor principle of action production (see section 1.6.2). This has the advantage of enabling movements to be produced in the absence of feedback, such as for movements to visual targets that are shorter than the feedback processing time (Wolpert, 1997). In this conception, trajectory computation is an on-line process that calculates the optimal solution given a cost function (Todorov, 2004; Todorov & Jordan, 2002).

PCT instead proposes an additional control system, distinct from the perceptual hierarchy, with projections to the units within the hierarchy. The reorganising system receives as input intrinsic error input signals, which quantify deviation from a set of biologically pre-programmed reference states (Powers, 2008; Powers et al., 1960). In simulations this intrinsic error signal is derived from a measure of global error in the hierarchy (Powers, 2008). When error exceeds a certain threshold for a sufficient amount of time the reorganising system begins to make alterations to the reference values and parameters of the units in the perceptual hierarchy, mostly in a trial and error manner. Changes continue until the intrinsic error returns to a sub-threshold value. New control units may also be developed from the ‘uncommitted neurons’ (Powers et al., 1960). As reorganisation is more trial and error, and inherently structural, it may account for large-scale changes such as those observed in child development and motor relearning following extensive neurological injury. Parameter optimisation within existing control networks may lead to smaller changes associated with skill learning though practice in healthy adults.

The perceptual basis of motor learning in motor theories has evident parallels with the pattern of cortical reorganisation following neurologic injury. This restructuring of the sensory and motor areas demonstrates the core dependency of motor control on perceptual inputs. Motor theory might suggest that functional recovery of task-oriented control may be reframed as a perceptual learning process rather than one of relearning movement patterns. This would explain why repetitive movement practice alone is not sufficient for improvement in ADL performance. Instead, task-oriented practice is required to learn which perceptual variables must be successfully controlled for task completion. In addition, the development of compensatory strategies following neurologic impairment might be expected given that they are adaptive solutions that achieve perceptual goals, and given constraints on movement arising from impairments. The exact method by which motor learning mechanisms act to bring about functional change can be considered to involve restructuring damaged hierarchies. This might involve selecting and optimising the appropriate perceptual references (or predictions), selecting appropriate cost functions, optimising the parameters of existing control structures to achieve stable control, or creating entirely new control structures by large scale cortical reorganisation.

1.6 Summary and synthesis

Neurological damage often results in heterogeneous impairments in movement (Kwakkel et al., 2008, 1999; Turner-Stokes et al., 2005). Impairments, particularly in arm-hand function, affect the ability of individuals to perform ADL and limit their independence and quality of life (Adamson, Beswick, & Ebrahim, 2004; Andrews et al., 1981; Hunter & Crome, 2002; Langhorne et al., 2011; Ward & Frackowiak, 2006). While spontaneous recovery of function is observed in the months following damage, few individuals with upper limb hemiparesis regain functional use of their hand (Dobkin, 2018). Sensory and perceptual impairments are common in individuals with motor impairments, and functional recovery of motor function is more limited in individuals who also experience sensory impairments (Connell et al., 2008; Tyson et al., 2008). This is not surprising given the neural interdependence of these sensory and motor systems (Mackay & Crammond, 1989; Pizzella et al., 1999; Tecchio et al., 2006).

Contemporary motor theories propose a common representation of perception and action in the brain (Friston et al., 2010; Friston et al., 2011; Powers, 1973, 2008; Prinz, 1997). This is based on the conception that motor action is directed toward producing and controlling sensory input, rather than shaping motor output. If this view is correct, motor recovery should be highly dependent on learning which perceptions must be controlled in a given task. This process might be better defined as perceptual learning rather than motor learning (Friston et al., 2012). This interpretation is supported by findings in neurorehabilitation. Cerebral neuroimaging following motor lesion shows that cortical reorganisation is not limited to motor cortical regions but also occurs in spared sensory regions (Rossini et al., 2007; Ward & Frackowiak, 2006). In addition, movement practice with the hemiparetic limb tends only to promote functional gains when task-oriented (Langhorne et al., 2011, 2009; Van Peppen et al., 2004), suggesting individuals learn how to produce and control task-relevant perceptions in a task rather than reproduce a specific pattern of movements.

In practice, motor rehabilitation may fall short of potential recovery outcomes because individuals simply do not receive a sufficient volume of arm-hand training in either inpatient or outpatient settings (Hayward, Barker, & Brauer, 2010; Richards et al., 2008). In addition to task-orientation, practice should be high-intensity and repetitive (Bell, Wolke, Ortez, Jones, & Kerr, 2015; Langhorne et al., 2011, 2009; Turner-Stokes et al., 2005). This requires a pragmatic solution: an easily accessible training platform that individuals can use in their own time. One potential adjunct to therapy that might enable users to increase the volume of task-relevant practice is RT, particularly if devices could be set up within the user’s home (Wu, 2013; Kan, Huq, Hoey, Goetschalckx, & Mihailidis, 2011; Poli, Morone, Rosati, & Masiero, 2013; Weightman et al., 2011). Of the available device types, end-effector devices seem the most suitable option as they are simpler, easier to move and set up, and more cost effective than other device types, and support ADL task-oriented (Balasubramanian et al., 2010; Maciejasz et al., 2014). However, few are currently commercially available and while there is substantial evidence that they can reduce motor impairment, there is more limited evidence that they promote functional recovery in terms of increased ADL performance (Chen & Howard, 2014; Kwakkel et al., 2008; Prange et al., 2006). However, devices for distal upper limb training may be more efficacious for improving ADL performance, due to the involvement of the distal upper limb in most ADL tasks (Sivan, O'Connor, Makower, Levesley, & Bhakta, 2011), particularly if devices train closely emulate movements required in ADL tasks. Beyond the development of efficacious training devices, neurorehabilitation practice may benefit by developing training that is informed by contemporary findings in motor control theory.

Neurorehabilitation theory recognises the critical role of structural changes to CNS organisation on recovery of function and skills, and neuroimaging studies are beginning to elucidate this process (Cheung et al., 2015; Rossini et al., 2007; Ward, 2006). In addition, motor control theory provides mechanistic accounts of underlying neural processes which may be disrupted in individuals with neurological damage. Computational models of movement have been leveraged to test these hypothesised mechanisms. Early models were descriptive - transfer functions derived from measured data to characterise the response of the human motor system (Craik, 1947; Kreifeldt, 1965; Navas & Stark, 1968). In comparison, contemporary models are often based on theoretical accounts and are used to simulate specific characteristics and mirror the hierarchical functional architecture of the CNS. Prominent examples of such theoretical models are PCT, OFCT and AI.

OFCT and AI models have demonstrated how forward and inverse probabilistic models can account for optimal and smooth action trajectories in the face of sensor and neuronal noise (Todorov, 2004a; Brown et al., 2011). AI models have simulated oculomotor pursuit tracking to simulate anticipatory eye movements during occlusion of a visual target (Adams, Perrinet, & Friston, 2012). These formulations account for how neural noise is attenuated in sensorimotor systems. For example, in AI, top-down predictions regulate synaptic weights for bottom-up error signals according to the uncertainty (distribution of the error). This may yet prove to be critical for rehabilitation because sensorimotor noise may be amplified following neurologic injury and age (Hasson, Gelina, & Woo, 2016). PCT simulations have demonstrated that hierarchical and parallel control can account for simultaneous control of multiple DoF (Marken, 1986), and elucidated how varying reference values can give account for changes in motor responses when intentions, or the dynamics of the feedback function are altered (Marken & Powers, 1989; Powers, 1978). These studies will be reviewed in a Chapter 4. One benefit of PCT is that it expounds a method to identify which perceptions are controlled by an individual in a given task: the test for the controlled variable (TCV; Runkel, 1990). This confers a practicable benefit for rehabilitation robotics. That is, as perception and action are purported to share common representation within the CNS (Section 1.5.2.), it follows that individuals must learn (or relearn) to control task-critical perceptual variables.

Another specific advantage of the computational modelling approach for the field of motor rehabilitation is that individual characteristics can be parameterised via optimisation to individual performance. This method has a strong precedent in cognitive and behavioural neuroscience, such as in reinforcement learning (Will, Rutledge, Moutoussis, & Dolan, 2017), AI (Adams et al., 2012), OFCT (Haruno & Wolpert, 2005), and PCT (Bourbon, Copeland, Dyer, Harman, & Mosley, 1990a). In robotic rehabilitation, it has been proposed that parameters of performance can be measured and model on an individual basis and used to assess impairment (Allen et al., 2007; Au et al., 2010; Oishi et al., 2011), and may be used to determine the schedule of training and level of assistance on-line via adaptive algorithms (Marchal-crespo, Novak, Zimmerman, Lambercy, & Gassert, 2015) in visuomotor tracking tasks. This may be achieved most readily with theoretically-driven computational models rather than descriptive transfer function models as parameters attempt to map to CNS functional architecture. Leveraging theoretically-driven computational models, paired with end-effector rehabilitation devices and visuomotor tasks may therefore enable personalised therapeutic gains. Kinematic (regarding movement parameters) and task performance based data may be collected with the devices (Maciejasz et al., 2014), these data may then be used to optimise computational models to manipulate task constraints, feedback and assistance. This may be necessary due to the heterogeneity of impairment and recovery following neurological damage (Kwakkel et al., 2008, 1999; Turner-Stokes et al., 2005). Developing such algorithms to assess impairment, performance and parameters of movement would require fitting computational models to individual task performance. PCT may be uniquely placed to be integrated with robotics in this manner as it has been proposed as a foundational generalised architecture for the development of robotics, and has been validated in simple tests of robotic and control, such as the inverted pendulum, multi-joint arms, and autonomous vehicles

(Young, 2017). However, several critical limitations may pose a barrier to the application of PCT computational models to inform robotic rehabilitation (Chapter 4). In this thesis we attempt to investigate these research questions.

One specific limitation to current computational models is that while they areoften optimised to human performance and validated with individual data, no formal tests of individual-specificity of computational models have been conducted. That is, the benefit of individualised models over general models has not been quantified. Thus it is unclear whether individual models may be reliably used to predict individual performance and therefore be harnessed to produce adaptive algorithms to improve performance. Second, sensorimotor delays in the CNS must be compensated to produce accurately-timed movements (Rohde & Ernst, 2016; Scott, 2008), yet PCT models have typically not incorporated analogues of these delays within computational models. It has not been systematically investigated how these delays might impact model performance, nor whether PCT models can compensate delays during object tracking. Perceptual anticipation (Poulton, 1952a, 1952b) poses am additional, but related problem for the PCT model. Movements that take account of future target displacement, in addition to intrinsic sensorimotor delays, have been simulated previously by models with a forward component (Foulkes & Miall, 2000). It is unclear whether perceptual anticipation could be simulated with hierarchical feedback controllers. Finally, PCT models must be shown to generalise across task constraints and apparatus to be implemented across different rehabilitation devices and tasks, using the same fundamental principles.

1.7 Research agenda and thesis outline

In the current thesis we commenced a research agenda to aim to inform robotic rehabilitation of arm-hand skills through computational modelling of motor control. We decided to focus on one particular motor theory, PCT for the reasons outlined in the previous section. The overarching aim of the research agenda was to develop a computational model that could account for individual human performance in a tracking task based on principles of perceptual control theory. This model would then be implemented in an adaptive algorithm for an end-effector device for arm-hand rehabilitation, From this aim a number of key objectives were identified. These are split into three phases, summarised in Figure 1.1. This thesis aimed to complete phases one and two.

In the first phase, we conducted two systematic reviews to consider existing research that laid the foundations of the current project. The first review aimed to establish whether end-effector devices for restoring hand function are efficacious. The review determined that there was evidence that this approach to rehabilitation actually promotes recovery in people with motor disabilities following neurological damage, and therefore that it is a promising technology for development in the manner outlined above. A second objective was to evaluate the state of the evidence for perceptual control models in the extant literature of tracking studies in healthy adults. This clarified that the PCT computational models were well suited to simulating healthy human tracking performance. Limitations of the evidence base for PCT computational models of tracking were identified, these were: a) The lack of a test of, or evidence for, the individual-specificity of computational models optimised to individual human data; b) Sensorimotor delays have not been sufficiently implemented within PCT models, and the effect of such delays on performance has not been evaluated; c) PCT models have not simulated human anticipatory tracking behaviour.

In phase two, the limitations in the PCT evidence base identified in phase one were investigated further to develop a model that could comprehensively simulate human tracking performance. This model would then be implemented within an adaptive algorithm for end-effector rehabilitation device in phase three. Phase two consisted of a series of manual tracking experiments with software simulations that made a number of novel contributions to the tracking-modelling literature.

The first experimental study (Chapter 5) develops a novel method for evaluating the individual specificity of computational models and demonstrated that an individually-optimised PCT model could simulate performance with a greater degree of accuracy than a general PCT model.

The second experiment (Chapter 6) aimed to determine whether PCT feedback models could compensate for sensorimotor delays and simulate anticipatory behaviour. We developed and tested several PCT feedback architectures, utilising visual position and velocity information, and systematically increased the delay parameter within the PCT models to determine the effect that this would have on model fit performance. We found that the deleterious effect of increasing delay on model simulation accuracy could be mitigated by fitting a feedback models which controlled a representation of global motion (velocity and position) rather than position alone. This demonstrates the sufficiency of the PCT architecture for delay compensation and anticipatory behaviour provided the appropriate perceptual variable is controlled. The methodology of evaluating the model fit at a range of delay values was also a novel contribution.

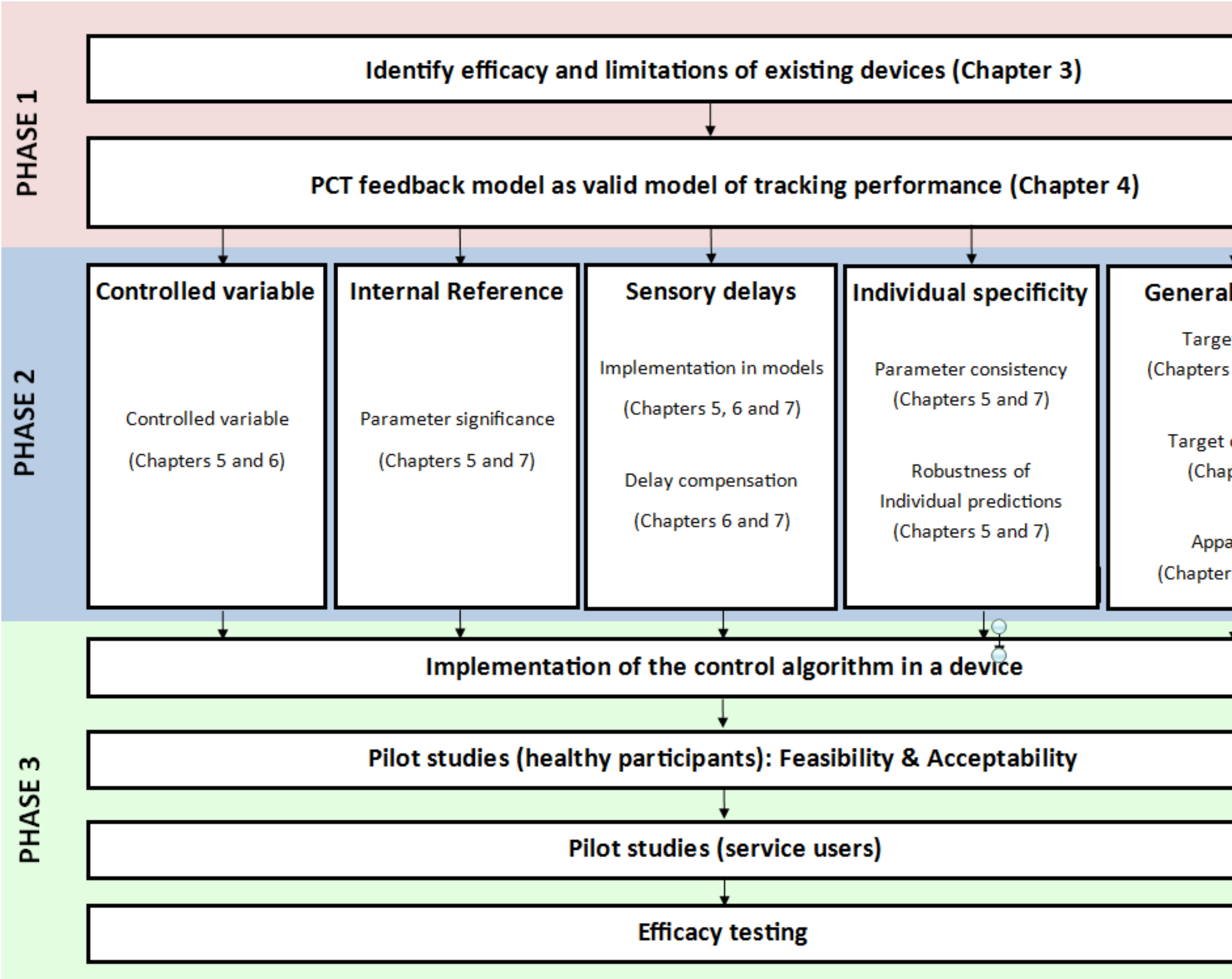
In the final experiment (Chapter 7) the superior model from Chapter 6 was optimised to individual tracking data and the test of individual-specificity developed in Chapter 5 was applied. This aimed to replicate the findings of Chapter 5 with a model of anticipatory performance. Several changes were made to the experimental procedure to additionally test the generalisability of the model across task constraints.

At the end of phase two (and of the thesis) we had a novel, improved, perceptual control model for implementation in a control algorithm for a rehabilitation device.

Phase three represents intended future work that aims toward implementing and testing a control algorithm for an end-effector device and evaluate the device with healthy and neurologically impaired populations. The device, driven by the PCT adaptive algorithm, should accurately track targets in order that it can provide assistance to a user while they attempt to track the target. Objectives in this phase of the agenda would focus on evaluating whether assistance or challenge can improve performance in healthy adults, and whether the device can simulate an individual's tracking movements. Key to the realisation of these goals would be to develop a learning algorithm such that the model optimises to track accurately (or track like the individual tracks).The final stages would involve safety and feasibility testing with the device, and finally evaluations with samples of individuals with motor impairments following neurologic injury.

In the current thesis, I present five chapters of original research that complete the first two phases of the research agenda.

Figure 1.1 Summary diagram of the research agenda



Chapter 2: General Method

2.1 Systematic review methods

2.1.1 Systematic review and meta-analysis of end-effector, distal upper-limb rehabilitation devices

End-effector distal upper-limb devices were chosen as the focus of the review for two reasons. Firstly, end-effector devices are low-cost peripherals with a proven safety record and a small footprint that are easily integrated with standard desktop computers. Thus they are good candidates for uptake in health services for home- and clinic- based training. Secondly, perceptual control models have previously been tested in tracking experiments with handheld devices such as joysticks and handles, as well as computerised mice. These models would therefore be well suited for simulating human interaction with such devices, and could also be used as controllers to drive these devices via force feedback.

We elected to use the systematic review approach. Systematic reviews allow for large amounts of research data to be condensed and synthesised into a palatable format, drawing robust conclusions based on high-quality research whilst filtering out redundant or low-quality findings (Mulrow, 1994). This method was suitable as there are many robotic devices for rehabilitation with very varied designs (Maciejasz et al., 2014). The systematic inclusion of devices and studies based on tight inclusion and exclusion criteria would enable the selection of a homogenous group of devices from which efficacy could be most robustly evaluated. Moreover, robotic rehabilitation devices differ widely in their level of development and implementation. Very few devices are commercially available or have undergone thorough testing in high-quality efficacy studies. Thus evaluating the methodological quality in terms of risk of bias is a necessary condition to assessing the efficacy of the devices. This is a fundamental aspect of the systematic review process which acts to control for conflation of conclusions from unreliable or invalid sources (Higgins et al., 2011; Smith, Devane, Begley, & Clarke, 2011). The most frequent outcome measure in the included studies was the Fugl-Meyer Upper Extremity Assessment (FMA; Fugl-Meyer, Jääskö, Leyman, Olsson, & Steglind, 1975), which was thus used in the meta-analysis to quantify the efficacy of hand and wrist rehabilitation with these devices, whilst controlling for methodological quality and sample size.

Unfortunately, very shortly prior to submission of the article to the intended journal (Journal of Neurorengineering and Rehabilitation), a very similar review was published (Veerbeek, Langbroek-Amersfoort, van Wegen, Meskers, & Kwakkel, 2016), which curtailed our ability to publish as we had intended. The review, as it was written for submission of JNER, is included in the thesis in Chapter 3.

2.1.2 Systematic review of the tracking modelling studies in perceptual control theory

Perceptual control theory was determined to be the most suitable theoretical mechanism to model human behaviour in the tracking task (for the rationale, see Chapter 1). Thus a systematic narrative review of modelling studies using perceptual control theory was necessary to evaluate the state of the evidence before conducting further experiments in the field. This would generate hypotheses and experimental designs that advance the research agenda to fill gaps in the existing literature and avoid hypotheses that have already been addressed. Addressing these issues would extend the evidence base to justify and enable the application of PCT models to rehabilitation devices. Moreover, it would provide methodological guidance and inform model building.

The review method was chosen for the same reasons as in the first review (Chapter 3). That is, the systematic narrative review method enables some confidence that all the relevant literature is included and evaluated. It was decided that a narrative review would be appropriate because of the range of hypotheses and experimental designs that would allow theoretically important themes to emerge. This is useful both because it aids comprehension of the results and their relevance, but also because it enables the state of the evidence to be evaluated across studies, that is, the extent to which each of the theoretical principles of the theory has been tested and received support.

2.2 Experimental methods

2.2.1 Tracking paradigm

Perceptual control has been most extensively tested within the tracking paradigm (Bourbon, 1996, 1999; Bourbon, Copeland, Dyer, Harman, & Mosley, 1990; Marken & Powers, 1989; Marken, 1986; Marken, 2013; Marken, 1991; Pavloski, Barron, & Hogue, 1990; Powers, 1978, 1989). As previously mentioned, the research agenda intended to 'fill gaps' in the research literature in order to derive a model that could drive an adaptive end-effector device for motor rehabilitation. Thus we also used the tracking paradigm.

Computerised tracking is a powerful experimental paradigm because it allows input signals and behaviours that occur in continuous time to be measured precisely and subsequently analysed (Powers, 1978). Moreover, the input signals and effector feedback function can be manipulated to alter the task. The temporal resolution of measurement is sufficiently high to capture relevant aspects of behaviour (Abdel-Malek & Marmarelis, 1988). The resultant data structure comprises momentary target positions, cursor positions, and time in sample intervals. These data can be easily extracted, analysed, and modelled in software environments such as Matlab.

Despite the tight experimental control offered by the tracking paradigm, the phenomenon under study in the task is critical to human performance (Bourbon & Powers, 1999). Visual tracking is fundamental to any process that relies on continuous visual perception, such as movement coordination (Rosenbaum, 1975). Manual tracking underpins object interception and avoidance, hand-eye coordination, and human-machine interaction such as steering to avoid obstacles whilst driving (Proteau, Roujoula, & Messier, 2009). The latter example is very relevant here as the output that an individual makes with his or her body does not match directly to the perceptual results. Instead a transformation occurs between the movements of the steering wheel and the movement of the vehicle (Gerisch, Staude, Wolf, & Bauch, 2013). This adds an extra level of complexity compared to tasks such as catching with one's hands, where the output actions actually determine the perceptual result (Marken, 2005). Many transformations such as these exist with tool use. These highlight the fact that the environmental feedback path lies not within the individual, but within his or her environment (Marken & Powers, 1989). Yet this does not affect the quality of the control of the individual's perception, as demonstrated by high performance in tracking tasks (Bourbon, 1996; Bourbon et al., 1990; Marken & Powers, 1989; Powers, 1978, 1989).

The tracking software used to collect data was the same for the first two experimental papers (Chapters 5 and 6), but a different program was used in Chapter 7. These will be outlined and compared in the following sections.

TrackAnalyze

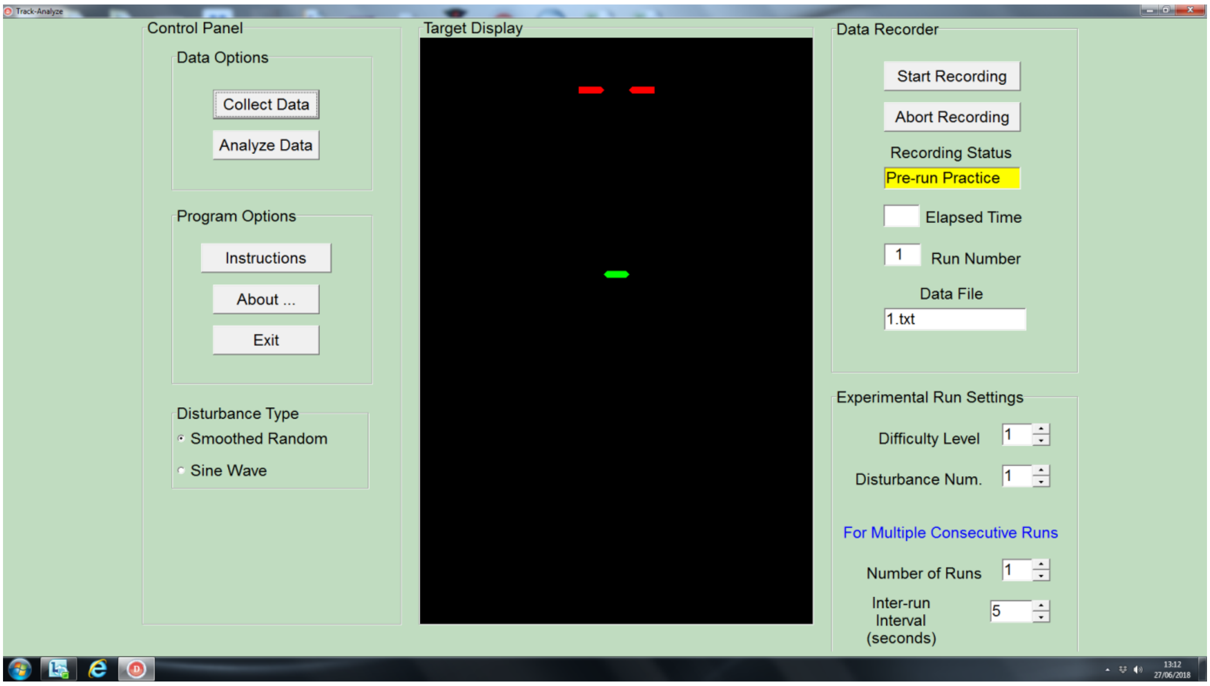
TrackAnalyze is a piece of computer software that was built for running demonstrations of perceptual control by William T. Powers and Bruce Abbott in 2008 (Powers, 2008). The program is coded in Object Pascal and runs on post-1995 Windows

Operating Systems. The code generates two separate windows.One window is used to run and collect experimental tracking data. A second window is used to import tracking data files, which can then be simulated in this window with a Position Control Model (PCM). Two adaptions to the program code were made by Bruce Abbott for our experiments. One enabled sinusoid signals to be generated and tracked. The second enabled the joystick to interface with the program.

Data collection window

The data collection window (Figure 2.1) allowed up to 15 one minute trials to be completed consecutively. Radio buttons allowed the experimenter to change the target pattern and difficulty level (speed) between ten signals that were generated upon opening the program (as outlined in Chapters 4 and 5). If consecutive trials were run the parameters of the models and the fit statistics, along with the target and cursor data would be saved to file automatically.

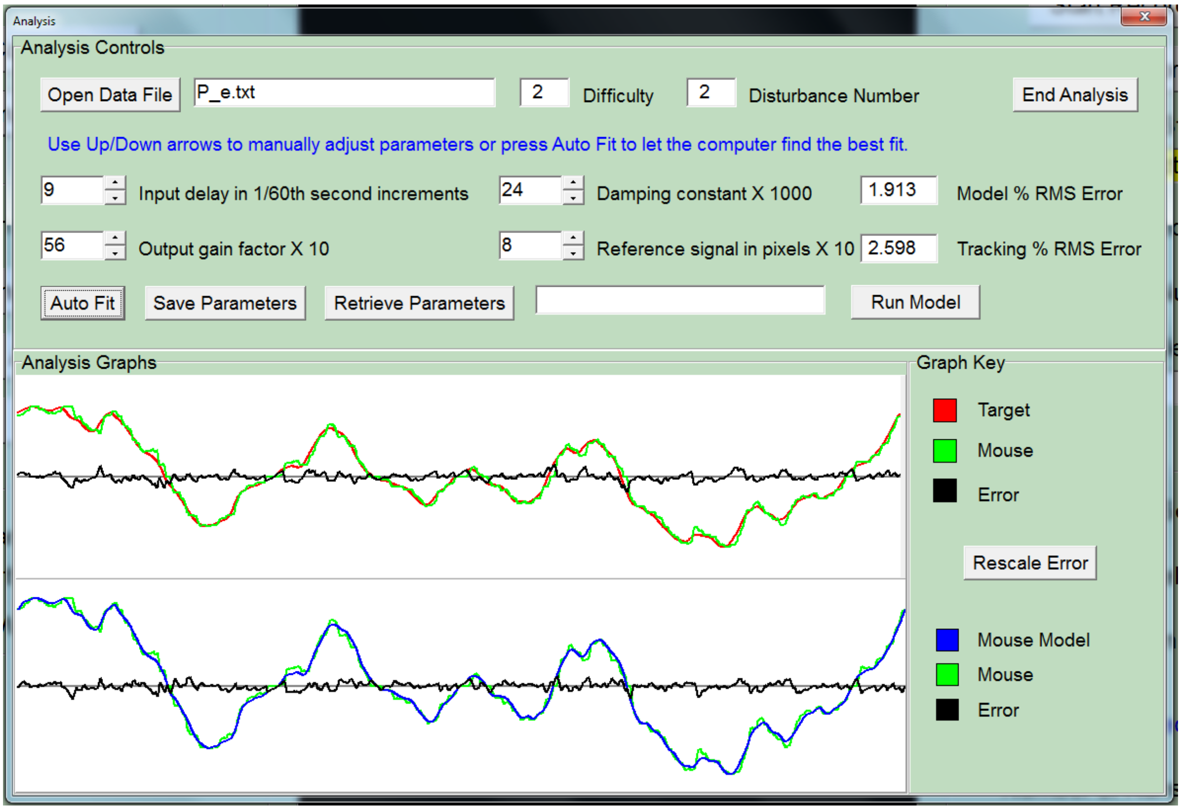
Figure 2.1 Screenshot of the data collection window: TrackAnalyze



Data analysis window

Model fitting could be conducted in the data analysis window (Figure 2.2). In this window, trial data could be loaded and a PCM could be optimised either manually, or by an automatic fitting routine. This optimisation algorithm was based on the principles of reorganisation in PCT. Parameters were independently altered to minimise the Root Mean Square Error (RMSE) value between the model-simulated cursor position and the human cursor position. The process changed each parameter recursively in the following order: Output gain, reference value, loop delay, damping constant. If a change increased the error, the next change would occur in the opposite direction. The magnitude of changes would decrease over multiple adaptations in the same direction. This was repeated 20 times for each parameter in the set, and then the set would be repeated five times with the final parameters as the initial conditions. The optimisation algorithm would cease if the change in error was smaller than a threshold tolerance level or after the five set iterations. The screen displayed graphs showing target and cursor time series across the one-minute trial being analysed. The upper graph contained the target time series (red), the participant cursor (green), along with the error (black) between the target and cursor. This error term, averaged over the course of the trial and scaled for the screen size is reported as the Tracking % RMSE. The lower graph displayed the participant cursor (green) and model-simulated cursor (blue), along with the error between the two cursors over time (black). This error term was used to calculate the model % RMSE value, which characterised the fit of the model cursor to the participant cursor. The maximum on-screen displacement was 19 cm for both the cursor and target.

Figure 2.2 Screenshot of the data analysis window: TrackAnalyze



TrackAnalyze contained some features that made data analysis difficult and time consuming. First, it did not store or export the model-simulated cursor trace; the output files only contained target and participant cursor positions. This restricted data analysis with the program. Second, whilst an optimisation algorithm could be used to fit the human tracking data currently loaded in the analysis window, it was not possible to load another set of parameters easily; often these had to be entered manually, which was time-consuming. This was necessary when fitting the individual model (average parameters from training) to test block data to validate the models, and for the self-aggregate analysis.

With regards to the second study, particular problems arose with TrackAnalyze because only the PCM could be selected, and all parameters were free in optimisation and could not be fixed at a value during optimisation. These reasons prompted the use of Matlab for data extraction, modelling, optimisation and preliminary data analysis in Chapter 6. TrackAnalyze was also difficult to edit as it was programmed in Object Pascal. For the final experimental study (Chapter 7), we required a tracking program that was compatible with the steering wheel, and easier access to change the program code to alter the design of the experiment.

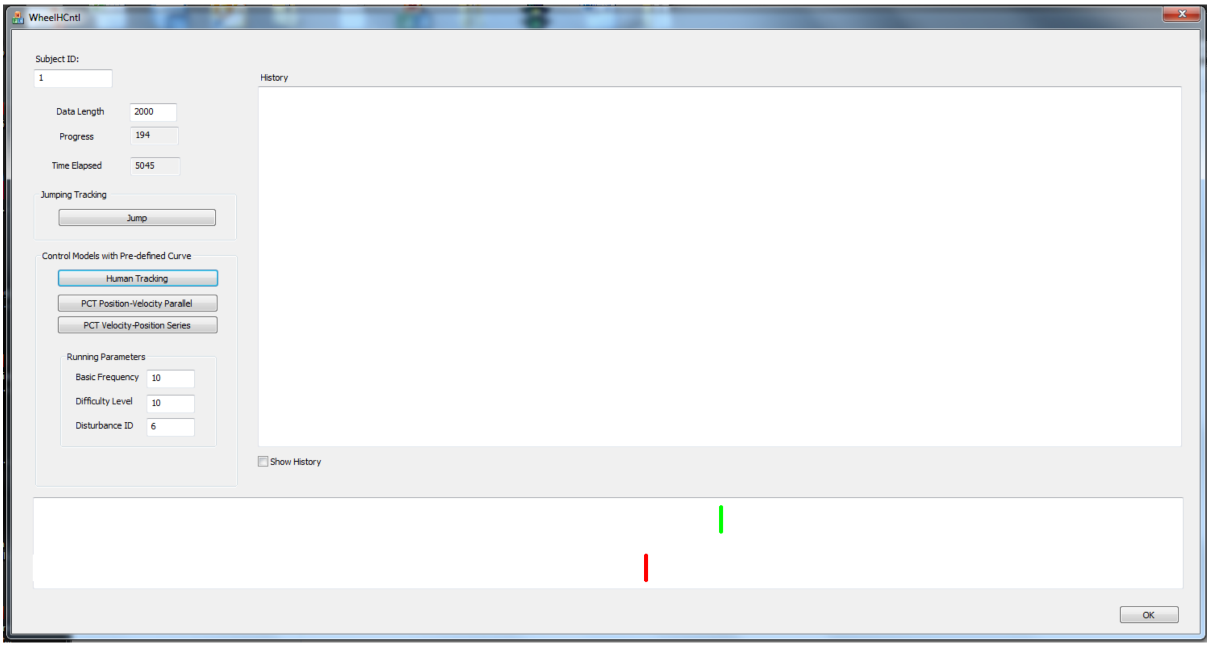
Finally, the optimisation algorithm did not run for a very large enough number of iterations and was very sensitive to local minima in the parameter landscape. Whilst this may not have been a problem for the four-parameter PCM, increasing the number of parameters may have challenged this optimisation algorithm and produced inadequate fits. The optimisation algorithm chosen for the subsequent experiments, the inbuilt Matlab function *lsqnonlin*, was significantly more powerful.

Custom tracking software

For Chapter 7, a second piece of tracking software was used (Figure 2.3). This was developed by Dr. Li, the computer programmer for the School of Psychological Sciences, in VisualStudio (C++). This program was developed based on my instructions in order to address several limitations with the TrackAnalyze program; liaison and feedback ensured that it fit the specifications that I set out. Firstly, it enabled the use of the ThrustMaster T300RS steering wheel rather than the SideWinder 2 joysticks that were used in the previous chapters. Secondly, the orientation of the tracking experiment was changed from vertical (y) to horizontal (x) as it better represented the perceptual results of moving a steering wheel in driving. Thirdly, the program allowed more flexibility to adapt tracking task constraints. The researcher could switch target characteristics 'on the fly'. Single sinusoid signals could be added together such that multiple sum-of-sines (pseudorandom) signals could be created. The fundamental frequency of the signal (the frequency of the lowest frequency component sinusoid) could be adapted to alter the speed the target moved at and therefore the difficulty, in a systematic way. The program sampled the target and cursor positions every 26 ms over each one-minute trial. No analysis window was present in this software so all modelling and data analyses were conducted in Matlab. Thus tracking data were exported to .csv files that would be imported into Matlab which had the functionality for model building. Throughout the project, models were adapted by Dr Li for this purpose within the software application, based on the instructions of the candidate. These can be identified in Figure Z by the radio buttons reading PCT Position-Velocity Parallel and PCT Velocity-Position series.

The maximum displacement of the cursor was 30.5 cm, the maximum displacement of the target was 28.5 cm.

Figure 2.3 Screenshot of the data collection window: custom tracking software



2.2.2 Individual modelling approach

Perceptual control theory promotes the use of the functional modelling approach, the aim of which is to establish the variables which the individual is controlling during a task, and predict their individual behaviour (Mansell & Huddy, 2018; Runkel, 1990). This is in stark contrast to the general linear model approach which aims to ascertain the relationship between an independent variable manipulation and a measured dependent variable across a group of individuals (Nelder & Wedderburn, 1972). Whilst the latter approach requires large sample sizes for sufficient power to generalise principles to populations, the functional modelling approach requires only one participant but a large volume of repeated measures data from that individual (Runkel, 2007).

In the functional modelling approach, a perceptual variable is hypothesised to be under control by a dynamical process, the mechanism of which is formalised in a computational model (Mansell & Huddy, 2018). The model is then optimised on a subset of the individual's data such that the parameters are determined that best fit that individual's performance. This model can then be validated with a second subset of the individual's data to establish whether the model makes accurate predictions of the individual's behaviour. Visual inspection of the model and human outputs side-by-side provides a test for face validity, whilst model simulation accuracy statistics can be produced (correlation coefficient or Root Mean Square Error (RMSE) to compare models

(Powers, 2008). The approach has two main advantages compared to group statistical modelling.

Firstly, models dynamically simulate the participant's behaviour during the task. This enables hypothesised mechanisms to be tested. If a model does not fit well, then it is unlikely that the variable included the model is the one the participant is controlling (Marken, 2014). Thus, whilst modelling does not allow us to be sure that the model replicates the mechanism that the participant uses, it can help to establish which models are unlikely candidates of the control process during the task. This is more powerful than statistical modelling of behavioural data with which one may learn of an association between inputs at the sample level, or even to estimate the output B given a specific value of input A, but does not indicate the mechanism (control law) by which the inputs interact.

A second advantage of the functional modelling approach is the inherent inclusion of individual differences in control characteristics and performance (Mansell & Huddy, 2018). Conversely, a general model cannot make specific predictions about individual behaviour. Predictions made by the individual modelling approach tend to be extremely highly accurate; approximately 98% of variance in individual behaviour can be accounted for by the model, even when the model is fitted to new targets (Bourbon, 1996; Bourbon et al., 1990). However, the individual modelling approach does not preclude group statistical analysis. Fitting individual models can be collated and analysed on a group level; allowing the advantages of both methods to be utilised. Both methods were used in tandem throughout the experimental work in this thesis (Chapters 5, 6 and 7). Group statistical analyses of individual model parameters were also conducted (Chapters 5 and 7).

I learned the individual modelling approach to pursuit tracking via the TrackAnalyze demonstration and materials of Living Control Systems III: The Fact of Control (Powers, 2008), in addition to self-directed reading of the PCT literature. The primary supervisor, Warren Mansell provided extensive support in the conceptual background to testing PCT. Many additional questions were addressed in correspondence with academics who work in PCT; notably, Dr. Abbott, Dr. Marken, Dr. Taylor and Prof. McClelland. Coding mathematical models and analysis scripts (Chapters 5 and 6) required additional learning, particularly of mathematics, control systems and programming in Matlab. I attended undergraduate mathematics modules (two semesters) and received regular tuition from Dr. Brown throughout the second year (approximately two hours per week). These sessions covered foundational control systems work, differential and difference equations, optimisation, system identification, and provided an initial introduction to Matlab. Unfortunately this tuition was brought to an end prematurely as Dr. Brown took sick leave. Therefore the remainder of learning, particularly in Matlab, was self-directed.

For Chapters 6 and 7, I extracted all tracking data from the tracking software as .csv files. I developed Matlab scripts to handle, extract and enter the data. I developed and wrote the computational models and analysis scripts.

2.2.3 Models of pursuit tracking

The foundational model used throughout the studies to model tracking performance was the PCM implemented in the analysis section of TrackAnalyze and adapted (unchanged) for use in Matlab. The PCM had four parameters (three free parameters when loop delay was constrained in Chapter 6). These were output gain, reference value and damping constant, in addition to loop delay.

I piloted a number of additional models to find a model that would adequately simulate tracking for sinusoid targets in Chapter 6. These models were assessed by four criteria:

a) Biological feasibility regarding sensorimotor delays
b) Adherence to principles of perceptual control theory
c) Parsimony (fewest parameters)
d) Model simulation accuracy (lowest would be best)

The methodology for testing the pilot models was to build alternative models, and optimise the model to the pilot data that was collected prior to data collection to test for bugs in the task and flaws in the experimental protocol. Five pilot participants' data were used. The pilot models would then be validated with data from a second data collection session. To meet criterion *a*, the models must have simulated performance as accurately, or more accurately than the PCM when model delays were 100 ms or above. This was assessed visually. Model simulation accuracy was also compared to the standard PCM. If overall control was substantially worse than the PCM, the pilot model was discarded.

Alternate models piloted were:

1) Proportional Integral Derivative (PID) position control (4 free parameters, 5 with loop delay)

PID control systems are abundant in control engineering applications. In fact, the perceptual control model is a Proportional Integral (PI) controller, a variant of the PID control that does not include a derivative component. The derivative component estimates the future rate of change of the error term based on its current rate of change and attempts to smooth the rate of change in the error to zero. This could potentially compensate for the effect of delay on performance. However, in practice the derivative component is very sensitive and can cause control instabilities. The piloted model did not produce accurate simulations of tracking performance at a biologically feasible delay value, only at particularly low delays (similar to regular PCT PI control) and was therefore rejected.

2) Parallel control of position of velocity (6 free parameters, 7 with loop delay)

In another pilot model, target-cursor position difference and target-cursor velocity difference were used as distinct inputs to two separate parallel controllers. Both controllers had a separate constant reference value, where the ideal reference values would be zero and zero respectively, but in practice were non-zero when fit to human performance. This model was consistent with perceptual control theory and gave very similar fits to the PCM while tracking pseudorandom and sinusoid targets. Thus it did not simulate sinusoid tracking accurately at longer delay values, and thus was not a suitable alternative model to the PCM and was rejected.

3) Hierarchical Control Model (HCM; 4 free parameters, 5 with loop delay)

Hierarchical models have a precedent in the PCT literature (Kennaway, 2004; Marken, 1986; Marken & Powers, 1989; Marken, 1990). The HCM is essentially the same as parallel control of the two perceptual variables, except that one control output (position) becomes the reference for the control output of the system below (velocity controller). This architecture was included in Chapter 6 as one of the comparison models. The HCM produced almost identical results to the parallel model outlined above. Whilst it did demonstrate marginal improvements relative to the PCM at longer delays when fitted to sinusoid tracking, simulation accuracy reduced as a function of increasing delay values similar to the PCM. This model was used in Chapter 6.

4) Position control plus target extrapolation (PEM; 4 free parameters, 5 with loop delay)

The PEM was included in Chapter 6. In this model, target velocity was measured with a delay. This velocity value was multiplied by a gain factor and added to the measured target position. This yielded an extrapolated target position. This extrapolated target position is taken from the delayed measured cursor position to form the error term for a usual PCM. Thus the extrapolation gain factor determines how far ahead or behind the target the model tracks and can be optimised separately for each individual. This model provides a similar fit to pseudorandom tracking performance compared to the PCM without extrapolation. For sinusoid targets, this model compares favourably to the PCM as the model simulation error does not increase significantly over the range of constrained delay values (See Chapter 6). This model was therefore a good alternative model to the PCM, as it fulfilled all the criteria and was implemented in the Chapter 6.

5) Hierarchical control with linear extrapolation of target position as the controlled variable (HEM; 5 free parameters, 6 with loop delay)

This architecture subsumes the theoretical propositions of the previous two models; that position and velocity inputs are integrated into an extrapolated position estimate and inputted to the position control unit, and, that the position control unit output is the reference for a downstream motor unit that outputs a velocity vector. In this model, a position extrapolation unit provides the reference value for a velocity control unit below it. This model implemented in both Chapters 6 and 7.

2.3 Experimental designs

2.3.1 Chapters 5 & 6

The data collection for the experiments in Chapters 5 and 6 was conducted within the same collection cycle. The primary hypothesis was originally to test the individual specificity of the models. However a secondary hypothesis was to establish whether a simple PCM could fit targets that were both unpredictable and highly predictable. I intended to optimise the models on one target type and fit to either the same target type or the other target type. Thus four conditions were included: one in which targets were pseudorandom in all three blocks, one in which sinusoid targets were tracked in all three blocks, and two conditions in which one target type was used in the first two blocks (session 1), but the other target type was tracked in the third block (session 2). Participants were randomly allocated to experimental conditions. The study included a difficulty titration procedure to ensure that participants tracked at approximately the same level of error to attempt to diminish the confounding effect of tracking performance on differential model fit. The experiment was run with TrackAnalyze and the Sidewinder Force Feedback 2 joystick (see later).

It became apparent during the analysis that participants' behaviour was qualitatively different when tracking pseudorandom and sinusoid targets, and that the PCM comprised very different parameter estimates for the two targets. Moreover, during the write up of these results we realised that the article aimed to address two broadly different groups of hypotheses. One group concerned individual specificity of the models, and the other concerned target predictability and model delays. My supervisors and I came to the conclusion that it would be best to split these into two separate research articles to enhance both readability and impact. Thus one study (Chapter 5) was conducted on individual specificity of the models in condition 1 (pseudorandom-pseudorandom). In Chapter 5, models were optimised to block 1 data (15 trials), and validated with block 2 and 3 data (15 trials each).

A second study (Chapter 6) investigated the disparity between parameters in models of sinusoid and pseudorandom tracking and thus used the two switching conditions (sinusoid-pseudorandom and pseudorandom-sinusoid). Block 1 was considered practice. Participants tracked different target types in blocks 2 and 3. In block 2 models were optimised to trials 6, 8, 10, 12, and 14, and validated on trials 7, 9, 11, 13, and 15. The same format was followed in block 3 for the other target type.

As previously mentioned, there were originally two hypotheses: whether models could show individual specificity, and whether models could simulate tracking of both predictable and unpredictable target patterns. Given the complexity of the two separate topics, we decided to split this into two research articles (Chapters 5 and 6) which would address each of these in turn and cross-reference each other.

2.3.2 Chapter 7

The experimental design was much the same in Chapter 7, although we attempted to address a number of key limitations with the first experimental design. The experimental procedure was still in the form of three blocks of data collection separated by one week. In this experiment, the speed of the target (fundamental frequency of the signal) was manipulated experimentally in a repeated measures fashion. Thus all participants tracked targets at the same difficulty levels. Secondly, the tracking software was designed such that each participant tracked the same set of target patterns. This contrasts with TrackAnalyze, which generates a new set of 10 pseudorandom target signals each time the program is opened. These adaptations served to minimise contributions to individual model parameters from task design.

The design for this experiment also comprised some additional aspects that have resulted in the acquisition of research data that has not been written up in paper format yet but allows for some additional tests of the theoretical models. This consisted of tracking data on unpredictable step input signals, and for sinusoid signals with a visual occlusion. The reason for collecting these is to, in future, draw further comparisons between feedback and prediction accounts of tracking behaviour. Irregular step input signals should enable only a position control strategy because there is no velocity or acceleration information available to the user. Although the time step is kept constant (1s) the user cannot predict the direction or size of the target 'jump'. In contrast, tracking over a visual occlusion of the predictable sinusoid target does not allow for position, velocity or acceleration comparison between the target and cursor. Thus the individual must use a stored representation of the target trajectory to maintain performance. Occlusion studies indicate that participants tend to track the amplitude of a predictable target accurately but tend to produce cursor movements at a non-constant phase relationship with the target (Fine, Ward, & Amazeen, 2014). That is, their tracking movements become increasingly phase delayed over the occluded duration. Models should be able to account for performance within both these conditions.

To advance the research agenda to apply PCT models to rehabilitation requires a test of whether a computational model can drive a device to replicate human tracking performance. We have made substantial progress with this aim within the PhD project. Initially, we attempted this with the force feedback joystick. This proved very difficult because the force required for a comparable displacement of cursor position increases as a function of angular deviation from 90 degrees (upright) joystick position. The force requirements can therefore be considered non-linear. This poses a significant challenge for models. We switched to a one DoF device, a steering wheel and linear force requirements.

Models can currently drive the steering wheel to produce cursor movements in real time that visually approximate human-like performance in the tracking task. However, these have to be optimised manually.

2.4 Apparatus

2.4.1 Microsoft Sidewinder Force Feedback 2 Joystick

The force feedback joystick was acquired because of its low cost, and easy compatibility with TrackAnalyze. A picture of the joystick is shown in Figure 2.4. Moreover, it is a powered end-effector, and such joysticks have been adapted into assistive rehabilitation device (Preston et al., 2014). Tracking can be performed with a mouse, but computer mice do not contain force feedback capabilities and thus there was no possible translation to rehabilitation robotics.

Figure 2.4 Image of the Microsoft Sidewinder Force Feedback 2 Joystick

The joystick had a number of limitations for use in tracking experiments. Firstly, it had some inherent stickiness in the centre that tended to cause a minor perturbation to movements when crossing the centre line that affected the cursor trace. Whilst this was the same across all participants and conditions, it could affect model fitting. In a general sense, the joystick is not wholly appropriate for the task because it has two degrees of freedom whilst the tracking task we used had only one. Therefore any displacements on the horizontal axis were not recorded, even when these may have had an effect on cursor position in the measured axis.

The extended aim of the research programme was to develop an assistive rehabilitation device, which would need to be driven by the computational models to track accurately. As the joystick rotates on a ball, there is a non-linear relationship between joystick position and the force required to move the joystick. At the poles of the range of movement the joystick experiences substantially more inertia than when it is positioned directly over the centre of the ball. This is problematic for the control model, which does not explicitly account for the non-linear dynamics of the joystick. For the second data collection cycle we opted to use a force feedback steering wheel.

2.4.2 ThrustMaster T300RS Force feedback steering wheel

The steering wheel cost £250 (figure 2.5). Two units were acquired, one for participant testing and one for software development. The steering wheel range of movement was 1080 degrees and the maximum torque output is 4 newton metres.

Figure 2.5 Image of the ThrustMaster T300RS steering wheel

The steering wheel conferred several advantages over the joystick. Firstly, there was no stickiness when the steering wheel was rotated; in fact the movement across the whole range was much smoother than with the joystick. This should eliminate a higher proportion of noise that is not due to the individual's dynamics. Secondly, as a one DoF device, it was restricted simply to rotation on the central axis. This meant that all movement was recorded in the one-dimensional tracking task. Third, the steering wheel could apply sufficient torque to produce movements of the wheel whilst the participant was holding it, and thus could potentially be used to provide assistive force as per the aim to develop a control algorithm for a rehabilitation robot. Finally, steering wheel and joystick manipulation require a very different array of movements to produce the same on-screen cursor displacement. By changing the device we would be able to demonstrate the model could generalise across different task constraints (horizontal tracking with the steering wheel). This would support the hypothesis that the individual was controlling a perceptual relationship (target-cursor alignment) but that the task constraints and actual produced movements in the task were inconsequential.

Moving to a single DoF device was assumed to alleviate some of the difficulties that we experienced in attempting to use computational models to drive the device. Piloting established that this was correct; models were more accurate when controlling the steering wheel than when they controlled the joystick. This may both be due to the increased smoothness of the steering wheel and the linear relationship between output torque and cursor position.

2.5 Data extraction

The data were extracted manually in Chapter 5. This was incredibly time-intensive. In Chapters 5 and 6, data were extracted via Matlab. The recorded cursor and target positions for each trial were sequentially loaded into Matlab and the models were optimised to the data at each of a given range of delay values determined by an integer number of samples. All fit statistics were generated at this stage and stored in excel files along with the parameter values at each value of delay.

In Chapter 6, the best fitting model for each delay was selected (lowest model simulation error) to form the individual model. These model parameters were then plugged in during the model validation stage. The model validation scripts would fit models with these parameters to the validation data. Spectral analysis was conducted with participant target signals, cursors, and model-simulated cursors at 200 ms. Finally, all resulting data were outputted to excel files in a format appropriate for import into SPSS and other statistical software packages. The whole process was automated from a central master script.

In Chapter 7, there was an additional stage of extraction due to the number of different target types used, and the validation of models to trials in different blocks. The models were optimised to individual performance at each of the delay values for each trial. These were then extracted by a separate script to derive the best fitting individual model for each target type. This file would be automatically pasted into the folders containing the validation files for that individual, such that the model validation scripts had access to the model parameters. Once more, the whole modelling and optimisation process was automated, and the final output was a large excel sheet with model fit data for both models for all target types. Spectral analysis was also conducted to establish the amplitude ratio and phase delay of the cursor relative to the target and the model-simulated cursor relative to the participant cursor for each optimum model.

In Chapter 7 there was an additional master script. This utilised the extracted individual model parameters from the files in the first block folders, and ran the validation procedure with these parameters for every individual's validation data. This process was also entirely automated.

2.6 Statistical analyses

Statistical analyses were conducted in either SPSS or Stata. SPSS was used for running ANOVAs with average data. However, given that each participant had many repeated measurements within each block, where appropriate a mixed model was used such that all data could be analysed for each individual, this was conducted in Stata. Choice of statistical analyses are broken down by paper in the next section

2.6.1 Chapter 3

A meta-analysis was conducted to determine the overall efficacy of the robots on Fugl-Meyer Upper Extremity scores. This required extraction of the relevant statistics from the articles where they were available, and transforming effect sizes into the same measure (Cohen's d). Following this, the effect sizes had to be weighted based on their sample size. The plots were generated in RevMan 5.

2.6.2 Chapter 5

This experiment focused on individual differences and individual specificity of the models. Thus the analyses selected addressed these hypotheses. Two separate measures of internal consistency were used; intra-class correlations and Cronbach's alpha. The former used the whole dataset whilst the latter used average data. Both methods were used to ensure that the high intra-individual consistency in average measurements also applied across individual trials.

It was not initially clear which statistical method would be most appropriate to detect individual differences in parameter estimates. In a meeting with the statistician, Dr Emsley, the potential use of linear mixed regression with participant as a random effect variable was discussed. A follow-up intra-class correlation would have established the proportion of variance that was accounted for by the participant variable. Ultimately this methodology was not used because of the precedent in the literature to investigate individual differences in parameters using an independent groups ANOVA with participant as an independent variable (Viviani, Campadelli, & Mounoud, 1987). We replicated this analysis within our sample for each of the model parameters.

An analysis was run to establish whether each individual's data were more accurately simulated by a model of their previous performance or by a general model (self-aggregate analysis). This was conducted with a repeated measures ANOVA. Dr. Emsley, advised using weighted averages of model fit statistics to account for large variability in model fit between individual models that comprised the aggregate 'aggregate' models further details are found in Chapter 5.

2.6.3 Chapter 6

In the second experimental study, we collected model fit data across a range of loop delay values for each participant. This posed a potential issue for statistical analysis because it would be unwieldly to test for differences between every delay value for each target and model. Initially we collected data for only 6 values of loop delay (17 ms, 50 ms, 100 ms, 150 ms, 200 ms and 300 ms). The article was written up such that in Experiment 1, ANOVAs and post-hoc t tests determined where statistical differences existed between every delay value. This determined that the 200 ms delay formed the optimum fit for pseudorandom targets. This replicated the estimated delay during tracking from previous studies ms (Khoramshahi, Shukla, & Billard, 2014; Parker et al., 2017; Viviani & Mounoud, 1987; Yu, Gillespie, Freudenberg, & Cook, 2014) , and the mean loop delays estimated for pseudorandom tracking in our first study (Chapter 4). Thus 200 ms was selected for further comparisons of the different models in Experiment 2 of Chapter 6. A repeated measures ANOVA was conducted for each target type, including the different models, and simulation accuracy was compared at 200 ms, and 17 ms. Further the difference in accuracy between 17 ms and 200 ms within each model was assessed.

When the paper was sent to the collaborator (Dr. Abbott) in March 2018, he raised concerns over the model architectures in Experiment 2. A lengthy period of discussion and piloting ensued to select alternate model architectures for the position model which would be more appropriate. Once the candidate model architectures were decided upon (April 2018), the data had to be remodelled. At this point, I had completed modelling for the next study (Chapter 7) and had advanced my programming skills further. When remodelling the results (end April 2018), I adapted the scripts to improve efficiency and altered several aspects of the modelling procedure. One significant change was the addition of statistical criteria to disambiguate the contributions of timing and amplitude errors to overall RMS error between two signals. Three parameters were calculated: Amplitude ratio, phase, and coherence.

First, time series signals were converted to the frequency domain by fourier transform. This transform determines the ratio of excited frequencies in a given signal (spectral power). Signals can then be compared within frequency bands. For example, a sinusoid target signal at .01 Hz in the time domain would produce a spike in the frequency domain at around .01 Hz. The participant’s cursor signal can then be compared with the target signal at this frequency. The magnitude of the real part of the power at a given frequency is the amplitude of the signal at that frequency. The relative amplitude of two signals at .01 Hz gives the amplitude ratio: the difference in magnitude of the target sinusoid and the movements of the cursor at that approximate frequency. The imaginary part of the number gives the phase. Phase represents any asynchrony between two signals at the frequency of interest. This is an angle, usually expressed in radians. In the current studies I converted this to a phase delay in time (ms) in order to express the tracking delay or advance relative to the target. Coherence is calculated by correlating the signals within the frequency domain, and thus gives an accuracy statistic, the relationship between the two signals across the range of frequencies present in the target signal, for example.

These three statistics enabled the independent characterisation of overshoot and undershoot (amplitude ratio) and time delays (phase delays) between target signals, cursor signals and model-simulated cursor signals. These statistics were calculated in Chapters 6 and 7 alongside RMSE.

In addition, the number of loop delay values over which the RMSE values were computed was extended in Chapter 6 to eleven values: 17 ms, 50 ms, 100 ms, 150 ms, 200 ms, 250 ms, 300 ms, 350 ms, 400 ms, 450 ms, 500 ms. Whilst this improved the methodological clarity of the study, it increased the complexity of the statistical analysis. Thus I opted to change the analysis method. A quadratic mixed effects regression model was used, where delay value was the predictor variable, model simulation error was the outcome variable and participant number was a random effect. This had two advantages. Firstly it enabled all data to be used rather than simply the average data for each participant. Second, it would result in the pattern of fit across delay values to be established without requiring numerous comparison t-tests to be conducted, which would have increased the likelihood of type I errors. Conversely, any correction would hugely increase the likelihood of type II errors. Following the regression models, comparison t-tests were conducted only for differences at 17 ms and 200 ms, for the reasons described in the previous paragraph. This method was used throughout the chapter and both regression equations and mean data were presented in graph format.

To conduct this quadratic mixed regression model, I adapted the guidance given by Dr. Emsley for a potential analysis in the previous chapter. I had learned to use Stata at that time and applied this knowledge to the current problem.

2.6.4 Chapter 7

This article used similar statistical methods as Chapter 5 with a few critical differences. First, model accuracy statistics (including phase and amplitude ratio estimates) were computed with one set of model parameters per participant. This set was the optimised to reduce model RMSE to a minimum value. In addition, the repeated measures ANOVAs only contained one independent variable in the study; block. In Chapter 7, three additional independent variables were added. Firstly, sinusoid targets were also modelled in addition to pseudorandom targets. Difficulty level was a second additional independent variable. Finally, there were two models rather than a single model. The resultant ANOVAs were thus large, three-way or four-way ANOVAs. The method of breaking down interactions into smaller ANOVAs was followed. The parameter regression was conducted in the same way as in Chapter 5. However, unlike in Chapter 5, we did not have optimisation data for all three blocks, therefore regression of parameter values and model fit could only be conducted within block 1.

2.6.5 Limitations of statistical analyses

In the first experiment (Chapter 4) we could not generate correlations in addition to model simulation Root Mean Square Error (RMSE) because the TrackAnalyze program did not output the simulated cursor positions nor provide a correlation coefficient in the readout. Ideally, in modelling, authors should report both correlation coefficients and a measure of error because it would be possible to have a highly correlated model that produces high error in fit, and similarly also possible to have a poorly correlated model with a reasonable fit (if there is a lot of signal noise). When data were analysed in Matlab in the second and third experiments (Chapters 5 and 6), this shortcoming was addressed by reporting correlation coefficients.

An additional statistical issue arose in difficulty titration procedure in the first study (Chapter 4). This procedure meant that participant’s tracked targets at different difficulty levels (target speeds) dependent on their ability in the task. This added a potential confound to the analysis as different speeds at the difficulty levels may have affected model parameters, inflating the individual differences between participants at different speed levels. This confound was ameliorated by running additional identical analyses on a subgroup that contained all the participants that completed the task at the middle difficulty (13 individuals). In Chapter 5, all 24 participants completed the experiment on the same difficulty level (difficulty level 2), this avoided the potential confound. In the final experimental study (Chapter 7), no difficulty titration procedure was used as difficulty level was manipulated (by adapting the fundamental frequency of sinusoid and pseudorandom signals).

2.7 Summary of methodologies used

This thesis reports three tracking studies and two systematic reviews. I personally conducted the literature search and screening for the first systematic review (Chapter 2), along with all extraction and analysis. For the second review, I conducted the literature search. Andrew Willett (summer intern undergraduate psychology) assisted in screening of the abstracts and full texts against the inclusion and exclusion criteria. I completed all extraction and analysis.

In both the first and second experimental studies (Chapters 5 and 6), the data were collected at the same time (80 participants). I collected all participant data using a program (TrackAnalyze) developed by Bruce Abbott and William Powers. This program was adapted by Bruce Abbott for these experiments. For the first experimental study only one of the four conditions (20 participants) were analysed. I conducted all the modelling within this program and ran statistical analyses in SPSS.

For the second experiment, two more conditions were used (40 participants). This left on condition (20 participants' data) that have not been analysed. I modelled the data in Matlab and analysed the data in SPSS and Stata.

The data for the final tracking experiment I collected participant data in a program developed by Dr Li. Data were collected on four different target types. Two of these (pseudorandom and sinusoid) were modelled and analysed for all 24 participants and reported in the paper. The remaining data for the other two targets (step signal and sinusoid with occlusion) are not reported in the thesis but I intend to analyse in future articles. I modelled the data in Matlab and analysed the data in SPSS.

I wrote all articles of the thesis. Comments and edits were suggested by the authors of each manuscript, and I made the corrections. Additional work was conducted to pilot the use of models in driving the force feedback steering wheel, this is not been reported within the thesis but we intend to write future research articles on this. Together, this work provides the foundational work towards development of an adaptive controller for an end-effector upper limb rehabilitation device, inspired by PCT.

Chapter 3: Home-based Rehabilitation: A Meta-analysis of End-effector Devices for Hand and Wrist Rehabilitation

Target Journal: *Journal of NeuroEngineering and Rehabilitation*

Maximilian G. Parker[1], Andrew P. Weightman[2], Warren Mansell[1] & Sarah F. Tyson[3]

Author Affiliations:

[1]Division of Psychology and Mental Health, School of Psychological Sciences, University of

Manchester

[2]Division of Nursing, Midwifery and Social Work, University of Manchester

[3]School of Mechanical, Aerospace and Civil Engineering, University of Manchester

3.1 Abstract

Aim: To assess the efficacy of distal end-effector training for reducing hand impairment and increasing functional abilities in patients with neurological conditions.

Methods: A systematic review was conducted in Scopus, PubMed, and IEEE Xplore up to December 2016. Studies were included that trained three or more individuals with neurological diagnosis with a distal end-effector device and data on one on more clinical outcome measure. All studies evaluated for risk of bias using the Cochrane risk of bias tool. A meta-analysis was conducted, pooling Fugl-Meyer test of Upper Extrimity (FM-UE) scores across six randomised control trials of training with the BiManuTrack device.

Results: Twenty-three clinical studies (eight devices) were included. Nine studies were Randomised control trials (RCT), 13 were uncontrolled pilot studies, and one was an uncontrolled randomised comparative trial. The participant pool was totalled 389 participants; 371 of these were adults stroke patients, 18 were children with Cerebral Palsy (CP). RCTs presented low risk of bias and consistently reported reductions in arm and hand impairment following training, and functional improvements as measured by self-report activity and participation measures. The meta-analysis showed no overall benefit of RT over conventional therapeutic methods. The pilot studies were assessed to have a high risk of bias. These also reported reductions in impairment and several studies report functional improvements. The studies varied widely in intervention length, and intensity. Clinical outcome measures were varied and many of the pilot studies did not include a follow-up.

Conclusion: There is strong evidence that distal upper limb, end-effector, RT can be efficacious in reducing impairment in stroke patients of all stages. There is some evidence that training improves functional outcomes for stroke patients. There is not a sufficient literature of trails to draw conclusions regarding efficacy in populations other than stroke.

3.2 Introduction

Neurological conditions such as stroke, CP, MS, spinal cord injury (SCI), and PD often result in profound motor impairments such as plegia, paresis, and spasticity, apraxia and coordination deficits, often in addition to sensory deficits and cognitive symptoms. The incidence of these conditions is very high, and incurs considerable economic and personal cost. In the UK over 200 individuals out of every 100,000 are diagnosed with having their first stroke every year in the UK (MacDonald, 2000), amounting to approximately 130,000 new diagnoses per year. The direct and indirect costs associated total to £7bn per annum in UK for stroke alone (MacDonald, 2000). Motor impairments frequently affect individuals' ability to perform ADL impacting their independence and quality of life (Bamdad, Zarshenas, & Auais, 2015; Imms, 2008; Ingall, 2004; Maher, Hons, Williams, Physio, & Cert, 2007). Dextrous movement of the wrist and hand is critical to performing such actions, yet impairments of the hand are both common and persistent (Timmermans, Seelen, Willmann, & Kingma, 2009). While individuals may recover function naturally, physical and occupational therapy are employed to facilitate recovery of motor abilities and maintain such abilities from deterioration.

Whilst it has been extensively demonstrated that repetition, intensity and task-specificity in active movement practice are key to optimal motor rehabilitation outcomes (Feys et al., 2004; Langhorne et al., 2011, 2009; Van Peppen et al., 2004), providing this level of high-intensity practice often requires one-to-one physical therapy and is labour-intensive and costly for health services (Barreca, Wolf, Fasoli, & Bohannon, 2003). Due to time and labour constraints services are stretched; Inpatient stroke survivors receive on average only 4 minutes of arm-hand training during rehabilitation therapy sessions, five times per week (Hayward & Brauer, 2015).

Robotic rehabilitation training provides an interactive and engaging platform for patients to practise movements safely with minimal therapist supervision, and could potentially be used as an adjunct to PT to enable patients to accumulate more practice than would usually be possible, potentially at reduced cost as robots become cheaper and more widely available (Wagner et al., 2011). A large number of devices have been developed (Maciejasz et al., 2014). There is growing evidence for the therapeutic benefit of such robotic devices for UL rehabilitation in stroke patients.

A number of systematic reviews of randomised control trials (RCTs) with commercialised robotic devices have been conducted that have shown that UL robotic devices can improve motor outcomes (Prange et al., 2006), (Kwakkel et al., 2008). Proximal upper limb (UL) rehabilitation in stroke patients found that RT is effective in reducing proximal UL impairment. However, these improvements do not generalise to the distal UL (hand and wrist), or improved users' ability to perform ADL (Basteris et al., 2014; Kwakkel et al., 2008). In contrast, RT of the distal UL can generalise to the proximal UL and reduce whole-arm motor impairment (Buttefisch, Hummelsheim, & Denzler, 1995; Krebs et al., 2007; Lambercy et al., 2011; Takahashi, Der-Yeghiaian, Le, Motiwala, & Cramer, 2008a) which may facilitate functional improvements due to the key role of the hand in everyday tasks (Sivan et al., 2011). Consequently, many devices to train the hand and wrist have been developed.

Exoskeleton and modular devices tend to support a large range of individual or synergistic movements throughout the whole limb and have a large number of degrees of freedom (DoF). Due to their complexity they tend to be expensive and take a long time to set up. Whilst commercialised modular and end-effector devices such as ArmeoPower and the MIT-Manus (inMotion) have been rigorously tested and shown to be efficacious, these devices have not been adopted by health services. This is likely due to the high cost of purchasing and maintaining devices. In contrast, end-effector devices tend to have fewer DoF and support a specific functional, task-oriented movement. These tend to be cheaper than exoskeletons and easier to use, with a smaller footprint. Comparisons of devices findings in lower limb RT have found end-effector devices to be of greater benefit than exoskeleton devices in improving gait in stroke patients (Mehrholz, Elsner, Werner, Kugler, & Pohl, 2013; Mehrholz & Pohl, 2012). It could be that as end-effectors do not constrain DoF at joints and therefore allows the patient to 'teach themselves' the muscle-joint configurations that enable them to complete tasks effectively, which might transfer to task performance when not using the robot. Distal UL end-effectors may therefore be a more suitable and efficacious adjunct to therapist-based interventions in the home or clinic (Balasubramanian et al., 2010; Brackenridge, Bradnam, Lennon, Costi, & Hobbs, 2016).

Previous reviews of distal UL RT have considered both end-effector, modular and exoskeleton systems and have only investigated efficacy in stroke patients (Balasubramanian et al., 2010; Lum, Godfrey, Brokaw, Holley, & Nichols, 2012). This scoping review aims to assess the efficacy of currently tested end-effector robotic devices that have been used for distal UL rehabilitation in patients with motor impairments across neurological diagnoses. We have three focused research questions: 1) Are distal end-effector devices suitable for those with motor problems due to a neurological condition other than stroke? 2) Does distal end-effector RT reduce impairment in the distal and proximal upper limb in stroke patients? 3) Does distal end-effector RT lead to improved functional abilities in stroke patients as measured by activity/participation outcome measures?

3.3 Method

3.3.1 Literature Search

A literature search was conducted in the Scopus, PubMed, and IEEE Xplore databases to identify end-effector devices that have been used for distal upper extremity rehabilitation in clinical trials published between 1990 and 2016[1] The following MeSH search terms were used: robot*, rehabilit*, train*, assist*, and hand, wrist, OR upper+extremity, upper+limb, distal. Reference and citation searches of selected papers were conducted to identify further studies suitable for inclusion. Articles were included if they fit the following criteria: (1) study used an end effector robotic or mechanical rehabilitation device to train distal upper limb movements, (2) Study assessed clinical outcome measures over the intervention period (pre-test, post-test design, (3) study used samples of three or more individuals with upper extremity motor impairment as a result of a neurological condition. RCTs comparing RT with occupational or physical therapy or a control therapy were included. Articles were excluded if: (1) the device used was not electrically or mechanically actuated, or required neural measurement or stimulation, (2) device was not an end-effector device (exoskeletons, modular devices, orthoses, gloves). In addition, comparative articles were excluded if (3) the comparisons were between individual robotic therapy and a non-control therapy, (4) the article was published in a language other than English.

Database searches and abstract screening were conducted by the first author (MP). Where any uncertainty regarding a device or study inclusion existed, inclusion decisions were decided by all authors. Data were extracted by the first author. Device design

[1] The database search was conducted a second time in September 2018 by the first author. These results are reported separately as their interpretation could be biased by the findings of the present review.

features, study design features, samples, training modalities and intervention protocol, assessment schedule, statistical methods, and clinical outcome data were extracted and tabulated.

3.3.2 Data Analysis

Risk of bias assessment

The first author assessed the risk of bias for each study included in the review using the Cochrane risk of bias assessment tool (Higgins et al., 2011); designed to give an indication which studies are more methodologically robust, and which findings should be interpreted with caution. The following risk criteria were evaluated: Sequence generation, allocation concealment, outcome assessor blinding, incomplete outcome data, selective reporting of outcome data. Two items from the tool were removed from the original checklist as they were not relevant to the selected studies: Blinding of participants and personnel, blinding of patient-reported outcomes. For each study, risk of bias on any one criterion was rated as either: high, low or unclear. N/A was reported where criteria were not relevant to study design.

Analysis

A pooled quantitative analysis will be conducted to compare the efficacy of training with robotic therapy against control treatments for each device which has been tested in multiple RCTs. As not all selected studies will include a control group, an additional narrative analysis of study designs, interventions, devices and outcomes will be provided.

3.4 Results

3.4.1 Results of the search

The literature search identified 3,581 records, of which 307 were screened for inclusion. Of these, 28 articles fit the inclusion criteria and were selected for the review. This yielded 23 clinical studies of eight devices. These studies could be further categorised into RCTs comparing the effects of robotic therapy with conventional therapist based interventions (nine studies), one uncontrolled randomised comparative trial, and pre-post training efficacy comparisons within a single patient group (13 studies). Figure 3.1 shows A PRISMA flowchart of the data extraction process

Literature search update 2018

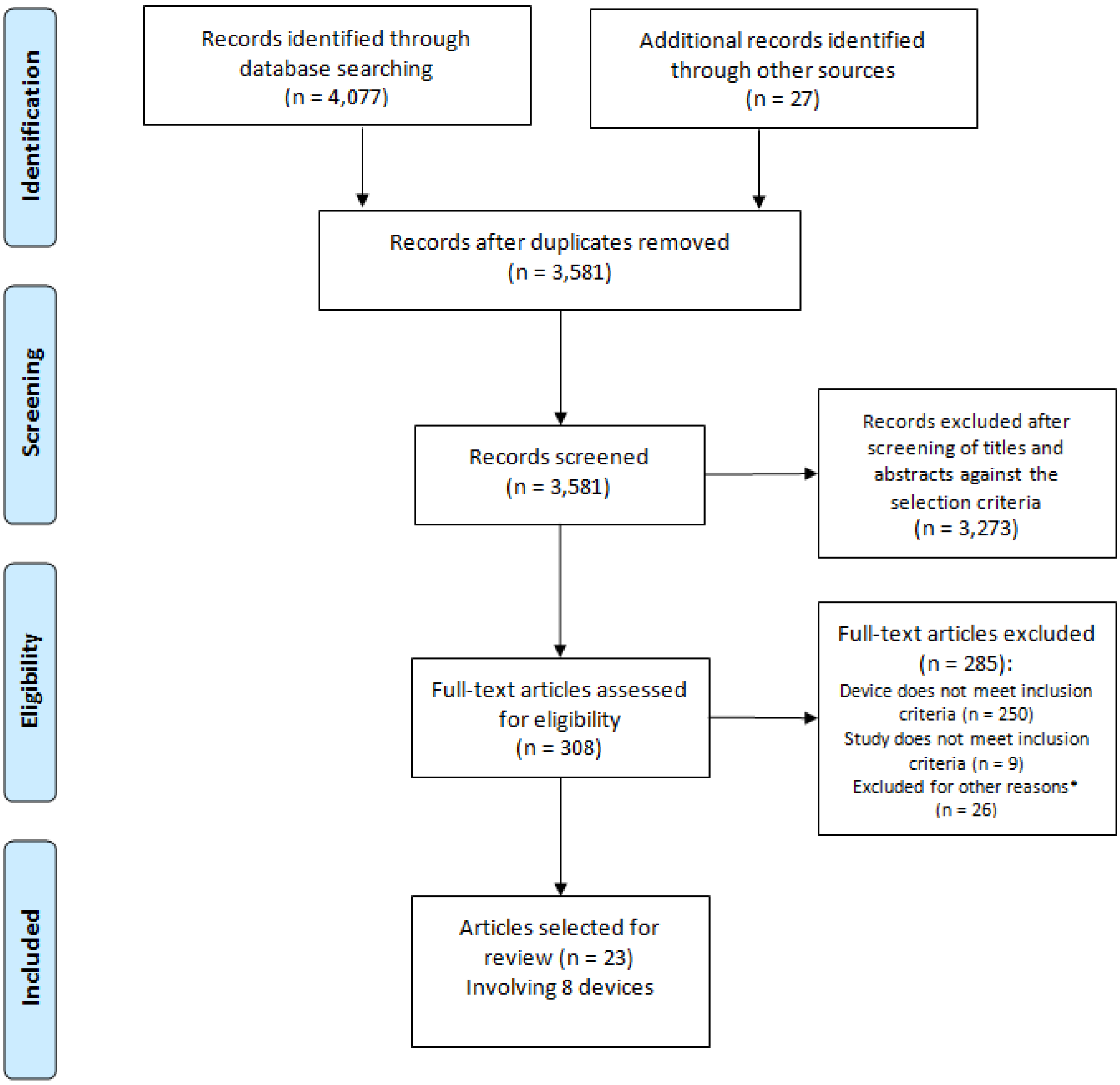
A second literature search in September 2018 identified 1303 articles after duplicates were removed. Of these 55 underwent abstract screening. Two articles were deemed to fit the inclusion criteria. These are briefly summarised below but not included in the review as to do so could introduce bias.

One study trained six subacute stroke patients with the Amadeo hand rehabilitation system with a virtual reality environment three days per week for six weeks (Huang, Naghdy, Du, Naghdy, & Murray, 2017). They found significant reductions improvement in FMA and MAS at post-test.

A second study used the CR2 haptic device, a reconfigurable end-effector manipulator that trained forearm pronation and supination, and wrist flexion, extension, adduction and abduction (Khor et al., 2017). Seven subacute to acute stroke patients were trained with the device for 6 weeks. Improvements in the FMA and range of movement were observed at post-test.

The findings of these studies corroborate the finding of the review that distal RT reduces upper limb impairment in stroke patients. However, the studies did not collect data on clinical outcomes relating to activity and participation. No conclusion can be drawn regarding efficacy of training for improving functional abilities on the basis of these articles. Follow-up assessments were not conducted in either study.

Figure 3.1 PRISMA flowchart detailing data extraction process



Designs

There was large variability in the design of the included studies; nine were comparative studies of which eight were true RCTs comparing the effects of an established, commercialised robotic therapy device with conventional therapist based interventions. The other 14 studies were pre-post intervention efficacy comparisons within a single patient group. Table 3.1 is a summary table of study designs.

Participants and sample sizes

The total number of participants across all studies was 389 including 371 adults with stroke and 18 children with CP. Of the participants with stroke: 286 were in the chronic phase of stroke recovery and were enrolled in 14 studies, 33 subacute phase patients were enrolled in four studies, and 27 acute phase patients were enrolled across two studies. One study of eight did not report participants' stroke recovery phase (Yeh, Lee, Chan, Chen, & Rizzo, 2014), another included 17 participants from both the subacute and chronic stages (Hwang, Seong, & Son, 2012). The average age of stroke participants enrolled across studies was approximately 60; however the range was very large and often not reported. Across studies that reported gender, 218 stroke participants were male and 114 female. There was heterogeneity in the severity of baseline motor impairment across studies; studies had different exclusion criteria relating to sensory and cognitive deficits, aphasia and additional motor impairments.

The remaining participants were 18 children with CP, enrolled in a single study (Weightman et al., 2011) and had a median age of seven and a half. Sample sizes across the studies varied largely, with RCTs tending to enrol a larger number of participants than pre-post intervention studies with a single treatment group. These tended to have fewer than 10 participants

Table 3.1 Design of studies of end-effector devices

Device/Reference	Study	Design	Participants	Clinical outcome measures
1. BiManuTrack	(Hsieh et al., 2011)	RCT (high intensity robot therapy vs. low intensity robot therapy vs. control therapy)	18 CS (HIRT: 6, LIRT: 6, CT: 6)	FMA, MRC, ABILHAND, MAL
1. BiManuTrack	(Liao, Wu, Hsieh, Lin, & Chang, 2012)	RCT (robot therapy vs. control therapy)	20 CS (RT: 10, CT: 10)	FMA, FIM, MAL, ABILHAND
1. BiManuTrack	(Wu et al., 2012)	RCT (robot therapy vs. control therapy)	42 CS (RT: 14, TBAT: 14, CT: 14)	FMA, MAL, SIS
1. BiManuTrack	(Hsieh et al., 2012)	RCT (high intensity robot therapy vs. low intensity robot therapy vs. control therapy)	54 CS (HIRT: 18, LIRT: 18, CT: 18)	FMA, MRC, MAL, SIS
1. BiManuTrack	(Wu, Yang, Chen, Lin, & Wu, 2013)	RCT (robot therapy vs. control therapy)	53 CS (URT: 18, BRT:18, CT: 17)	WMFT, MAL, ABILHAND

Device/Reference	Study	Design	Participants	Clinical outcome measures
1 BiManuTrack	(Yang, Lin, Chen, Wu, & Chen, 2012)	RCT (robot therapy vs. control therapy)	21 CS (URT: 7, BRT: 7, CT: 7)	FMA, MRC, MAS
2. Amadeo	(Sale, Mazzoleni, et al., 2014)	RCT (robot therapy vs. control therapy)	20 AS (RT: 11 subjects, CT: 9 subjects)	FMA, BB, MRC, MI, MAS
2. Amadeo	(Orihuela-espina et al., 2016)	RCT (robot therapy vs. control therapy)	17 SA (RT: 9 subjects, CT: 8 subjects)	FMA distal subscale, MI prehension subscale
2. Amadeo	(Hwang, Seong, & Son, 2012)	Uncontrolled randomised comparative trial (full term vs. half term robot therapy)	17 SA/CS (FTI: 9 subjects, HTI: 8 subjects)	JTHT, SIS, FMA, AS, NHPT
1. BiManuTrack	(Hesse et al., 2003)	Proof of concept trial, pre-post intervention	12 CS	RMA, MAS
3. Haptic Knob /Rehaptic Knob	(Lambercy et al., 2009)	Proof of concept trial, pre-post intervention	9 CS	FMA, MSc, MI, MAS

Device/Reference	Study	Design	Participants	Clinical outcome measures
3.Haptic Knob/Rehaptic Knob	(Lambercy et al., 2011)	Proof of concept trial, pre-post intervention	13 CS	FMA, MI, MSc, MAS, FTHUE, NHPT
3.Haptic Knob/Rehaptic Knob	(Metzger et al., 2014)	Proof of concept trial, pre-post intervention	6 SA	FMA
2. Amadeo	(Sale, Lombardi, & Franceschini, 2012)	Proof of concept trial, pre-post intervention	7 AcS	FMA, MRC, MI, AS BI FIM, COPM
2. Amadeo	(Stein, Bishop, Gillen, & Helbok, 2011)	Proof of concept trial, pre-post intervention	12 CS	FMA, MAL, NHPT, MAM, JTFT, SIS
2. Amadeo	(Pinter, Pegritz, Pargfrieder, Reiter, Wurm, Gattringer, Linderl-Madrutter, et al., 2013)	Exploratory study, pre-post intervention	7 SA	MI, RMI, MRS, NIHSS, BI
4. Novint Falcon	(Yeh et al., 2014)	Proof of concept trial, pre-post intervention	8 Stroke	WMFT, TEMPA, BBT

Device/Reference	Study	Design	Participants	Clinical outcome measures
5. Restricted Space Assisted Movement Device	(Weightman et al., 2011)	Proof of concept trial, pre-post intervention	18 CP	COPM
6. Wrist Manipulator	(Colombo et al., 2005a)	Proof of concept trial, pre-post intervention	7 CS	FMA, MSS, MRC, MPS
6. Wrist Manipulator	(Colombo et al., 2005b)	Proof of concept trial, pre-post intervention	8 CS	FMA, MPS
6. Wrist Manipulator	(Colombo et al., 2007)	Proof of concept trial, pre-post intervention	8 CS	FMA, MPS

Device/Reference	Study	Design	Participants	Clinical outcome measures
7. ReachMAN	(Yeong, Baker, Melendez-Calderon, Burdet, & Playford, 2010)	Proof of concept trial, pre-post intervention	3 SA	FMA, ARAT, CM
8. Haptic Interface for Finger Exercise	(Uros Mali, Goljar, & Munih, 2006)	Proof of concept trial, pre-post intervention	9 CS	Motor component of the FIM

Note CS – Chronic Stroke, **SA** – Subacute Stroke, **AcS** – Acute stroke

Interventions

Table 3.2.presents a summary of interventions and study findings. There was large variability both the duration and period of robotic and control training, and the training protocol used. The duration of training programmes across the selected studies ranged from 20-105 minutes per session, three to five sessions per week, for up to eight weeks. Studies averaged four weeks of training.

Whilst RT mostly involved performing repetitive movements, the specific movements trained depended on those supported by each device. Training sessions often began with passive movement of the user's arm or hand and developed to active-assistive or resistive repetitive movement training with the device. Training was often achieved through a series of interactive virtual reality games or tasks.

Control therapy protocols also differed, though tended to use conventional OT techniques such as weight bearing, stretching, muscle strengthening, balance, fine motor skills training, bilateral motor tasks and functional task training.

Training protocols across studies of the same device tended to be homogenous. Some studies allowed participants to undergo other treatments and interventions outside of the training protocol, whilst others did not allow this.

Devices

The eight end-effector devices selected varied widely in mechanical design, however tended toward few DoF (Table 3.3), few motors and a small footprint; as might be expected of end-effector devices. The HIFE and Wrist Manipulator devices train only a single flexion and extension movement of the individual finger and the wrist respectively, whilst other devices allow the user to switch between multiple supported movements (the Bi-Manu-Track and ReachMAN devices), or support multiple simultaneous or synergistic movements (Haptic Knob, Novint Falcon, and the RSAMD).

Five of the devices supported functional or task-related movements, particularly those that support dextrous hand skills such as hand grasp (Amadeo, Haptic Knob), knob twisting (Haptic Knob, BiManuTrack, and eating movements (ReachMAN) and tend to have virtual reality games that relate to ADL activities. The other devices aimed to restore anatomical range of movement at single or multiple joints (not related to any specific functional task). Only one device, the Bi-Manu-Track (Stefan Hesse, Schulte-Tigges, Konrad, Bardeleben, & Werner, 2003), enabled simultaneous bilateral movements. The Bi-Manu-Track, Amadeo, and Novint Falcon are commercially available devices.

Clinical outcome measures

The total number of clinical outcome measures used across the studies was 26. We aimed to simplify the interpretation of these outcome measures by categorising them according to the World Health Organisation (WHO) International Classification of Functioning, Disability and Health (ICF) criteria (World Health Organisation, 2001). We therefore split outcome measures into behavioural measures of activity/participation or impairment; patient self-reported measures of activity/participation; listed in Table 3.4.

No single outcome measure was assessed in all studies. The FMA was used the most commonly used clinical outcome measure; participants were assessed on the FMA in 17 of the 22 studies. One study assessed outcome measures every day over the training period, 12 studies assessed outcomes at the start and end of the intervention period, three studies assessed outcomes at the start, midterm and end of the intervention, six studies assessed outcomes at the start and end of the intervention and conducted follow up assessments at four to eight weeks post intervention end.

Table 3.2 Summary of results from studies of end-effector devices

Device/Reference	**Study**	**Training**	**Assessment/ follow-up**	**Analysis**	**Findings**
1. Bi-ManuTrack (Hesse et al., 2003)	(Hsieh et al., 2011)	Total 1800-2100 min training: Five 90-105 min/w for four weeks. HIRT: 300-400 cycles of mode 1, 300-400 cycles of mode 2 and 75-100 cycles of mode 3 training, 5 min of passive range of movement training and 15-20 min of functional activities training. LIRT: identical except that in each training mode half the number of cycles was practiced. CT group received individual conventional OT.	Pre and post intervention	ANCOVA for treatment effects with pre-treatment scores as covariate and post treatment scores as dependent variable. Post hoc pairwise comparisons (Tukey method) and partial $\eta 2$ effect size	HIRT group showed better FMA improvement than the LIRT group ($d = 0.32$). Difference between LIRT and CT groups not significant ($d = 0.05$). HIRT group better improvement in MAL QOM scores than LIRT ($d = 0.57$) and CT ($d = 0.49$). No difference between LIRT and CT ($d = 0.12$). Non-significant improvements in MRC, MAL-AOM, and ABILHAND for HIRT compared to LIRT and CT groups.

Device/Reference	Study	Training	Assessment/ follow-up	Analysis	Findings
1. Bi-ManuTrack (Hesse et al., 2003)	(Liao et al., 2012)	Total 1800-2100 min training: Five 90-105 min sessions per week for four weeks. CT group received 90-105 minutes of OT (dose matched). RT group practised 300 to 400 forearm cycles, of mode 1 and mode 2, and 75-100 cycles of mode 3 plus 15 minutes of functional activity training. Both groups underwent treatment as usual.	Pre and post intervention	ANCOVA for treatment effects with pre-treatment scores as covariate and post-treatment scores as dependent variable. Pearson's r as effect size measure	Significant difference in favour of RT group for FMA (d = 0.52), MAL-QOM (d = 0.53) and MAL-AOM (d = 0.52) and ABILHAND (d = 0.60). No change in FIM scores for both groups.

Device/Reference	Study	Training	Assessment/ follow-up	Analysis	Findings
1. Bi-ManuTrack (Hesse et al., 2003)	(Wu et al., 2012)	Total: 1800-2100 minutes of training. Five 90-105 minute sessions per week for four weeks. RBAT group: Thirty minutes in modes 1 and 2, and 10 minutes in mode 3 in addition to 15-20 minutes of functional activity training and 5 minutes of tone normalisation. CT group: Weight bearing, stretching, strengthening, coordination, uni- and bilateral fine motor tasks, balance and compensatory functional task practice.	Pre and post intervention	Chi Square or Fishers exact test for categorical variables, ANOVA for continuous data, or ANCOVA with pre-test scores as covariate.	Significantly larger improvement in SIS total score ($d = 0.57$), strength subscale ($d = 0.82$) and physical function domain ($d = 0.75$) (RBAT over CT). No significant differences between groups on FMA overall score, MAL (either AoU or QoM).

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
1. Bi-ManuTrack (Hesse et al., 2003)	(Hsieh et al., 2012)	Total 1800-2100 min training: All groups received 90-105 min per day, 5 days per week, for 4 weeks. 90-105 min session includes: 70 min RT, 15-20 min functional task practice. HIRT: 600-800 reps mode 1 and 2 and 150-200 repetitions of mode 3. LIRT: 300-400 reps mode 1 and 2, 75-100 mode 3. CT group: Duration matched OT including neurodevelopmental, muscle strengthening, fine motor training and functional task training.	Pre, midterm, and post intervention	Intention to treat analysis. ANCOVA for primary and secondary outcome measures, post-hoc analyses for comparison of groups.	Significant improvement in FMA in all three groups (HIRT: $d = 0.61$; LIRT: $d = 0.31$; CT: $d = 0.28$). FMA changes at midterm and end of treatment favouring HIRT over LIRT ($d = 0.22$), and CT ($d = 0.23$). No significant difference between LIRT and CT ($d = 0$). Improvements in MRC and both subsections of the MAL across groups from baseline to post-test. No differences between groups. HIRT group reported improvement in SIS. LIRT group improvement the strength. No difference in SIS..

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
1. Bi-ManuTrack (Hesse et al., 2003)	(Wu et al., 2013)	Total: 1800-2100 min of training. Five 90-105 min sessions per week for four weeks. BRT group: 75-80 min RT (equating to 300-400 reps in modes 1 and 2 and 50-80 reps mode 3), and 15-20 minutes of functional activity training. CT: Duration and intensity matched. Weight bearing, stretching, strengthening of paretic arm, coordination, unilateral and bilateral fine motor tasks, and balance tasks. Participants did not undergo any other therapy during study.	Pre and post intervention	Chi Square or Fisher's exact test for baseline comparisons. For pre-post comparisons between groups, ANCOVA with baseline as covariate. Post hoc contrasts to further determine differences between groups	Significant difference in the time subsection of the WMFT between groups. Post-hoc tests indicated that URT group had a lower WMFT-time score than the CT group, but this was not significant ($d = 0.28$). No significant differences in WMFT overall score or FAS (functional ability subscale), or MAS, MAL and ABILHAND overall scores or their subscales.

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
1. Bi-ManuTrack (Hesse et al., 2003)	(Yang, Lin, Chen, Wu, & Chen, 2012)	Total: 1800-2100 min training. Five 90-105 min sessions per week for four weeks. BRTP group: 75-80 min RT (equating to 300-400 reps in modes 1 and 2 and 50-80 reps mode 3), and 15-20 mins of functional activity training. CT group: Duration and intensity matched. Weight bearing, stretching, strengthening of paretic arm, coordination, unilateral and bilateral fine motor tasks, and balance tasks. No other therapy for duration of study	Pre and post intervention	Chi Square or Fisher's exact test for baseline comparisons. For pre-post comparisons between groups, ANCOVA with baseline as covariate. Post hoc contrasts to further determine differences between groups	No differences in FMA overall score, and FMA proximal subscale between BRTP and CT groups ($d = 0.17$). Significant differences in the MRC proximal subscale favouring the BRTP group over the CT group ($d = 0.36$. Significant differences in distal MRC subscale favoured CT over BRTP ($d = 0.32$). Non-significant improvements across conditions in FMA overall score and both proximal and distal subscales. No change in MRC, grip strength or MAS.

Device/Reference	Study	Training	Assessment/follow up	Analysis	Findings
2. Amadeo, Tyromotion GmbH	(Sale, Mazzoleni, et al., 2014)	Total 800 minutes of training: Twenty 40 minute sessions over four or five weeks. All patients received standard treatment of at least three hours of physiotherapy daily. In addition, the CT sessions consisted of 40 minutes of personalised OT focused on recovery of hand function. EG sessions consisted of 10 minutes of passive upper limb mobilisation and 30 minutes of hand training with the device.	Pre and post intervention and 8 week follow up	Repeated measures ANOVA to compare within groups, Friedman tests for ordinal variables. No between group comparisons.	RT: significant improvements on the FMA ($d = 0.75$), BB ($d = 0.69$), MI (d = .68), MRC ($d = 1.01$), MAS ($d = 0.41$). Improvements retained at follow-up assessment FMA ($d = 0.69$), BB ($d = 1.02$), MI ($d = 0.90$), MRC ($d = 1.07$), and MAS ($d = 0.17$). CT: Significant improvements in FMA ($d = 1.22$), BB ($d = 0.42$), MI ($d = 0.78$), MRC ($d = 0.66$). Improvements retained at follow up BBT ($d = 0.78$).

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
2. Amadeo, Tyromotion GmbH	(Orihuela-espina et al., 2016)	Total: approximately 2320 min of training for both groups. Four 40 min sessions then 36 60 min sessions (totalling 40 sessions). Five sessions per week. RT: 300 passive reps, 300 reps partial assistance or resistance. 100 active movements were practised CT: OT: 300 reps passive movement, warm up, strengthening exercises and personalised active training exercises.	Pre and post intervention	Wilcoxon Rank Sum with continuity correction or Fisher's exact test for baseline comparisons. Wilcoxon Rank Sum tests for comparative differences (RT vs. CT)	Significant difference between RT and CT in FMA distal score improvement from pre-test to post-test favouring RT group (d = 1.19). Non-significant difference in MI prehension score between RT and CT, favouring RT group (d = 0.93).

Device/Reference	Study	Training	Assessment and follow up	Analysis	Findings
2. Amadeo, Tyromotion GmbH	(Hwang et al., 2012)	Total 400 (HTI) or 800 (FTI) mins of training: Five 40 min sessions per week for two weeks (Half time intervention) or four weeks (full time intervention). FTI sessions consisted of simulated grasp and release training and virtual reality training with the device (20 sessions). HTI included 10 sessions of passive range of movement training then 10 sessions of training identical to the FTI group.	Pre and post intervention, two and four week follow up	Paired t tests to compare individuals over time points. Wilcoxon test for each group across time points. Repeated measures ANOVA for within and between group interactions	Improved JTHT for FTI (post $d = 1.51$; follow up $d = 1.56$) and HTI (post $d = 0.94$; follow up $d = 0.94$) at end of and follow-up. Improved FMA score, retained at follow-up for both groups: FTI distal (post $d = 2.15$; follow-up $d = 1.58$), FTI proximal (post $d = 0.62$; follow-up $d = 0.77$), HTI distal (post $d = 1.41$; follow up $d = 0.00$). FTI larger improvement in JTHT (post $d = 0.43$, follow up $d = 0.50$), and FMA Distal (post d = 0.04, follow up $d = 0.15$), and FMA proximal (post $d = 0.41$, follow-up $d = 0.64$) than the HTI group.

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
1. Bi-ManuTrack (Hesse et al., 2003)	(Hesse et al., 2003)	Total: 225 mins training: Five 15 min sessions per week for three weeks. Participants also underwent 45 mins of PT and OT, five times per week for this period.	Pre and post intervention and 12 week follow up	Wilcoxon sign rank test for comparing pre-post change	Significant decrease in MAS wrist and finger subscale scores. Non-significant improvement in RMA or elbow MAS subscale. (Unable to compute effect sizes from median data).
3. Haptic Knob and ReHaptic Knob (Lambercy et al., 2007; Metzger, Lambercy, Chapuis, & Gassert, 2011)	(Lambercy et al., 2009)	Total 1080 mins training: Three 60 minute sessions per week for six weeks. Training consisted of 15 mins muscle stretching, 20 mins of hand opening and closing with Haptic Knob, 5 min break, 20 mins PS exercises with the Haptic Knob.	Pre and post intervention. Six week follow up	T-tests used to compare assessed outcomes with baseline scores. Unclear whether corrected for multiple comparisons	Improved FMA (post $d = 0.38$; follow up $d = 0.64$), MI (post $d = 0.26$; follow up $d = 0.35$), distal FMA (post $d = 0.26$; follow up $d = 0.52$), proximal FMA subscale (post $d = .358$; follow up $d = 0.54$), MAS elbow (post $d = 0.10$; follow up $d = 0.10$) post-test and 6 weeks.

Device/Reference	Study	Training	Assessment and follow up	Analysis	Findings
3. Haptic Knob and ReHaptic Knob (Lambercy et al., 2007; Metzger et al., 2011)	(Lambercy et al., 2011)	Total 1080 min training: Eighteen one hour sessions over six weeks. Training comprised 10 min of muscle stretching followed by 5 sets of 10 exercise trials with rests.	Pre and post intervention. Seven week follow up	Two-tailed Friedman test to compare primary outcome measures with baseline scores, bonferroni corrected. Post-hoc analysis with Wilcoxon sign rank tests for baseline to follow-up. Secondary outcomes not corrected.	Significant improvement in FMA overall score (post $d = 0.26$; follow up $d = 0.43$), distal subscale (post $d = 0.20$; follow up $d = 0.41$), MI overall score (post $d = 0.27$; follow up $d = 0.43$), shoulder elbow portion of the MI (post $d = 0.32$; follow up $d = 0.40$), and MSc (post $d = 0.30$; follow up $d = 0.33$) post training, retained at follow up. Non-significant improvements in MSc. No change on FTHUE or NHPT.

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
3. Haptic Knob and ReHaptic Knob (Lambercy et al., 2007; Metzger et al., 2011)	(Metzger et al., 2014)	Total 720 minutes training: Four 45 minute sessions per week for four weeks. Each session consisted of three (randomly selected from 7) neurocognitive exercises focusing on hand sensorimotor functioning each lasting 15 minutes.	Pre and post intervention four week follow up	Confidence intervals used as measure of change from baseline to post-test	Sample too small for statistical tests. Participants showed improvements in FMA.
2. Amadeo, Tyromotion GmbH	(Sale, Lombardi, & Franceschini, 2012)	Total 800 min of RT: Five 40 min sessions per week for four weeks. Sessions: 10 mins passive upper limb mobilisation and 30 mins hand RT. Also received standard treatment (3 hours physiotherapy daily).	Pre, midterm and post intervention	Repeated measures ANOVA, Friedman tests for ordinal variables	Significant improvements on MRC flexion (d = 0.73) and extension (d = 0.30), non-significant improvements on FMA (d = 1.26), MI (d = 0.36), MAS Hand (d = 0.42), and COPM (d = 0.55).

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
2. Amadeo, Tyromotion GmbH	(Stein, Bishop, Gillen, & Helbok, 2011)	Total: 1080 minutes of training: Three one hour sessions per week for 6 weeks. Sessions consisted of 40 minutes of active-assistive hand exercise plus two 10 minute games to encourage isometric digit flexion and extension. Participants did not undergo any other therapy for the duration of the study.	Pre, midterm and post intervention	Paired t-tests (baseline vs treatment)	Significant improvements on FMA ($d = 0.46$) (both proximal and distal subsections), MAL (both AoU ($d = 0.58$) and QoM ($d = 0.51$), MAM ($d = 0.51$), JHFT ($d = 0.14$)

Device/Reference	Study	Training	Assessment and follow up	Analysis	Findings
2. Amadeo, Tyromotion GmbH	(Pinter et al., 2013)	Total 900 min RT: Fifteen 20 min sessions over 3 weeks. Also a conventional training programme: OT, ADL training, PT, strength training, lymph drainage, partial massage and cognitive training.	Pre and post intervention	Paired t-test pre-post training comparisons. Correlational analysis for fMRI component	Significant improvement in MI (d = 0.34), MI subscale pinch grip (d= 0.61), and grip force (d = 1.00). Non-significant improvements in BI (d = 0.71), NIHSS (d = .649), and RMI (d = 0.57).
4. Novint Falcon, Novint Technologies	(Yeh et al., 2014)	Total 720 min training: Twenty-four 30 minute sessions over 8 weeks. Two tasks, pinch strengthening and pinch lift, using dual Novint Falcons on haptic VR platform.	Pre and post intervention. Four week follow up	Wilcoxon rank sum test for pre-post-follow up comparisons.	Significant improvements in TEMPA (d = 0.40) and BBT (d = 0.18). Non-significant improvement in WMFT score (d = 0.18).

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
5. Restricted Space Assisted Movement Device (Weightman et al., 2010)	(Weightman et al., 2011)	Median total 75 mins of training. Four weeks of training. Children instructed to use the device as much as they wanted in this time.	Pre and post intervention	Wilcoxon tests compared pre-test with post-test outcome scores, criterion value corrected for multiple comparisons.	Significant improvement in COPM
6. Wrist Manipulator (Colombo et al., 2005a)	(Colombo et al., 2005a)	Total 600+ mins training: 20 mins twice per day, 5 days per week for three or more weeks. Also received 45 minutes of PT 5 days per week.	Pre and post intervention	Wilcoxon signed rank to compare pre-post change	Significant improvement in FMA ($d = 0.52$). Non-significant improvement in MSS ($d = 0.79$). Non-significant, modest improvements in MPS ($d = 0.24$), and MRC flexion ($d = 0.35$) and extension ($d = 0.31$).

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
6. Wrist Manipulator (Colombo et al., 2005a)	(Colombo et al., 2005b)	Total: 600 mins: 20 mins twice per day, 5 days per week for three weeks. Patients also received 45 minutes of PT5 days per week.	Pre and post intervention	Not specified	Significant improvement in FMA. Non-significant improvement in MPS. Data presentation insufficient to compute effect sizes.
6. Wrist Manipulator (Colombo et al., 2005a)	(Colombo et al., 2007)	Total: 600 mins: 20 mins twice per day, 5 days per week for three weeks. Patients also received 45 minutes of PT 5 days per week.	Pre and post intervention	Paired t-tests to compare pre-post change	Significant improvement in FMA ($d = 0.53$). Non-significant improvement in MPS ($d = 0.24$).

Device/Reference	Study	Training	Assessment/ follow up	Analysis	Findings
7. ReachMAN (Yeong, Melendez-Calderon, Gassert, & Burdet, 2009)	(Yeong et al., 2010)	Total 240 or 360 ms training: Two or three 30 min sessions per week for four weeks. Each session consisted of 10 series of 10 movements each for reaching, PS, grasping, and finally PS and grasping. If no movement then a series would be restricted to three movement trials.	Pre and post intervention	No statistical tests used due to small sample size	Sample too small for statistical tests. One participant showed improvements in FMA, ARAT, CM.
8. Haptic Interface for Finger Exercise (Mali & Munih, 2006)	(Mali et al., 2006)	Total: 900-1050 mins training: One 30-35 min session per day for a month. Five finger training tasks taking totalling 6-7 mins per finger per day.	Every day over the one month intervention	No statistical test to determine whether change in M-FIM significant	Sample too small for statistical tests. Participants showed improvement in M-FIM scores over the duration of treatment.

Table 3.3 Selected end-effector devices

Device/Reference	Supported Movements	Active DoF	Controller	Actuation	Training Modalities
1. Bi-Manu-Track (Hesse et al., 2003)	Forearm PS, Wrist FE	1	Impedance control	Electric motors	Bilateral and unilateral passive, resistive and active-assistive
2. Amadeo Tyromotion GmbH	Individual fingers and thumb FE Hand grasp and release	5	Impedance control	Electric motors	Passive, active, active-assistive
3. Haptic Knob/ ReHaptic Knob (Dovat et al., 2006) (Metzger et al., 2011)	Forearm PS, hand grasp and release, knob twisting	2	Impedance control	Electric motors	Passive, active-assistive
4. Novint Falcon, Novint Technologies	Finger pinch	3	Impedance control	Electric motors	Passive, active-assistive
5. Restricted Space Assisted Movement Device (Weightman et al., 2010)	Shoulder, elbow, forearm, wrist *	2	Impedance control	Electric motors	Passive, active, active-assistive

Device/Reference	Supported Movements	Active DoF	Controller	Actuation	Training Modalities
6. Wrist Manipulator (Colombo et al., 2005a)	Wrist FE	1	Admittance control	Electric motors	Passive, active-assistive
7. ReachMAN (Yeong et al., 2009)	Shoulder and elbow *, forearm PS, fingers/thumb grasp	3	Different control strategies for each DoF: Impedance control for grasp, force amplification for reaching, admittance for PS	Electric motors	Passive, resistive, active-assistive
8. Haptic Interface for Finger Exercise (HIFE) (Mali & Munih, 2006)	individual finger FE	1	Impedance control	Electric motors	Passive, active-assistive

Supported movements:* *FE *- flexion/extension,* ***PS*** *- pronation/supination, * - No specific anatomical movement.*

Table 3.4 Clinical outcome measures used across studies

Clinical Outcome Measures used in selected studies		
Behavioural measures of activity/participation	**Behavioural measures of impairment**	**Self-report measures of activity/participation**
Action Research Arm Test (ARAT; Carroll, 1965)	Ashworth Scale (AS; Ashworth, 1964) Modified Ashworth Scale (MAS) (Bohannon & Smith, 1987)	ABILHAND (Penta, Tesio, Arnould, Zancan, & Thonnard, 2015)
Box and Blocks Test (BBT; Cromwell et al., 1960)	Chedoke-McMaster Stroke Hand Impairment Inventory (CM) (Gowland et al., 1993)	ABILHAND-Kids (ABILHAND-K; Arnould, Penta, Renders, & Thonnard, 2004)
Functional Test of the Hemiparetic Upper Extremity (FTHUE; Wilson, Baker, & Craddock, 1984)	Fugl-Meyer Test for the Upper Extremity (FMA; Fugl-Meyer et al., 1975)	Barthel Index (BI; Mahoney & Barthel, 1965)
Jebsen Taylor Hand Test (JTHT; Jebsen, Taylor, Trieschmann, Trotter, & Howard, 1969)	Motor Assessment Scale (MSc; Carr, Shepherd, Nordholm, & Lynne, 1985)	Canadian Occupational Performance Measure (COPM; Law et al., 1990)
Manual Ability Measure-36 (MAM; Chen & Bode, 2010)	Motor Power Score (MPS; Aisen et al., 1997)	Functional Independence Measure (FIM; Granger, Hamilton, Keith, Zielezny, & Sherwin, 1986)
Nine Hole Peg Test (NHPT; Wade, 1992)	Motor Status Score (MSS; Aisen et al., 1997)	Motor Activity Log (MAL; Taub et al., 1993)
Test Evaluant les Membres Superieurs des Personnes Agees (TEMPA; Chen & Bode, 2010)	Motricity Index (MI; Collin & Wade, 1990)	Stroke Impact Scale (SIS; Duncan, Bode, Min Lai, & Perera, 2003)

Clinical Outcome Measures used in selected studies		
Behavioural measures of activity/participation	**Behavioural measures of impairment**	**Self-report measures of activity/participation**
Wolf Motor Function Test (WMFT; Wolf, Lecraw, Barton, & Jann, 1989)	Medical Research Council Test of Muscle Strength (MRC; (Paternostro-Sluga et al., 2008)	
Rivermead Mobility Index (RMI; Collen, Wade, Robb, & Bradshaw, 1991)	National Institutes of Health Stroke Scale (NIHSS; Goldstein et al., 1989)	
Rivermead Motor Assessment (RMA; Lincoln & Leadbitter, 1979)		

3.4.2 Risk of bias in included studies

Table 3.5 displays a summary table of detailing the risk of bias in included studies on each of the measures. Figure 3.2 displays the risk of bias graph.

Allocation

This criterion could only be relevantly applied to the RCTs included. Whilst participant allocation was randomised in all the RCTs using random number tables, allocations could not be concealed from therapists delivering the intervention or researchers in all cases. This was particularly evident in one RCT (Orihuela-espina et al., 2016), in which the authors note that allocation concealment was not possible due to the open-plan environment in which the intervention was delivered, and therefore represented a high risk of bias. Two RCTs did not explicitly mention whether participant allocation was concealed and therefore risk of bias was regarded as unclear (Sale, Franceschini, et al., 2014; Yang, Lin, Chen, Wu, & Chen, 2012). All studies that were not RCTs were rated high risk of bias as the one sample research design (lacking a control group, random allocation, and concealment) is highly prone to bias.

Blinding

Given the nature of the interventions, it would not be possible for therapists delivering or participants receiving the therapy to be blinded, however participants were often blinded to the research hypotheses and assessor blinding should be possible. In many cases the outcome assessments were made by an independent therapist, blinded to research protocol and allocations, in only one of the RCTs was this not the case (Orihuela-espina et al., 2016). Eight of the 13 proof of concept trials did not report whether the assessors were independent of the research time or blinded to the allocations and were rated unclear risk of bias (Colombo et al., 2005a, 2005b, 2007; Pinter, Pegritz, Pargfrieder, Reiter, Wurm, Gattringer, Linderl-madrutter, et al., 2013; Stein et al., 2011; Weightman et al., 2011; Yeh et al., 2014; Yeong et al., 2010), in the remaining five studies the assessors were blinded and received the rating of low risk of bias (Lambercy et al., 2009, 2011; Mali et al., 2006; Metzger et al., 2014; Sale et al., 2012).

Incomplete outcome data

Outcome data were complete in all but four of the studies. Three of these studies were large RCTs in which the risk of bias due to attrition was addressed in the statistical analysis, we therefore rated the risk of bias was consequently regarded as low (Hsieh et al., 2012; Hwang et al., 2012; Wu et al., 2013). In the other study (Weightman et al., 2011), the single drop out was deemed unlikely to affect the results. In one study, participant dropout was not reported and could not be determined from the data presentation, and so risk of bias was determined to be unclear (Mali et al., 2006).

Selective reporting

All clinical outcomes stated in study method sections were reported in 21 studies, representing a low risk of bias. One study reported results of a single subscale of the FIM that had been assessed (Mali et al., 2006), and consequently received a high risk of bias rating. In another study, a proportion of the data fell below the effective range of the tests and were not reported (Yeong et al., 2010)

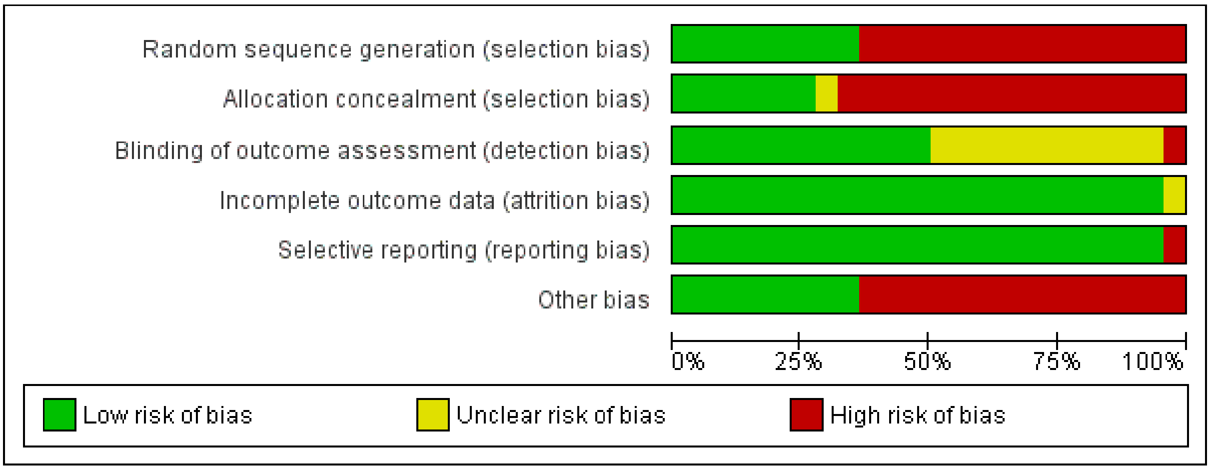
Table 3.5 Summary risk of bias table

Study	Device	RCT	Main Patient demographic	Adequate sequence generation	Allocation concealment	Blinding (assessor)	Incomplete outcome data	Free of selective reporting
Hsieh et al. (2011)	1	Y	CS	+	+	+	+	+
Liao et al. (2012)	1	Y	CS	+	+	+	+	+
Wu et al. (2012)	1	Y	CS	+	+	+	+	+
Hsieh et al. (2012)	1	Y	CS	+	+	+	+	+
Wu et al. (2013)	1	Y	CS	+	+	+	+	+
Yang et al. (2012)	1	Y	CS	+	?	+	+	+
Hwang et al. (2012)	2	Y	S	+	+	+	+	+
Sale et al. (2014)	2	Y	AS	+	?	+	+	+
Orihuela-Espina et al. (2016)	2	Y	SA	+	−	−	+	+
Hesse et al. (2003)	1	Y	SA	−	−	+	+	+
Lambercy et al. (2009)	3	N	CS	−	−	+	+	+
Lambercy et al. (2011)	3	N	CS	−	−	+	+	+
Metzger et al. (2014)	3	N	SA	−	−	+	+	+
Sale et al. (2012)	2	N	AS	−	−	+	+	+
Stein et al. (2011)	2	N	CS	−	−	?	+	+
Pinter et al. (2013)	2	N	SA	−	−	?	+	+
Yeh et al. (2014)	4	N	S	−	−	?	+	+
Weightman et al. (2011)	5	N	CP	−	−	?	+	+
Colombo et al. (2005)	6	N	CS	−	−	?	+	+

Study	Device	RCT	Main Patient demographic	Adequate sequence generation	Allocation concealment	Blinding (assessor)	Incomplete outcome data	Free of selective reporting
Colombo et al. (2005b)	6	N	CS	–	–	?	+	+
Colombo et al. (2007)	6	N	CS	–	–	?	+	+
Yeong et al. (2010)	7	N	SA	–	–	?	+	?
Mali, Goljar, and Munih (2006)	8	N	CS	–	–	+	?	–

Note. + *- Low risk of bias,* – *- High risk of bias,* ? *- Unclear risk of bias, CS – Chronic Stroke,* ***SA*** *– Subacute stroke,* ***AS*** *– Acute stroke,* ***S*** *– Stroke recovery stage undefined,* ***CP*** *- Cerebral Palsy,* ***Y*** *– Yes,* ***N*** *– No*

Figure 3.2 Risk of bias graph



3.4.3 Effects of interventions

Efficacy across RCTs

Nine RCTs were selected that tested the efficacy of distal UL training with the end –effector devices. Across these studies, training was associated with improved clinical outcomes across the ICF domains. Findings demonstrated reductions in impairment in both distal and proximal sections of the UL (FMA, MI; Hsieh et al., 2012; Hwang et al., improvements in UL strength (MRC; Hsieh et al., 2012), reductions in UL spasticity (MAS; Hsieh et al., 2011; Sale, Mazzoleni, et al., 2014), and improvements in functional ability and manual dexterity (BB, JTHT, SIS, MAL; Hsieh et al., 2011; Hwang et al., 2012; Sale, Mazzoleni, et al., 2014). These improvements were maintained at follow up assessments (Sale, Mazzoleni, et al., 2014).

When recovery assisted with RT with the device was compared with recovery due to control conventional OT approaches, RT typically led to greater reductions in impairment (FMA; Hsieh et al., 2011; Hsieh et al., 2012; Liao, Wu, Hsieh, Lin, & Chang, 2012; Orihuela-espina et al., 2016; Yang et al., 2012), strength (MRC; Yang et al., 2012), and ability and ADL performance (ABILHAND , SIS; Liao et al., 2012; Wu et al., 2012).

Three RCTs investigated whether higher training intensity or dosage led to improved clinical outcomes. In these studies, the higher intensity groups showed improved gains in recovery (Hsieh et al., 2011; Hsieh et al., 2012; Hwang et al., 2012).

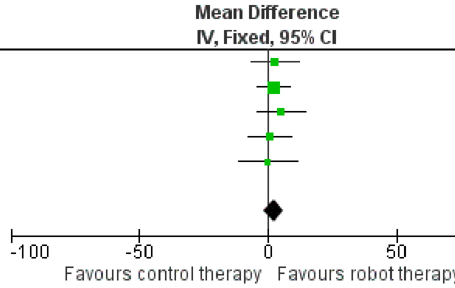
Meta-analysis of training effect

The included RCTs compared the effects of training with the BiManuTrack (six studies) or Amadeo devices (two studies) against control therapy. Five of the BiManuTrack RCTs measured FMA improvement over the intervention period. We conducted a pooled comparison across these studies of FMA improvement between participants who received training with the BiManuTrack and those in the control therapy conditions. The average effect was not significant, showing no significant difference in reduction in motor impairment between groups (Figure 3.3). The two Amadeo studies did not measure the same clinical outcomes and so a pooled analysis could not be made.

Figure 3.3 Forest plot of improvement in FMA: BiManuTrack versus CT

	Robot Therapy			Control Therapy				Mean Difference
Study or Subgroup	Mean	SD	Total	Mean	SD	Total	Weight	IV, Fixed, 95% CI
Hsieh et al. (2011)	5.33	8.25	9	2.83	11.77	9	16.6%	2.50 [-6.89, 11.89]
Hsieh et al. (2012)	5.22	8.55	18	2.95	11.06	18	35.1%	2.27 [-4.19, 8.73]
Liao et al. (2012)	6.3	8.92	10	1.3	12.38	10	16.4%	5.00 [-4.46, 14.46]
Wu et al. (2012)	3.85	10.93	14	3.14	11.88	14	20.5%	0.71 [-7.75, 9.17]
Yang et al. (2012)	2.7	9.71	7	2.7	11.87	7	11.4%	0.00 [-11.36, 11.36]
Total (95% CI)			**58**			**58**	**100.0%**	**2.18 [-1.65, 6.01]**

Heterogeneity: Chi² = 0.60, df = 4 (P = 0.96); I² = 0%
Test for overall effect: Z = 1.12 (P = 0.26)



Efficacy across pilot studies

In pilot studies comparing efficacy of RT in a single sample, training of the distal UL with the selected end-effector devices consistently resulted in a reduction in motor impairment in the distal, and often proximal, upper limb demonstrated by significant improvements in FMA (Colombo et al., 2005b, 2005a, 2007, Lambercy et al., 2009, 2011; Stein et al., 2011) and MI (Lambercy et al., 2011; Pinter, Pegritz, Pargfrieder, Reiter, Wurm, Gattringer, Linderl-Madrutter, et al., 2013) and MRC (Sale et al., 2012). In addition, there is some evidence that training with the devices reduced spasticity as measured by the AS/MAS (Lambercy et al., 2011), and increased strength (Sale et al., 2012). There was consistent evidence to suggest that these reductions in impairment may translate to improvements in ability and activity as measured by JTHT (Stein et al., 2011), BBT (Yeh et al., 2014), MAL (Stein et al., 2011), COPM (Weightman et al., 2011) and TEMPA (Yeh et al., 2014).

Impact of stroke recovery phase

Significant improvements in clinical outcome measures were observed across all stroke recovery phases when training with robotic devices. Two studies trained acute stroke patients with the Amadeo device and found improvements in outcome measures across both the impairment, and activity and participation level domains (Sale, Mazzoleni, et al., 2014; Sale et al., 2012). Similarly, significant and non-significant improvements were found across outcome measures in studies of subacute patients (Hwang et al., 2012; Pinter, Pegritz, Pargfrieder, Reiter, Wurm, Gattringer, Linderl-madrutter, et al., 2013). Most studies used samples of individuals with chronic stroke and demonstrated considerable gains.

3.5 Discussion

This scoping review aimed to evaluate the state of the evidence for distal end-effector RT for the functional restoration of the hand and wrist in individuals with UL disability. The review included 22 studies of RT with clinical samples totalling 389 participants. We found only one study that investigated the effects of training with one of these devices in a non-stroke population, which was CP (Weightman et al., 2011).

3.5.1 Randomised control trials

Nine of the included studies were RCTs comparing either RT with BiManuTrack or Amadeo device with a control conventional therapy in stroke patients. These were generally of high methodological quality; eight with a low risk of bias in all key domains identified by the Cochrane risk of bias tool (Higgins et al., 2011). These studies showed consistent reductions in motor impairment in both distal and proximal sections of the UL and improvements in activity and participation outcomes across all stroke phases. Improvements were retained in the two studies that conducted follow-up assessments. Two studies in this review directly tested the hypothesis that training effects are dose-dependent. Both found that increased duration or intensity of training led to improved motor outcomes (Hsieh et al., 2011; Hwang et al., 2012), as could be predicted based on previous review findings (Prange et al., 2006). If robotic therapy was used as an adjunct to therapist-based therapy in the home or clinic environment to increase the dosage of training this may result in improved motor and functional outcomes (Lum et al., 2012). Improvements were typically larger in subacute and acute patients trained with the Amadeo device than in the patients with chronic stroke trained with the BiManuTrack. Whilst we cannot draw a definitive conclusion, recovery rate exponentially decays following brain trauma so patients in the acute/subacute recovery phase generally exhibit accelerated recovery over those the chronic phase, It is likely that the RT simply facilitated this recovery.

Meta-analysis of RCTs with the BiManuTrack showed no difference in efficacy between RT and CT. There is no reason to expect that RT should produce improvements beyond that of therapist-based methods of equal duration or intensity (Kwakkel et al., 2008). Consequently, it should not be expected that RT should surpass the efficacy of conventional approaches. Whilst the meta-analysis showed no difference in efficacy of RT over conventional therapy, the pooled sample size was not sufficient to assess non-inferiority or equivalence so conclusions must be tentative. Equivalent or not, patients receive a limited, suboptimal volume of practice of UL movements in the clinical setting (Hayward & Brauer, 2015); robotic rehabilitation devices have the potential to complement conventional therapist based interventions by increasing the dosage of repetitive movement practice beyond the level that can be achieved in the clinic alone.

3.5.2 Uncontrolled pilot studies

The other 13 studies were uncontrolled pilot studies, typically assessed as having a higher risk of bias. These studies demonstrated consistent reductions in impairment of the UL and some evidence of improved outcomes in the activity and participation domain for stroke patients, retained at follow up in the four studies that conducted these assessments. However, these latter studies typically had very low sample sizes. Reported gains are therefore likely to be understated as studies were underpowered to find clinically significant improvements, particularly in measures of activity and participation. However, without inclusion of a control group, it we are unable to discriminate effects due to training from those due to natural recovery. This is of particular concern in studies of acute and subacute stroke patients in which natural recovery might account for a large proportion of improvements. Only one study tested RT in a non-stroke population (CP) (Weightman et al., 2011). Therefore we are unable to draw conclusions of the efficacy RT in this population.

3.5.3 General discussion

Across studies there was evidence for a reduction in motor impairment associated with RT and evidence of functional improvements. These findings are consistent with other studies of *distal* UL RT which found a reduction in motor impairment in the affected arm and preliminary evidence of increased activity and functional use of the upper limb (Balasubramanian et al., 2010). In contrast, systematic reviews of *proximal* UL RT have found no such improvements in activity and participation measures (Kwakkel et al., 2008; Prange et al., 2006). This difference may be attributable to the crucial role of the hand in ADL tasks (Faria-Fortini, Michaelsen, Cassiano, & Teixeira-Salmela, 2011). Whilst RT for the hand and wrist reduced impairment and spasticity in both distal and proximal sections of the upper limb (Hesse et al., 2003; Hwang et al., 2012; Buttefisch et al., 1995; Krebs et al., 2007; Takahashi et al., 2008), proximal training tended only to reduce impairment in the elbow and shoulder but not in the hand and wrist (Kwakkel et al., 2008; Prange et al., 2006), thereby limiting translation to ADL abilities. It is currently unknown why distal RT reduces proximal UL impairment. It may be the case because end-effector training of the hand and wrist indirectly trains the shoulder and elbow when using the device, specifically when the upper arm is not restrained or stabilised (Hesse et al., 2005; Lambercy et al., 2009; Lambercy et al., 2011) or due to increased use of the proximal UL outside of training as distal training increases the functionality and use of the affected arm in everyday tasks (Balasubramanian et al., 2010).

Whilst distal UL RT seems to be efficacious in improving motor and functional outcomes, the efficacy of any single device (with the exception of the BiManuTrack and Amadeo) cannot be established due to the aforementioned limitations inherent to the testing conditions of the uncontrolled pilot studies. The quality of the evidence for training with the Amadeo and BiManuTrack systems is high and we can draw robust conclusions of their efficacy.

Of the 23 studies, only six studies conducted follow up assessments necessary to preclude gains due to practice effects and the outcome measures used across studies were inconsistent. Frequently studies were underpowered. Addressing these limitations in future research would require the inclusion of a control group and sufficient sample sizes to allow clinically important change in activity and participation measures to be detected is crucial for establishing the efficacy of developed devices. Assessments should include at least one measure for each of the ICF domains (World Health Organisation, 2001) and conduct follow-up assessments.

Only one of the included studies addressed RT in a non-stroke population. Whilst a small number of research groups are applying rehabilitation robotics to individuals with CP (Chen & Howard, 2014; Meyer-Heim & van Hedel, 2013), MS (Basteris et al., 2011; Casadio, Sanguineti, Solaro, & Morasso, 2007; Feys et al., 2009; Octavia, Feys, & Coninx, 2015; Vergaro et al., 2010), and CSI (Chen & Howard, 2014; Cortes et al., 2013; Vanmulken, Spooren, Bongers, & Seelen, 2015; Zariffa et al., 2012), there is currently insufficient evidence to determine whether RT would be efficacious in these populations, this should be a research priority.

Due to the broad range of device designs, it is unclear which design features are key to promoting such improvements. Whilst future research should draw comparisons between designs and their ability to promote motor and functional recovery, efforts should concentrate on developing devices that are cheap to produce, with a small footprint and ease of use by patients and care professionals as this will be key to their adoption by health services, either in the home or clinic environment.

3.5.4 Conclusion

We have presented a review of end-effector devices for hand and wrist rehabilitation across neurological conditions. Individuals across the acute, subacute, and chronic stages of stroke recovery who received RT with the selected devices showed consistent reductions in motor impairment in both distal and proximal sections of the UL. In addition, the review found some evidence that RT resulted in an improvement in activity and participation outcomes across all stroke phases. Whilst distal UL RT with end-effectors seems efficacious, it is unclear which specific device features are key to promoting recovery of UL function. We only find one end-effector device that has been tested in a non-stroke population. Research priorities should include:

i) Comparisons of efficacy of rehabilitation robots across neurological populations other than stroke
ii) Development of end-effector devices focusing on ease of implementation to health services (low cost, ease of use, low maintenance)
iii) Cost analysis comparing robotic therapy with conventional therapy approaches

Chapter 4: Manual Tracking According to Perceptual Control Theory: A Systematic Review of Methodology and Findings

Target Journal: *Psychological Bulletin*

Maximilian G. Parker[1], Andrew B. S. Willett[2], Andrew P. Weightman[3], Sarah F. Tyson[4], & Warren Mansell[1]

Author Affiliations:

[1]Division of Psychology and Mental Health, School of Psychological Sciences, University of

Manchester

[2]Program in Narrative Medicine, Columbia University

[3]School of Mechanical, Aerospace and Civil Engineering, University of Manchester

[4]Division of Nursing, Midwifery and Social Work, University of Manchester

4.1 Abstract

Objective: The aim of the review was to present a systematic review of the findings of experimental studies of manual tracking performance, simulated with models based on perceptual control theory (PCT).

Methods: A literature search was conducted within the PsychInfo, Scopus, Web of Science and Science Direct databases. This compiled all peer-reviewed journal articles that simulated individual manual tracking data using a PCT model. Articles were included if they simulated human manual tracking data with a computational model based on PCT, although studies with neuro-atypical samples were excluded. To supplement this search, reference lists of included articles were also searched for related publications. A narrative review of the tracking studies was conducted alongside a qualitative assessment of their methodological quality.

Results: Thirteen studies (N = 53 participants) met the inclusion criteria and were reviewed. The review found that analyses of tracking performance suggest that individuals act as negative feedback control systems to control their perceptions against disturbances. In addition, individuals intentions and control strategies can be characterised within parameters of control models. There was some evidence that perceptual control models could emulate tracking in multiple Degrees of Freedom (DoF). Several theoretical principles were not modelled within tracking studies, such as PCTs mechanism of learning, known as reorganisation. Models were not fit to tracking performance for target types other than smoothly varying pseudorandom signals.

Conclusions: The studies support a negative feedback control explanation of manual tracking. However, the models must be tested across more varied task designs to address remaining critiques. One such critique might be that feedback is too slow to account for anticipatory behaviour. Another may be that software implementations may not explain the dynamics of interacting in a physical environment. Implementing the software models into robotic systems would test the robustness of these theoretical models. We recommend future research directions and set methodological guidelines for PCT computational modelling experiments.

4.2 Introduction

The mechanism of motor control has been the subject of investigation across the domains of physiology, biomechanics, neuroscience and psychology for many years. Since their inception, behaviourist and cognitivist accounts of motor control expounded a linear causative model whereby stimuli motivated actions (Bourbon & Powers, 1999). This basic view of linear causality was challenged by demonstrations that action is dynamically controlled and thus the motor system may be viewed as a servo-control mechanism in which movements result from dynamical, negative feedback error correction (Craik, 1947). This led to a line of enquiry in which the system was characterised and modelled with transfer functions (Navas & Stark, 1968; Neilson, Neilson, & O'Dwyer, 1988; Noble, Fitts, & Warren, 1955; Poulton, 1952a). In many contemporary accounts, feedback control operates alongside prediction (Friston et al., 2011; Miall & Wolpert, 1996). This could provide solutions to issues with movement timing and delays (Wolpert, Miall, & Kawato, 1998), and motor learning (Brown et al., 2011; Wolpert, Ghahramani, & Flanagan, 2001). However, predictive accounts must overcome a significant challenge: non-linearity in the neurophysiological mapping of inputs to outputs makes forward and inverse predictions computationally intensive (Latash, 2012; Scott, 2008). The complexity of action selection is amplified further when applied to multi degree-of-freedom biomechanical systems with intersegmental dependencies, such as human limbs (Wolpert, 1997), as the computations may become intractable. An alternative hypothesis reverses the control problem. Rather than predicting actions, humans control their perceptions; this is the central tenet of perceptual control theory (PCT; Powers, 1973).

PCT does not require predictions of motor output. Instead, perceptual inputs are maintained at desired (reference) states via negative feedback processes (Powers, 1973; Powers et al., 1960). These reference states quantify individual perceptual goals (Marken, 2013a). Actions are varied as necessary to achieve these goals (Powers, 1973), particularly in the face of disturbances. Complex behaviour emerges from a hierarchy of control units. At each level of the hierarchy there are many single control units each controlling different perceptual variables. The hierarchy operates as a two-way cascade. Bottom-up projections between hierarchical levels carry increasingly integrated perceptual information to superordinate levels. Top-down projections set the reference value (perceptual goal) for units in subordinate levels of the hierarchy. At any single control unit, comparison of reference value and incoming perceptual signal yields an error term. This error term is amplified to form the top-down projection to the control unit below. At the lowest hierarchical level, physical outputs produce movements that alter the environment in which the organism is situated. This changes the pattern of sensory stimulation. Thus the feedback effect via the environment closes the loop. In the perceptual hierarchy, learning is enacted by a reorganising system which projects to units in the hierarchy (Powers et al., 1960a). When an error term crosses a threshold value and persists, the reorganising system will alter the organisation of the hierarchy, properties, and parameters of the control units in a trial-and-error fashion until control is re-established and error reduces.

Powers introduced PCT in two papers in 1960 (Powers et al., 1960a, 1960b), and later expanded the theory (Powers, 1973). However, its first experimental demonstration was published in 1978 (Powers, 1978). In this seminal paper, Powers laid the foundations for analysing individual intentions in manual tracking tasks (Box 1). The paper formalised a perceptual control model of behaviour in a manual tracking task (Box 2), demonstrating the primary principle of the theory; that perceptual variables are controlled to internally specified reference goal states by negative feedback control. Control theory predicts that a disturbance applied to the cursor in the task should be compensated by behaviour to maintain the variable in this goal state. This hypothesis has been supported as an almost perfect negative correlation between a disturbance applied to the cursor and the individual's handle movements has been found in a series of compensatory tracking experiments (Marken, 1980; Powers, 1978). Conversely, very low correlations are observed between the input (cursor position) and the participant's control movements (Marken, 1980; Powers, 1978); thus supporting the hypothesis that individuals vary actions to control their perceptions during manual tracking.

Although correlational analyses of tracking behaviour provide clear evidence to support the core principle of perceptual control, correlations do not elucidate the *mechanism* by which these perceptions are controlled. To uncover this mechanism, PCT advocates the functional modelling approach (Mansell & Huddy, 2018; Runkel, 2007). Under the approach, the researcher first makes an inference of which perceptual variable is controlled in the task, and applying disturbances to the variable. If the variable is under control, the individual will maintain it within a goal state. In this case the expected effect of the disturbance will not be observed. This process is the test for the controlled variable (TCV; Runkel, 1990). Once a possible controlled variable has been identified, a mechanistic hypothesis can be tested by constructing a computational model. The fit of this model to an individual‘s tracking data can be assessed. Multiple models may be compared for their fit to the data and compared. Since Power’s demonstration of the individual as a perceptual control system (Powers, 1978), he and other researchers have used the functional modelling method to further test the principles claims of PCT.

Models have been extended to account for control of multiple perceptual variables simultaneously through hierarchical control (Marken, 1986; Marken, 1991). Others have attempted to determine individuals’ intentions (reference values) and quantify individual differences in tracking performance and parameters (Bourbon et al., 1990; Parker et al., 2017; Powers, 1978, 1989). However, some critiques of the theory have not yet been addressed. For example, that due to the intrinsic delays in processing sensory feedback in the CNS, feedback must be too slow of coordination of fast movements (Desmurget & Grafton, 2000; Hollerbach, 1982). Although PCT offers a theoretical explanation for delay compensation through hierarchical control, this proposal has not been tested with a computational model. Similarly, PCT’s learning mechanism, reorganisation, is well developed conceptually but is yet to be modelled with human experimental data. These limitations may explain why PCT has not achieved the status of a mainstream contemporary theory of action control. As a review of the evidence for PCT in tracking studies has not been conducted, the extent to which principles of PCT and its critiques have been addressed is not clear.

The current article reports a systematic scoping review of PCT modelling studies in manual tracking experiments. The review has three objectives: 1) To collate and summarise the findings within the PCT tracking literature, 2) To evaluate the methodologies of existing studies, and 3) To identify investigative priorities for future research, and 4) To relate findings to other contemporary approaches to action control.

Box 1 The tracking paradigm

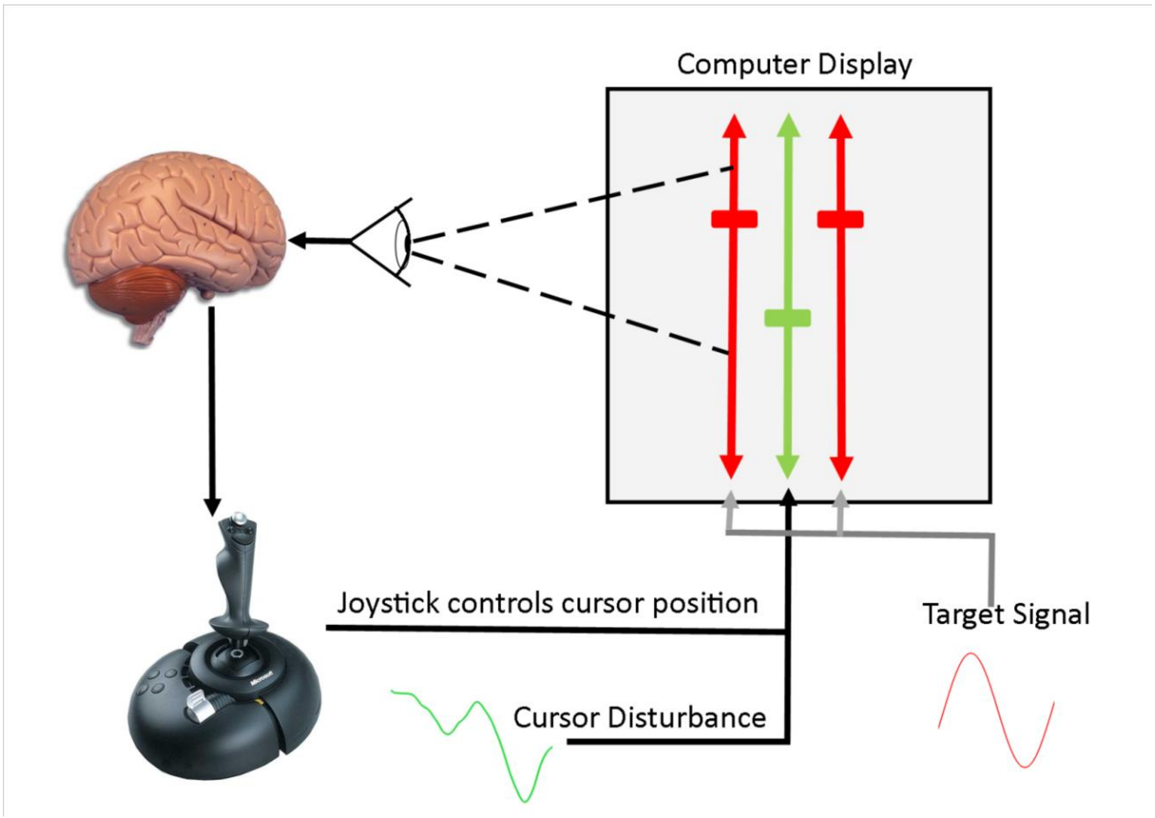
Experiments evaluating PCT mostly use a continuous-time manual tracking paradigm. This is because perceptual control is a dynamic process. To study continuous control, the task must supply continuous data. The tracking paradigm can be easily manipulated to make inferences about intention in behaviour, and models can be developed and compared to test for hypothesised controlled variables.

There are two typical variants of the tracking paradigm: compensatory and pursuit tracking. In compensatory tracking, the target marks remain stationary in the centre of the screen whilst in pursuit tracking (Figure 4.1), the target signal varies over the course of the trial. The cursor position in both setups is determined by the position of the joystick, linearly scaled to the screen pixels. In some versions of the tasks the cursor position is also affected by a computer generated disturbance signal.

Common patterns for both target signals in pursuit tasks, and disturbances in both tasks, include triangular waves, sinusoids and pseudorandom signals.

All studies included in this review use a variation of either one of these task designs. Notable variations include tracking in two dimensions (Marken, 1991) and multi-cursor displays (Marken, 1986; Powers, 1978).

Figure 4.1 Diagram of a computerised pursuit tracking task



Note the depicted task uses a sinusoid target signal and a pseudorandom disturbance to cursor movement. Adapted from Parker et al. (in preparation)

Box 2 Basic architecture of a perceptual control model of tracking performance

The standard perceptual control model of tracking consists of a single control unit (Figure 4.2). The input to the control unit is the distance between the cursor and target marks as its input. The input function transforms this input into a perceptual signal. The model compares this perceptual signal to a reference signal. The value of the reference signal is dependent on the intended distance between the cursor and target. Subtraction of the input signal from the reference signal gives an error term. This error term is transformed into an output signal via the output function. The effect of the output on the environment, and therefore the controlled perceptual variable, is mediated by the environment function. The environment function in the tracking case represents the relation between the output signal and its effect on the controlled variable, the target-cursor distance. The change in this controlled variable is then fed back into the control system as input.

In a typical PCT model of a control unit there are four parameters, which may be fixed or free parameters for optimisation.

Loop Gain: This parameter is a constant that proportionally multiplies the error term (constant of proportional integration). According to the theory, each of the functions (input, output and environment) would have an associated gain. In models, the loop gain represents the sum of the gains at these functions and is usually placed in the output function.

Reference Value: The reference value is a constant that specifies the target-cursor distance that the model intends to maintain. This represents the perceptual goal of the participant in the task. For example, if the participant was instructed to keep the target and cursor aligned, the model reference value should be close to zero.

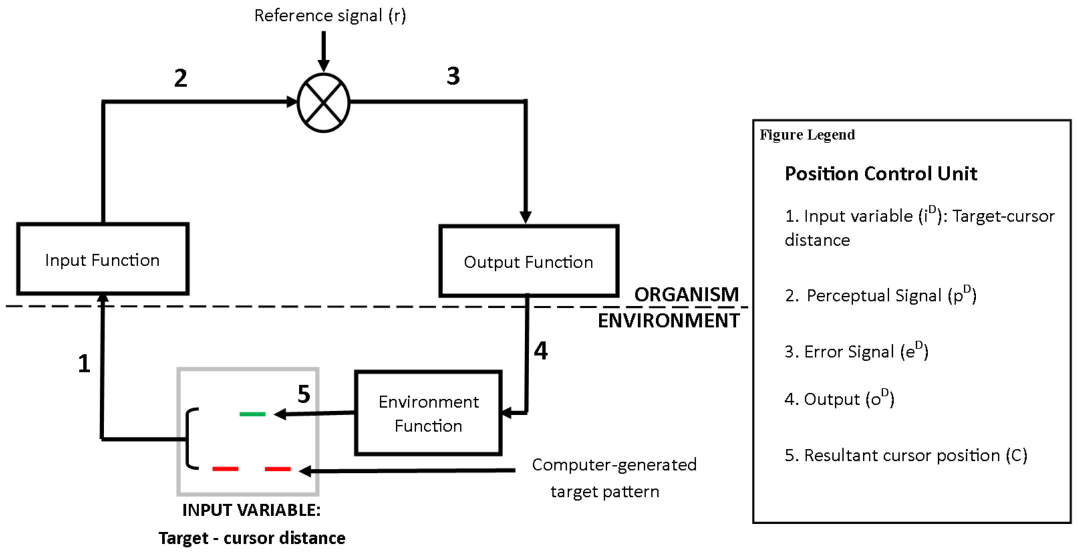
Note that in PCT the reference signal of a living organism is dynamic and internally-specified (top-down projections from higher control units). This is not readily apparent when a single control unit is modelled in this manner.

Leak Rate or Slowing Factor: The slowing factor sets the rate of the leak of the leaky integrator. The leaky integrator is a type of low-pass filter which ensures that a proportion of the output is ‘leaked’ at each iteration of the loop.

Loop Delay: Delays exist in the CNS which necessitate that action is coordinated based on outdated (previously sampled) sensory information. The model may include a delay interval. The loop delay value specifies the interval required for changes to input to circulate round the loop, back to input.

In some of the included experiments, the models have been expanded by adding further control units in a parallel or hierarchical structure.

Figure 4.2 Single unit PCM architecture and equation.



Adapted from Parker et al. (in preparation).

4.3 Method

4.3.1 Literature search

The literature search was conducted in the Scopus, PsychInfo, Science Direct and Web of Science databases by the first author (MP). The search terms were “Perceptual control theory” OR “control theory” OR “control system theory” AND model AND tracking. A citation search was also conducted on Powers’ seminal 1978 paper. Studies were included if they fulfilled the following criteria:

a) They were studies of manual tracking (one or two dimensions)

b) There was a perceptual control model of a single individual

c) The sample included one or more neurotypical adult participant

Only peer reviewed articles and book chapters were included.

4.3.2 Article screening

Article screening was conducted in the Covidence[2] software package. Title and abstract screening was conducted by the first and second authors. The first and second authors conducted full text screening of the articles that remained after title and abstract screening.

4.3.3 Data extraction and analysis

Data were extracted from the included studies by the first and second authors. Data included study hypotheses, samples, and details of the tracking task used. A narrative review was conducted by the first author. Articles grouped according to the principles of PCT that were tested. A narrative assessment of methodological quality was conducted by the first author against criteria outlined in the following section. The narrative format was chosen because no existing assessment tool was deemed appropriate given the heterogeneity of study methodologies.

4.3.4 Assessment of Methodological Quality

The custom methodological quality assessment considers methodological standards for experimental design in psychology, as well as accepted standards for control system design and evaluation.

[2] Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia.

Participants

It is regarded as good practice to make power calculations to determine the number of participants required to have sufficient power to draw generalisable conclusions from the data (Button et al., 2013). The need for this has become more apparent since the recognition of a replication crisis within behavioural sciences (Pashler & Wagenmakers, 2012). Required sample sizes will necessarily differ depending on the experimental design. In repeated measures designs, such as those typically used in individual modelling studies, models must be tested on their fit to that same individual's behaviour. This reduces the number of required participants (Dupont & Plummer, 1990). A long run-in or practice period is generally desirable to establish that the participant's performance has stabilized asymptotically (Parker et al., 2017; Powers, 1989). Notable exceptions are studies in which motor learning is the focus of investigation.

Models

The design and selection of models should consider a number of key factors. Critically, models should be parsimonious (Konishi & Kitagawa, 2007); model parameters should therefore be evaluated for their uncertainties and contribution to model fit (García, Prett, & Morari, 1989). When comparing models, improvements in accuracy should be balanced against increases in the number of parameters. This is because model accuracy will improve as a function of the increase in the number of parameters (Konishi & Kitagawa, 2007), making models susceptible to overfitting at the expense of generalisation to new datasets (Konishi & Kitagawa, 2007). If multiple models have been designed, models can be compared with the Aikake Information Criterion (AIC; Akaike, 1974) or Bayesian Information Criterion (BIC; Schwarz, 1978) which both assess the fit to data based on likelihood but account for the number of parameters of the model.

Parameter optimisation and model validation

Parameter optimisation is used to find the best fitting model parameters for a dataset. Optimisation methods range from manual techniques to sophisticated algorithmic solutions. Optimisation methods should be powerful enough to account for the number of parameters and their interactions. As the number of parameters increases, so too does the complexity of the landscape. Optimisation algorithms may get trapped in local minima (Lindfield & Penny, 2017), which may result in suboptimal parameter selection (Bäck & Schwefel, 1993). For generalisability, models should be optimised on an array of data. This may reduce the likelihood of selecting anomalous parameter values. Computational advances in recent years have yielded a number of powerful optimisation approaches (Lindfield & Penny, 2017). These are easy to implement in software packages such as MatLab. Examples are genetic algorithms (Grefenstette, 1986) and least squares algorithms (Luenberger, 1968), and simulated annealing.

It is also essential that models undergo validation on a second to avoid inflation in estimates of the fit to the data (Lillacci & Khammash, 2010; Oberkampf, Trucano, & Hirsch, 2004). In striving for a higher accuracy of fit to the training data, one might model specific aspects of that trial that do not generalise to other trials (Busemeyer & Wang, 2000).

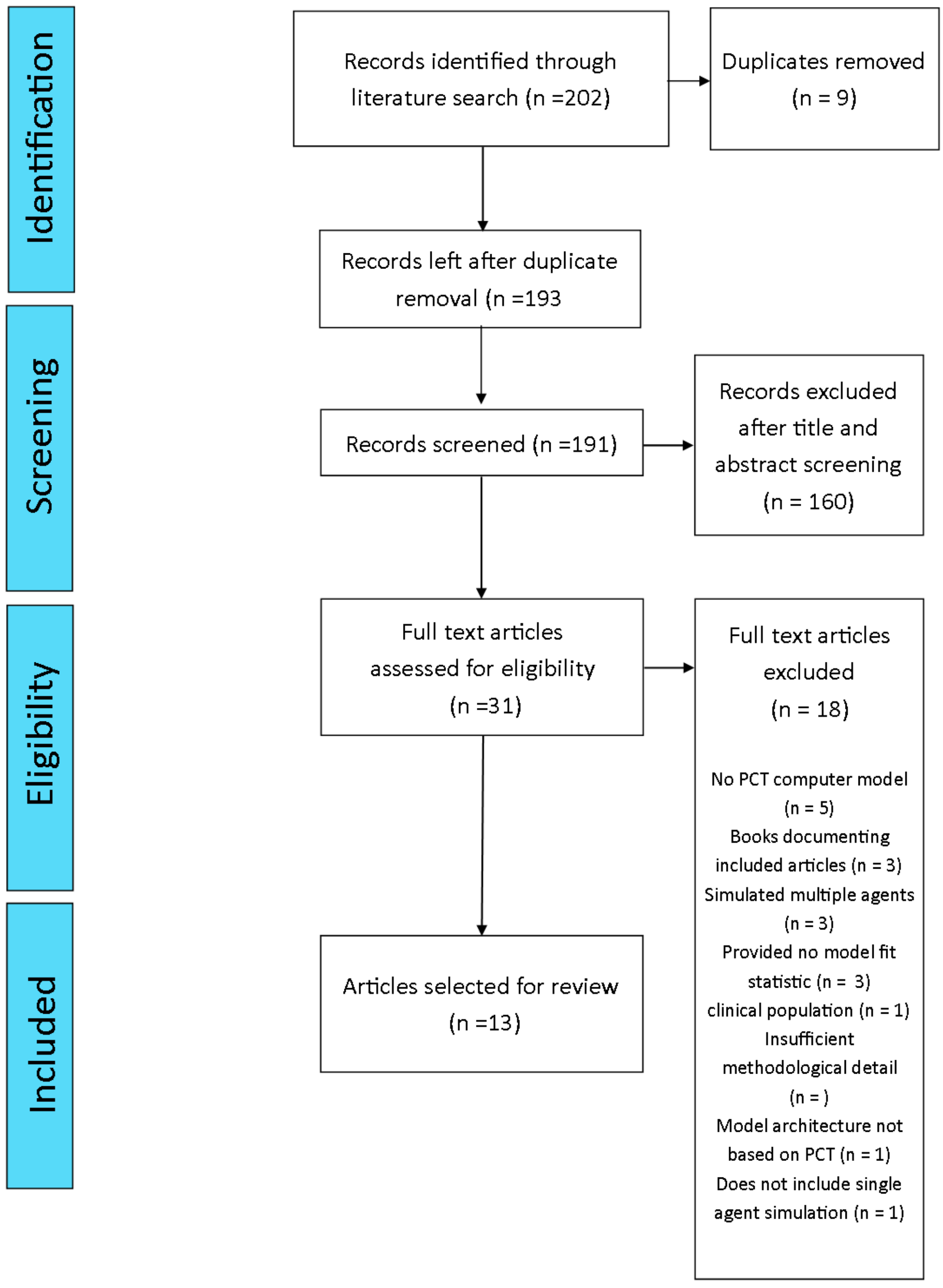
Accuracy metrics

The model's behaviour should visually emulate participant behaviour on inspection of the data. Quantitative metrics should also be used to assess the fit (Luenberger, 1968). Several metrics are available including correlations, R^2, Sum of Squared Error (SSE) and Root Mean Square Error (RMSE) and others (Pitt, Myung, & Zhang, 2002). Additionally, frequency analysis may be used to determine the magnitude ratio, and phase difference between two signals; allowing for disambiguation of tracking error (Cofré Lizama, Pijnappels, Reeves, Verschueren, & Van Dieën, 2013; Inoue & Sakaguchi, 2014; Ishida & Sawada, 2004; Yu et al., 2014). Phase difference calculates any lead or lags of the cursor relative to the target (timing difference) and may be expressed as phase angle or in time. Amplitude ratios calculate errors in reproducing the displacement of the target with the cursor. Generalisability quotients can be reported for model selection that penalize models for complexity to control for overfitting (Busemeyer & Wang, 2000; Forster, 2000; Pitt et al., 2002). Tasks may be employed in which humans do not reach a performance ceiling. If the model can replicate imperfect performance this may be a better determinant of model validity than simulating perfect performance.

4.4 Results

The literature and citation search identified 193 articles. A flowchart of the data extraction process can be found in Figure 4.3. Following the screening process, 13 articles were found to fit the inclusion criteria and were thus included within the review. Table 1 presents a summary of the included studies and their experimental designs. Table 2 displays the tabulated results of the methodological quality assessment.

Figure 4.3 PRISMA flowchart of data extraction process



4.4.1 Hypotheses

The hypotheses of the articles can be broadly categorized into six groups. Some articles contained a number of hypotheses that cut across the groups; in those cases the experiment number is specified in brackets. These numbers correspond to those in Table 4.1.

Five studies explicitly tested the principle that the *individual acts as a negative feedback control system.* Two compensatory tracking studies hypothesised that the correlation between the input (cursor position) and the movements produced by the participant (output) would be very low; whilst disturbances to the cursor position would be highly negatively correlated with the movements of the participant (Marken & Horth, 2011; Powers, 1978). Three studies compared the fit of open-loop and closed-loop negative feedback PCT models to tracking behaviour under different test conditions (Bourbon & Powers, 1999; Marken & Powers, 1989; Marken, 2013b). The authors hypothesised that PCT models would more accurately emulate participant behaviour than open loop models under these task conditions.

Three studies applied *the test for the controlled variable* (TCV; (Marken, 1988b; Runkel, 1990). In tracking the TCV assesses which aspect of the display was controlled by the participant (Marken, 1986; Marken, 2014; Powers, 1978). Often these studies utilised the stability factor, which calculates the ratio of observed to expected cursor variance and measures the likelihood that a given cursor relationship is under control by a participant.

Two studies attempted to explicitly test *the relevance of an internally specified reference value.* One hypothesised that when the participant attempted to control at a variable reference (changing over a single trial), the reference could be reverse calculated from their outputs (Experiment 2 of Powers (1989)). Another hypothesised that the reference value parameter would be consistent over time and uniquely contribute to model fit variance (Parker et al., 2017). In three studies a non-zero reference value was included as an optimised parameter that, along with gain or other parameters, was used to simulate later performance (Bourbon, 1996b; Bourbon et al., 1990b; Parker et al., 2017), and two in which participants were required to hold a constant or smoothly varying non-zero reference value and it was hypothesised that the model would accurately emulate this (Marken & Powers, 1989 (Experiment 3); Powers, 1978).

Two studies investigated *simultaneous control of multiple degrees of freedom.* These studies implemented hierarchical and parallel control models. The first study hypothesised that the participant could coordinate coherent action with two handles (Marken, 1986), independently compensating for disturbances (Experiment 1); second, that this ability could be maintained despite interaction forces (Experiment 2); and third, that it may appear, from an observer's perspective, that two cursors move as a functional group and may therefore be controlled by a single paddle (one DoF), when in fact the cursors are controlled independently and simultaneously (Experiment 3). In the second article, it was hypothesised that both dimensions in a two dimensional tracking task are controlled independently even in the case where it would be possible to control them with a single degree of freedom (Marken, 1991).

Three studies attempted to evaluate the degree to which PCT models show *individual specificity*. Two studies hypothesised that model fit to individual participant performance would still be very accurate if the individual was tested either one year (Bourbon et al., 1990) or five years later (Bourbon, 1996). One study hypothesised that models optimised to an individual's performance would more accurately simulate their performance than would a general model (Parker et al., 2017).

A final study investigated *reorganisation* (Pavloski et al., 1990). The authors hypothesised that reorganisation could be quantified within long tracking trials by changes in the loop gain parameter.

4.4.2 Participants

The total of 53 participants served across studies. Studies tended to have small sample sizes. In five studies a single author of the article was the only participant (Bourbon, 1996, 1999; Marken, 2013b; Powers, 1978, 1989). The largest reported sample size was 20 participants (Parker et al., 2017).

4.4.3 Models and model parameters

Nine studies implemented single position control unit architecture, in which the controlled perceptual variable was the difference in position between the cursor and target (see Table 4.1). One study implemented a single control loop that instead controlled the visual angle between the cursor and target (Marken, 2014). Two studies implemented hierarchical architectures in which a position control unit was the subordinate unit (Marken & Powers, 1989; Marken, 1986). One study implemented a parallel architecture of two position control units (Marken, 1991). Three studies included a comparison with an open loop model (Bourbon & Powers, 1999; Marken & Powers, 1989; Marken, 2013b; Powers, 1978).

All closed loop models contained a loop gain parameter. A sensory delay was implemented in three studies (Parker et al., 2017): in two of these this was implemented post-hoc as a phase delay to the resultant model data rather than as a parameter of the model (Marken, 2013b; Pavloski et al., 1990). A leaky integrator output was implemented in six models. In five of the six studies this was implemented as a slowing factor (Table 4.1) which acted to reduce the change in output per iteration. In one model the leaky integration was implemented by a damping constant that acted to proportionally reduce the current output before adding the new output on the current iteration (Parker et al., 2017). Reference values were optimised as a free parameter in four studies (Bourbon, 1996, 1999; Bourbon et al., 1990; Parker et al., 2017). In seven studies, the reference value was assumed to maintain a zero difference between cursor and target. All models implemented a loop gain. For hierarchical model in Marken's 1986 paper, and the parallel model in his 1991 paper, gains and slowing factors were implemented in each unit of the architectures (Marken, 1986; Marken, 1991). In the other paper with a hierarchical model, the slowing factor was only included in the unit at the lower level (Marken & Powers, 1989). One study evaluated the significance of the parameters of the models in predicting the model output (Parker et al., 2017).

4.4.4 Apparatus

The tracking apparatus used varied across studies. Seven studies used a computerised handle, four studies used a mouse, one used a joystick and one used two game paddles.

4.4.5 Parameter Optimisation and Model Validation

Models were predominantly optimised manually (Table 4.2), by an iterative pseudorandom selection process (Monte Carlo). Powers employed a simple iterative heuristic optimisation procedure for the gain and slowing factor in one paper (Powers, 1989). In another, a computational optimisation procedure was used as part of the TrackAnalyze program (Powers, 2008). This optimisation method was based on the E. Coli optimisation process implemented in a demonstration in the Living Control Systems III software suite (Powers, 2008). Trials usually lasted 40 seconds or one minute. The longest was six minutes. The number of trials and practice trials are given in Table 4.2.

Model validation with new data was conducted in three of the 12 included studies (Bourbon, 1996; Bourbon et al., 1990; Parker et al., 2017). In these studies models were validated on new data collected a few minutes after collection of the optimisation data (Bourbon et al., 1990), one week later (Parker et al., 2017), one year later (Bourbon et al., 1990), or after five years (Bourbon, 1996). In all these studies the number and length of trials was specified and can be found in Table 4.2.

Table 4.1 Summary table of study research questions and experimental designs

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Powers (1978) 1	1	Compensatory	Stationary	PS, .2Hz	Handle		2% RMS; S in range of -4 to -9	Not reported
2		Compensatory	Stationary	PS, .2Hz	Handle		2% RMS; S in range of -4 to -9	Not reported
3		Compensatory	Stationary	PS, .2Hz	Handle		S in range of -4 to -9	Not reported
4		Compensatory	Stationary	PS, non-linear feedback function	Handle	PCM	2% RMS	Model replicates behaviour 2% RMSE

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Powers (1978) 5		Four cursor pursuit	4 PS signals	None	Handle		S in range of -4 to -9	Not reported
6		Four cursor pursuit	4 PS signals	None	Handle		Not reported	Not reported
Marken (1986) 1		Compensatory with two cursor and one target	PS	Two PS disturbances	Game paddles	Hierarchical (4 units)	S = -11.04 and -10.70	r > .98
2		Compensatory with two cursor and one target	PS	Two PS disturbances, and interaction effect of game paddles	Game paddles	Hierarchical (4 units)	S for controlled quantities in the order of -10	r > .98

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Marken (1986) 3		Compensatory with two cursor and one target	Constant	One PS, one constant, interaction between handle outputs to cursor movements	Game paddles	Hierarchical (4 units)	S= -12.78 and -11.73	r > .98
Marken & Powers (1989) 1		Horizontal Pursuit	PS	None	Mouse	PCM	Not reported	r = .94-.98
2		Horizontal Pursuit	PS	Random mouse-cursor reversals	Mouse	Hierarchical Model (2 units), open loop model	Not reported	Hierarchical: r = .95, 5%, RMSE. Open loop: r = .906

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Marken & Powers (1989) 3		Horizontal Pursuit	PS	None	Mouse	Hierarchical Model (2 units)	Not reported	r = .94
4		Horizontal Pursuit	PS	PS	Mouse	Hierarchical Model (2 units)	Not reported	r = .97
Powers (1989) 1	1	Compensatory	stationary	Smooth PS	Handle	PCM	Not reported	Not reported
2		Compensatory	stationary	Smooth PS	Handle	PCM	Not reported	r = .999 when using reference value reverse estimated)
3		Compensatory	stationary	Smooth PS	Handle	PCM	Not reported	Not reported

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Pavloski, Baron, & Hogue (1990) 1	2	Horizontal Compensatory	Stationary	Smooth PS	Handle	PCM	Not reported	1.12% RMSE
Bourbon, Copeland, & O'Dwyer (1990) 1	10 (Total)	Pursuit	Triangular (Constant velocity)	None (C1), PS (C2)	Handle	PCM	Limited pixel related RMSE reported	C1: r = .985-.987 C2: .r= .961-.996
2	1	Pursuit	Triangular wave (Constant velocity	None (C1), PS (C2)	Handle	PCM	Limited pixel related RMSE reported	C1: r = .989 C2: r = .996

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
3	9	Pursuit	PS	None (C1), PS (C2)	Handle	PCM	Limited pixel related RMSE reported	C1: r = .997 C2: r = .992-.996
Marken (1991) 1	4	Compensatory (2d)	Stationary	PS (C1), PS (C2) PS and mouse disturbance (C3)	Mouse	2 PCM (parallel)	Not reported	C1 r =.986 C 2: r =.988 C3: r =.985
2		Compensatory (2d)	Stationary	PS (C1), PS (C2) PS and mouse disturbance (C3)	Mouse	2 PCM (parallel)	Not reported	Not reported

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Bourbon (1996)	1	Pursuit	triangular wave or PS	PS	Handle	Position control	Limited pixel related RMSE reported	r = .974-.997
Bourbon (1999) 1	1	Pursuit	Triangular (Constant velocity)	None	Handle	PCM, open loop model	Not reported	Not reported
2		Pursuit	Triangular (Non-constant velocity)	None	Handle	PCM, open loop model	Not reported	Not reported
3		Pursuit	Triangular (Non-constant velocity)	PS	Handle	PCM, open loop model	Not reported	Not reported

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Marken & Horth (2011)	6	Compensatory	stationary	PS (3 difficulties: centre band frequency)	Mouse	Position control	RMS% Difficulty 1: 6.4, Difficulty 2: 7.0, Difficulty 3: 50	Not reported
Marken (2013) 1	1	Compensatory	stationary	PS	Mouse	PCM, open loop model	1% RMSE	PCT model: R^2 = .99, Open loop model: R^2 = .12
2		2 target compensatory	stationary	None	Mouse	PCM, open loop model	Not reported	PCT model: R^2 = .91, Open loop model: R^2 = .91

Study and experiment number	Sample	Compensatory or pursuit	Target	Disturbances	Apparatus	Model	Performance	Model fit
Marken 2013 3		2 target compensatory	Stationary	PS	Mouse	PCM, open loop model	Not reported	PCT model: R^2 = .87, Open loop model: R^2 = .47
Marken (2014)	2	Pursuit	PS	None	Mouse	angle control model	Between 3 and 6% RMSE	Between 6-10% RMSE for the models at smallest separation
Parker et al. (2017)	20	Pursuit	PS	None	Joystick	Position control	Restricted to around 3%	2.05%, 1.82% RMSE

Note **PS**: Pseudorandom, C: Condition

Table 4.2 Table of Methodological Quality Assessment

Author/Year	Trial duration (s)	Subject prior practice	Number of optimisation trials	Optimisation	Validation trials	Model parameters	Disturbance frequency	Sample rate (s)	Power analysis conducted
Powers (1978)	60	Practiced	Not reported	Manual	Not reported	Gain	~ .2Hz	1/60th	No
Marken (1986)	120	Practiced	Last 90 seconds	Manual	Not reported	Gain, Slowing	.02Hz	Not reported	No
Marken & Powers (1989)	40	Practiced	Gain optimised on a previous trial	Manual	20 seconds of one trial	Gain	Not reported	1/25th	No
Powers (1989)	60	Practiced	Not reported	Manual	Not reported	Gain Slowing	Not reported	1/30th	No
Pavloski, et al. (1990)	360	None	Not reported	Manual	Not reported	Gain	Not reported	Not reported	No

Author/Year	Trial duration (s)	Subject prior practice	Number of optimisation trials	Optimisation	Validation trials	Model parameters	Disturbance frequency	Sample fate (s)	Power Analysis conducted
Bourbon et al. (1990)	60	Practiced	unclear, 104 over optimisation and validation	Manual	See optimisation	Gain, Reference	Not reported	1/30th	No
Marken (1991)	120	Seven trials in each condition	last three runs in each condition	Manual	Not reported	Not Reported	~ .4Hz	1/16th	No
Bourbon (1996)	60	Practiced	Unclear,	Manual	2 trials	Gain, Reference	Not reported	1/30th	No
Bourbon (1999)	60	Practiced	3 trials	Manual	None	Gain, Reference	Not reported	Not reported	No
Marken & Horth (2011)	60	Unspecified	12 trials	Manual	Not reported	Gain, Slowing, Reference	Not reported	1/30th	No

Author/Year	Trial duration (s)	Subject prior practice	Number of optimisation trials	Optimisation	Validation trials	Model parameters	Disturbance frequency	Sample rate (s)	Power analysis conducted
Marken (2013)	60	Unspecified	Unspecified	Manual	Not reported	Gain, Slowing, Reference	Not reported	Not reported	No
Marken (2014)	60	Practiced	10	Manual	Not reported	Gain, slowing	Not reported	Not reported	No
Parker et al. (2017)	60	Practiced	15	Computational algorithm	30	Gain, Loop Delay. Reference Damping	No disturbance	1/60th	No

4.4.6 Experimental designs and findings

Study designs and findings are summarised within the framework of principles outlined in the previous section.

The individual as a negative feedback control system

Two compensatory tracking experiments with a pseudorandom disturbance to cursor position reported correlations between the recorded variables (Marken & Horth, 2011; Powers, 1978). The correlation between cursor and handle movements fell between 0 and .1, whereas correlations between disturbance and output tend to be in the region of -.98 (Marken & Horth, 2011; Powers, 1978). Marken and Horth (2011) included a number of difficulty levels, which resulted in widely variable tracking performance (See Table 4.1).

Three studies compared closed-loop, negative feedback models to open loop models in a pursuit tracking task (Bourbon & Powers, 1999; Marken & Powers, 1989; Marken, 2013b). Contrary to the perceptual control model which views behaviour as the control of perceptual input, the open loop model views behaviour as directly caused by the input (target position). In the 1999 study, the target moved in a regular (experiment 1), or irregular (experiments 2 and 3) triangular wave pattern. In the first two experiments the cursor position was determined only by handle movements. In the third experiment, the cursor position was jointly determined by handle movements and a pseudorandom disturbance. Three models tracked the target in each condition and simulated cursor traces were plotted against the participant's. Two of the models were linear causal (open loop) models whilst the third was a PCM. One linear model failed to track the target accurately when the target velocity became unpredictable (condition 2). When the disturbance was introduced, both linear models failed because they did not compensate for the disturbance (condition 3). The control model compensated for the disturbance and tracked the target in all conditions. The authors concluded that participants use negative feedback control to compensate for disturbances and track unpredictably moving targets.

In experiment 2 of the 1989 study (Marken & Powers, 1989), the feedback connection between the handle movements and the cursor movements was reversed at intervals during the tracking trial. This resulted in a temporary runaway of the participant's cursor in the direction opposite to the target that lasted approximately 500 ms before the participants reversed their handle movements to continue tracking accurately. The authors conducted an open loop analysis of this these data. Under the open loop assumption, they predicted that the target and cursor movements would correlate throughout this period. That is, the target movement would determine the participant's cursor movements if it was the cause of their behaviour. This was not the case. The correlation between the target and cursor was significantly lower than the correlation between the PCT model-simulated cursor and the cursor movements produced by the participant in this situation (.91 and .95 respectively). The authors concluded that following the switch in direction of the handle's effect on the cursor position, the participant changed their control strategy to restore the negative feedback relationship.

In one article (Marken, 2013b) a position control and an open loop model were compared for their fit to tracking data in three conditions. The first was a standard compensatory tracking design (closed loop task), the second was a tracking reaction time task (open loop), and the third was the reaction time task (open loop) with a disturbance to cursor position (closed loop). The closed loop models fit the tracking behaviour of the participant more accurately than the open-loop models in the closed loop conditions (experiments 1 and 3). In the open loop experiment both models performed equally well (Table 4.1).

Test for the controlled variable

The first three experiments presented in Powers' 1978 paper used the compensatory paradigm with a pseudorandom disturbance. In each experiment the participant was instructed to hold a different relationship between the cursors and the target. Thus the participant had to alter their reference value between experiments. In the first experiment, the participant was instructed to keep the cursor aligned with the target. In the second experiment, a fixed non-zero reference was kept with the cursor. In the third experiment the participant was instructed to keep the cursor alternately above or below the cursor by 2 cm. The change followed presentation of a cue. The fourth experiment was not relevant to the TCV. In the fifth experiment, a four cursor tracking paradigm was used in which the handle affected the position of cursors one and three in the opposite direction to cursors two and four. The participant was asked to stabilize one of the cursors, and each cursor moved according to a separate pseudorandom disturbance. Powers calculated the stability factor to determine the quality of control in the first three experiments, and to determine which cursor was under the control of the participant in experiment 5. The stability factor calculates the ratio of observed cursor variance to expected cursor variance (Equation 1) where the expected variance is determined by the effect that a known disturbance would have on the cursor if uncontrolled by the participant. A low negative value indicates the variable is under control, a value around 0 indicates no control. Negative integers approximate the number of standard deviations away from no control the participant is exhibiting.

In the first three experiments of Powers (1978) the stability factor ranged from -4 to -9, indicating the participant exerted control over the target-cursor relationship. In the fifth experiment the stability factor was in the same range for the controlled cursor, for the uncontrolled cursor S was in the range of -1 to 1, indicating no control. Powers therefore demonstrated that the stability factor can be used to determine which aspect of the display the participant is controlling in the task.

In another study, a novel three cursor task was used in which the game paddles affected two of the three cursors (Marken, 1986). In the first experiment, the position of cursor one was determined jointly by game paddle one and a pseudorandom disturbance; the position of cursor two was determined jointly by game paddle two and a separate pseudorandom disturbance. The position of cursor three was determined only by another pseudorandom disturbance. Participants were instructed to keep a constant distance between the three cursors. The stability factor was used to demonstrate the relationship between cursors, rather than the position of any one cursor, was the object of control. The stability factor for the controlled variable (distance between cursors one and two, and between cursors two and three) for the six participants had an average stability factor of approximately -11.04 and -10.70 respectively. Stability factors for cursors one and two were -1.04 and -1.07 respectively. This was taken to show that the relationships between the cursors, rather than the cursor positions themselves, were the controlled quantities in the task. The stability factor was used to assess the quality of control in the other two experiments of this paper; these experiments are summarised in the section entitled ‘Control of simultaneous degrees of freedom’.

In one study, the TCV was applied to the tracking scenario by fitting two alternate models, a position control and an angle control model (Marken, 2014). The target followed a pseudorandom pattern. There was no cursor disturbance. The distance separating the cursor and target was manipulated experimentally to affect one variable (angle), but not the other (distance). It was hypothesised that if angle was the controlled variable, then performance should suffer as a function of the distance between the cursor and target. This was observed to be the case. A version of the TCV where the controlled variable is tested by model simulation was used. The distance control model did not show the decrement to performance that the participant exhibited as a function of increasing separation between the cursor and target, whereas the angle control model did. The angle control model resulted in a more accurate fit to the human data; particularly at larger separation values. The author concluded that this demonstrated that visual target-cursor angle, rather than visual target-cursor distance, was the controlled variable in this task.

The importance of an internally-specified reference value

In contrast to other control theoretic approaches, PCT specifies that the intended state of a controlled variable is internally-specified in the reference value (Powers, 1973; Powers et al., 1960a). In seven of the included studies, the reference value was set to zero (see Table 4.2) based on the assumption that if the participants are instructed to align the target and cursor the reference value would be zero. However a key prediction of the theory is that this value can take alternate values based on the individual's intention. Six studies investigated tracking with non-zero reference values.

In another study, the Powers attempted to simulate tracking with a varying reference value (Powers, 1989). This study used the standard compensatory tracking paradigm with a pseudorandom disturbance to cursor position. In the middle section of the tracking trial the participant was asked to move the cursor in a variable relationship with the target. This resulted in behaviour that, to an observer, would seem random. However, Powers estimated this time-varying reference signal and then simulated the section of tracking with a PCT model with this estimated reference signal. The estimated reference signal was inferred from the error signal (the time integral of the handle position), and the hypothetical perceptual signal by reverse-engineering from the observed cursor position via the model equation. The addition of the perceptual signal and error signal yielded a time-variable reference signal (series of reference values). This value was implemented in the model. Consequently, the model replicated the behaviour of the participant almost exactly; r = .998. Powers concluded that individuals' intentions are encoded in the reference value, and this can be determined via the PCT model, even when their intentions are not to keep the target and cursor aligned.

Five studies claimed to provide evidence that the reference signal does take non-zero reference values; even in cases where the participant is instructed to keep the cursor and target aligned (Bourbon, 1996; Bourbon et al., 1990; Marken, 1986; Parker et al., 2017; Powers, 1978). In the two Bourbon studies, the reference value parameter was optimised for each individual. The parameters took on different, non-zero values between individuals and allowed for specific predictions to be made of individual's performance over one (Bourbon et al., 1990) and five years (Bourbon, 1996). In another study, an analysis of individual differences in parameter values was conducted. Significant individual differences were found in the estimates of all parameters including the reference value. Moreover, high consistency was observed in each individual participant's parameter estimates over one week. A stepwise regression analysis of the contribution of each parameter to model simulation accuracy demonstrated that the reference value parameter made a significant unique contribution to the model fit. The authors concluded that the reference value parameter is an essential element of the control scheme and is integral to predictions of individual behaviour. Please see the section on individual specificity for a summary of the research findings of these three studies.

Simultaneous control of multiple degrees of freedom and hierarchical control

Two studies developed models that simulated human performance under conditions requiring simultaneous control of multiple degrees of freedom (Marken, 1986; Marken, 1991). Experiment 1 of Marken's 1986 study was previously described in a previous section (Test for the Controlled Variable). In an extension of this paradigm within the same paper (Experiments 2 and 3; Marken, 1986), the game paddles had crossover effects on the two cursors. That is, the participant had to compensate for the effects of disturbances to one paddle caused by their movement with the other paddle. Participants could keep a fixed distance between the three cursors. Marken concluded that this demonstrates coordinated action with two limbs at endpoint, and is analogous to controlling two degrees of freedom in the same limb with intersegmental interaction forces, such as the forearm and upper arm (Marken, 1986). A hierarchical PCT model was constructed which accurately simulated the behaviour of the participant in all three experiments. This hierarchical model consisted of four control units, two on a subordinate level and two on a superordinate level. The subordinate units were position controllers and the higher level units determined the dynamic reference values for these subordinate units based on the required direction of movement of the three cursors. This enabled the model to dynamically alter the two cursors to maintain the given relations between the three cursors. In simulations, the model cursor and participant cursor were extremely highly correlated (r = .98).

Another study implemented a two-dimensional compensatory tracking task (Marken, 1991).The position of the cursor was controlled by mouse movements. In one version of the task the movement of the mouse in one dimension resulted in a disturbance to the controlled perception in the other dimension as a side effect. The resultant cursor movements were diagonal, thus it seemed as if the participant was controlling a single degree of freedom. A model of two separate control units, each controlling cursor position in a dimension, at the same perceptual level, accurately simulated the movements of the participants in the task. This indicated that a single apparatus could be moved variably, to control two separate perceptual degrees of freedom.

Individual Specificity

Three studies attempted to investigate the predictive capacity of individual models. Two related studies investigated the consistency in predictions of individual models over one and five years respectively (Bourbon, 1996; Bourbon et al., 1990). In these pursuit experiments, models of performance were constructed when participants tracked triangular waves of a constant velocity. Models were then fit to a new validation dataset when participants tracked the similar targets (experiments 1 and 2), or pseudorandom targets (experiment 3), whilst a pseudorandom disturbance also affected cursor position. These studies demonstrated that over one and five years, participant's models could make extremely accurate predictions of their tracking movements to new targets.

One study tested the individual-specificity of model fits to pursuit tracking performance (Parker et al., 2017). All targets were pseudorandom and there was no disturbance to the cursor. Models were fit to data collected at one time point and fit to new data collected immediately after, or one week later. It was found that the estimated parameters of models optimised to participant performance across three blocks showed high consistency, in addition to significant individual differences between participant's parameters. Moreover, a PCT model optimised to each individual's training data (block 1) accurately simulated those individuals' tracking data in the other blocks. Moreover, models more accurately fit the individual from whose data they were optimised than an aggregate model of the other participants; the authors concluded that PCT models show individual specificity in predictions.

Reorganisation

A single study aimed to investigate the effect of learning on performance (Pavloski et al., 1990). The study consisted of two experiments. In the first, a standard compensatory tracking paradigm was used. One participant completed six minutes of continuous tracking and an estimate of the value of the loop gain was estimated for each one-second segment. The analysis demonstrated that this parameter value increased as a function of time as the individual learned. In the second experiment a dual task paradigm was used in which participants had to complete a numerical tracking task simultaneously with compensatory manual tracking task. One participant with practice at the task could engage in both simultaneously with visible decrement to performance. The other participant, who had had less practice, split their attention between both tasks. The authors interpreted this finding to demonstrate that participant one had reorganised to build a superordinate control unit that enabled simultaneous control of both tasks whilst the other participant had not.

Accuracy metrics

Reporting of tracking performance and model fit was inconsistent across the studies both in terms of the accuracy metrics used, and the detail in which these were reported (Table 4.1). Tracking accuracy was reported in the Root Mean Square Error (RMSE) between the participant cursor and the target across runs in four studies. These ranged from 2% to 50% of the total target displacement and depended on the difficulty of the target or disturbance (fundamental frequency). Three studies reported the quality of control by the participant using the stability factor; stability ranged from -4 to -12, indicating varying ability to compensate disturbances and exhibit high control. Two studies gave the error in pixels (an unstandardised measure). Tracking performance was not reported in five studies.

Model simulation accuracy was assessed by the correlation or RMSE between the model-simulated cursor movements and the participant cursor. Correlations were reported in six studies and ranged from r = .961-.999 for PCT models. Four studies reported RMSE scaled to target/disturbance maximum displacement. Values ranged from 1.12% - 10%. Two studies did not report a single accuracy metric and instead relied on visual inspection of the target, cursor and model cursor time series. No studies reported magnitude ratio or phase statistics.

No studies reported other accuracy metrics which may have been more informative, such as phase and amplitude.

4.4.7 Methodological quality of the included studies

A summary table of the methodological quality of the studies is provided in Table 4.2. This includes the key criteria that were assessed: Samples and power calculations, model characteristics, optimisation and validation procedures. Accuracy metrics are reported in Table 4.1.

Participants

Many of the included studies aimed to demonstrate that a simple control process underlies some behaviour that may appear to be caused by a manipulation of the task or instructions. This conclusion was drawn from the visual similarity (and correlation) between the cursor movements the participants made and the model-simulated cursor movements. As these demonstrations had very small sample sizes and reported only descriptive statistics, this constitutes considerable risk of bias. This risk of bias is reduced with increasing sample size so those studies that had 6, 9, 10 and 20 comprise relatively lower risk. None of the studies conducted *a priori* power calculations.

Whilst each study reported that participants were practiced at the task, the volume of practice is reported only in 3 studies (Table 4.2). In several studies the author was the only participant (Bourbon, 1996, 1999; Marken, 2013b; Powers, 1978, 1989). These participants may be expected to have had an extremely high volume of practice. It is possible that participants were not sufficiently well practiced for performance to have stabilised in studies in which only a few minutes of practice were given (Table 4.2). However, a lower volume of practice would be more likely to introduce a negative bias to measures of model simulation accuracy whereas increased practice is unlikely to affect simulation error due to performance asymptote.

Models

In all studies, the models developed were theoretically grounded and had few parameters which were decided *a priori* based on the theorised architecture. It is therefore unlikely models were over fit. PCT Model equations were reported in detail in the articles. However, of the three studies that compared open-loop models with control models, the open-loop models were underspecified in two studies (Bourbon & Powers, 1999; Marken & Powers, 1989). In studies that compared models, none used an information criterion to account for the number of free parameters when measuring simulation accuracy. This may have affected the findings of studies, penalising models with fewer parameters (open loop models typically), and benefitting hierarchical models (as every added control loop adds several free parameters).

Parameter optimisation and validation

Studies typically did not separate optimisation and validation trials. In such cases, model simulation accuracy was reported for the trial or trials on which the parameters were optimised. This is poor methodological practice and likely led to positively biased accuracy measures (Table 4.2). Four studies validated models with separate trial data (Bourbon, 1996a; Bourbon et al., 1990; Marken & Powers, 1989; Parker et al., 2017). In all but one study (Parker et al., 2017), manual parameter estimation routines were applied. This is only likely to be more problematic for models with larger numbers of parameters, such as the hierarchical models. This may have negatively biased accuracy for these simulations.

Accuracy metrics

Accuracy metrics were applied and reported inconsistently, which made interpreting simulation accuracy difficult. Five studies did not report a measure tracking performance and one additional study reported RMSE in pixels rather than as distance or as a percentage of target displacement or screen size (Table 4.2). It is therefore difficult to establish whether the model simulation accuracy is high because the model fits well or because the participant performed very accurately. No studies disambiguated errors in amplitude production from those in timing, preferring more general simulation accuracy statistics such as correlation coefficients and RMSE.

4.5 Discussion

This review aimed to summarise the state of the evidence for principles of perceptual control in modelling studies of manual tracking performance. Thirteen tracking-modelling studies were identified that investigated various theoretical principles of the theory. The extent to which these principles were supported within studies varied widely. For example, one core principle, that individuals control their perceptions via negative feedback, has been supported by many studies using several methods. Other elements of the theory, namely reorganisation, have not been investigated or demonstrated comprehensively within PCT tracking studies. Another aim of the review was to critique the methodologies of the included studies. In the following sections we first discuss the methodological quality of the included studies. Subsequently, we evaluate the strength of the evidence for each of the theorized elements of PCT and indicating shortcomings and future research priorities.

4.5.1 Methodological quality of the included studies

Participants

According to the perceptual control methodology the functional modelling approach (Mansell & Huddy, 2018; Runkel, 2007) aims to make claims about individuals rather than groups of participants. It is therefore necessary to gather a large volume of data for each individual participant, so that a model can be fit to an individual's performance. The ultimate test of the theory is the extent to which the model can account for the individual's behaviour (Mansell & Huddy, 2018). Although studies did not conduct *a priori* power calculations and typically had very small sample sizes, the single case or small sample designs of the included studies may have been appropriate for determining each individual's control strategy. This is evidenced by the very high (significant) model fit accuracy reported in the studies, which give support for the PCT model as mechanism of tracking performance within the studied individuals. Findings are consistently replicated across studies investigating a similar hypothesis, establishing that findings are generalisable across studied individuals. However, such individuals were often authors or participants familiar with the task and the theory.

It cannot be taken for granted that the model would fit as accurately for all individuals. Experiments with larger samples could elucidate whether this was the case. Crucially, experiments should use the functional modelling approach. The alternative, applying inferential statistics to observed data, can produce ambiguous and incorrect relationships when researchers do not take account of the dynamic and intentional basis of behaviour (Powers, 1990). Model fit data should be collected and then inferential statistics then used to establish whether the model architecture can fit many participants' behaviour as accurately. The functional modelling approach does not preclude the use of a group statistical approach.

Inferential statistics could also be used for model selection. One limitation of the included studies is that although they provide a model fit statistic, this is often ambiguous without a standard with which to compare it. Whilst a high model fit value demonstrates that the model can account for a large proportion of the variance in the participant's behaviour, this might simply reflect the participant's good tracking performance. That is, a model that fits the target accurately would be a good fit to a well-practiced participant's tracking movements. Comparing multiple models for their fit to the participant's behaviour enables researchers to dispose of models with inferior fits and localise on a solution. This methodology was demonstrated in one study (Marken, 2014), which compared two PCT models to determine which perceptual variable was controlled in the task (angle or position).

Optimisation and validation

In the included studies there was inconsistent reporting of the number of practice, optimisation and validation trials. This makes it difficult to assess whether a sufficient volume of data were collected for each participant and the level of experience the participants had with the task. This ambiguity also makes replication difficult.

With regard to optimisation procedures, PCT proposes its own optimisation method for altering elements of the perceptual hierarchy to enhance control: the reorganisation algorithm (Powers et al., 1960b). This has not been explicitly modelled within the included tracking studies. In fact, only one of the included studies used a computational optimisation algorithm. Despite this, models tended to accurately simulate tracking performances. This may be because the models usually comprised only two or three parameters (Table 4.2) and thus may have operated accurately under a broad range of parameter values. However, for models with a larger number of parameters, such as the hierarchical models, it is critical that a powerful parameter optimisation method is used. A larger number of non-independent parameters results in a complex parameter space and optimisation can easily get caught in local minima. Using a systematic optimisation approach is desirable for both validity and replicability (Lindfield & Penny, 2017). The E. Coli method used has been described and the code is freely available[3]. However, this process has few iterations and this may result in suboptimal fits. This is not likely to be a problem for models with few parameters such as the canonical PCT model.

Only three models were validated with new data that the model was not trained on. This may have resulted in inflation of the model fit to participant performance. This should

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[3] The Living Control Systems suite can be downloaded at: http://www.billpct.org, the accompanying book is called Living Control Systems III: The Fact of Control

be taken into account when interpreting the model fit statistics. Future studies should separate model optimisation and validation trials.

Accuracy metrics

The correlation coefficients were very large in the included tracking studies, indicating that the models demonstrated the same general pattern of tracking as the participants. Although this shows a high degree of similarity between the movements of the model and participants' cursors, the correlation coefficient is not best suited to detecting error that results from a constant offset in position or time (phase delay). It may be useful for studies to report a measure of residual error metrics that are sensitive to such constant displacements in addition to the correlation coefficient. Critically, characteristic errors such as overshoots and constant phase delays should be produced by the models when simulating performance. This could be confirmed by calculation of magnitude ratio and phase difference (Cofré Lizama et al., 2013; Inoue & Sakaguchi, 2014; Ishida & Sawada, 2004; Yu et al., 2014). These criteria would disambiguate errors in timing due to neural feedback delays, and those that result from applying an inappropriate force when tracking targets.

Summary of methodological quality

Many of the principles of PCT have been tested in a series of single cases or small samples. Thus many of the foundational theoretical principles have been evidenced in a number of separate studies, which have been replicated. However, some specific hypotheses have not been tested in multiple experiments. Therefore, whilst findings of an individual study may be significant, they have not been shown to generalise across a pool of participants (e.g. reorganisation). This should be taken into account when interpreting the findings. In addition, most studies did not meet the criteria set out in Section 4.3.4. Specifically, reported accuracy metrics may be somewhat inflated as a result of reporting fit statistics to optimisation trials rather than validating models with separate datasets. Future experiments should aim use larger samples and follow more rigorous validation and verification procedures. Finally, it is recommended that correlations are reported alongside a measure of residual error. In the following section the findings of the studies are discussed in relation to the identified theoretical themes.

4.5.2 State of the evidence for fundamental principles of perceptual control theory

The individual as a negative feedback control system

The studies extensively demonstrate the necessity of negative feedback in tracking. This is intuitively evidenced by the control movements observed during tracking of pseudorandom targets in pursuit tracking. Specifically, the correlations that show participants maintain alignment with the target in compensatory paradigms by acting against unseen disturbances (Marken, 1980; Marken & Horth, 2011; Powers, 1978). In the real world disturbances may act at multiple levels of the perceptual hierarchy simultaneously, and in different modalities. For example, whilst driving a vehicle, wind and other vehicles will act as separate tactile and visual disturbances that must be compensated simultaneously to stay on the road. Indeed any motor plan would be destabilized by disturbances that occur during action execution (Bourbon & Powers, 1999); particularly in cases where these are indistinguishable from the participant's own movements, such as in compensatory tracking tasks (Powers, 1978, 1989). This is not the case for purely open loop models which are unable to compensate for disturbances during movement, as demonstrated by model comparisons (Bourbon & Powers, 1999; Marken & Powers, 1989). However, whilst negative feedback is necessary in such conditions, this does not preclude an open loop or feedforward process within action control. Indeed, most contemporary theories of motor control propose hybrid models that comprise both feedback and predictive components and thus cannot be reduced to the open loop model (Adams et al., 2013; Friston et al., 2011; Wolpert, Ghahramani, & Jordan, 1995; Wolpert & Kawato, 1998). Authors claim that prediction is necessary because feedback control necessarily acts in a delayed fashion and thus cannot account for movement control shorter than the feedback delay period (Desmurget & Grafton, 2000).

In order to test whether a predictive component is necessary within action control, studies need to test perceptual control models under conditions in which prediction is possible, or even necessary. In such cases, participants tend to make use of target predictability to anticipate the target movement when tracking periodic targets. This is in contrast to participant tracking of unpredictable signals, where participants exhibit a delay of approximately 180 ms-450 ms (Abdel-Malek & Marmarelis, 1988; Noble, Fitts, & Warren, 1955; Parker et al., 2017; Stark, Iida, & Willis, 1961), depending on the type of target tracked. Perceptual control models of tracking have thus far only been tested in unpredictable conditions, except in the first experiment of the Bourbon study where participants tracked a triangular wave of constant velocity with no disturbance to the cursor position (Bourbon et al., 1990b). In this case, the perceptual control model performed slightly less accurately than the open loop model (Bourbon & Powers, 1999). This difference in accuracy is likely due to the control model ‘reacting’ to the target movement and therefore producing a small response delay, whereas the open loop model tracked without such delay. In fact, the superiority of the open loop models in this case was likely artificially reduced by the fact that the PCT model did not include a delay parameter. If an appropriate loop delay was introduced into the model, the model should track with an appropriate response delay relative to the target trace (Abdel-Malek & Marmarelis, 1990; Neilson, Neilson, & O’Dwyer, 1993) and produce significantly higher error.

In fact, only one of the studies included a delay as a parameter within the PCT model. In this study the loop delay was estimated to be around 180 ms when participants tracked pseudorandom signals (Parker et al., 2017). This represents an estimate for individuals’ sensorimotor delay in tracking, and corroborates other estimates (Abdel-Malek & Marmarelis, 1988, 1990; Hill, 2009; Hill & Raab, 2005; Noble et al., 1955). As delays are intrinsic to the CNS, appropriate delay values should be maintained in models that track predictable targets, even if participants’ actual track on or ahead of target (without a phase delay). This would pose a significant challenge for the PCM as this model (with an incorporated delay) cannot track any target without a phase delay in the response. Thus in the case where the target signal is periodic, such as a sine wave, constant velocity triangular wave, or circle or ellipse in the two dimensional case, where the participant tracks without a phase delay (Poulton, 1952b, 1952a; Viviani & Mounoud, 1990), a more complex model is required.

One PCT solution is that anticipatory behaviour may be an emergent property of hierarchical control (Powers, 1973). That is, integration of sensory signals from lower level units enables control of higher order variables. Downstream reference signals would specify an updated estimate for the position controller that accounts for the sensory delay. A prototype for such a model was suggested in a conference paper by Martin Taylor (Taylor, 1995). In this model, target signal velocity is estimated and fed into a PCM via the reference value, such that the position controller effectively tracks to an estimate of the target position ahead of where the target actually is, based on an extrapolation of the target velocity, thereby compensating for sensory delays. Such hierarchical control systems must be tested for their fit to tracking behaviour under predictable conditions. This would determine whether feedback control architectures can simulate anticipatory movements of participants in the task whilst retaining a biologically feasible estimate of sensory delay. In a more extreme case, tracking situations could be envisaged where there is no available visual information for feedback control, for example, during visual occlusion of a moving target (Rosenbaum, 1975). If the target is moving in an unpredictable fashion, the participant would be unable to track the target during occlusion (highlighting the necessity of perceptual feedback for successful control). However, if the target moved in a periodic fashion, but becomes occluded for some interval, then the participant is able to track to a memory of the target pattern in the absence of visual information, but produces significant phase error and amplitude reduction (Fine et al., 2014). This phase error indicates a loss of synchronisation of the cursor and target in time. The presence of this error indicates that memory-based prediction is insufficient for accurate tracking. However, the fact that participants are still able to track the general pattern of the input signal over the occlusion indicates that the participant is able to extrapolate or recall target movements prior to occlusion to produce a similar pattern (Miall, Weir, & Stein, 1993; Stenger, Thayananthan, Torr, & Cipolla, 2006; Zago, Iosa, Maffei, & Lacquaniti, 2010). This may be explained by the imagination mode in PCT (Powers, 1973; Powers et al., 1960b). This involves a control unit at one level receiving a simulated, rather than actual, input from memory by feeding a downstream reference value from that unit into its input function (breaking the hierarchical cascade of perceptual information). Whist the imagination mode has never been tested experimentally with computational models of tracking, it has recently been implemented in a computational model of self-efficacy (Vancouver & Purl, 2017).

Testing for controlled variables

The TCV has been established to be useful in determining which aspect of a display is the variable controlled by the participant (Marken, 1986; Marken, 2014; Powers, 1978). Moreover, the comparative study of angle control and PCM (Marken, 2014) demonstrates that it can be used for model testing by manipulating a variable (target-cursor separation) that should affect one controlled variable (angle) but not the other (position). Comparing the pattern of results for the participant and the models shows which model is more likely to be correct. It has been proposed that this could also be used to investigate the contribution of levels in a hierarchical model. The basic idea would be to apply disturbances to potential controlled variables at different levels of the hierarchy. A disturbance at a higher level should take longer to be responded to than that of a lower level (Powers et al., 1960b). Thus observing the effect of this disturbance on behaviour may reveal the hierarchical level of the controlled variable. Evidence that this is the case comes from a study where participants could control three different aspects of the same display with a single response, a key press (Marken, Mansell, & Khatib, 2013). Higher order perceptual variables produced longer reaction times. In the case of predictable targets, where participants may be extracting phase and amplitude information (course anticipation) or extrapolating position with velocity, these would operate at hierarchically different levels. A disturbance to one of these variables (e.g. a step change to the phase or velocity) should lead to different a longer response delay in the participant's tracking performance, which could enable differentiation of which strategy was used in the task.

The importance of the internally-specified reference value

Once the controlled variable has been established, such as by the TCV, the specific value to which the participant attempts to control the perceptual variable must too be established: the reference value. The reference value is a key concept within PCT. It is essential because it quantifies the intentional goal of the individual within the same quantitative unit in which the perceptual input to that loop is specified (Powers, 1978). This enables a direct error calculation to be made for each controlled variable. In the task, participants are usually instructed to align the cursor with the target, which represents the experimenter specifying the reference value that the participant should keep. Thus, in many experiments, the reference value within a model was fixed at the integer zero (zero difference between the target and cursor). Provided that the participants followed the instructions of the experimenter this gave a relatively accurate model fit to the tracking data (Bourbon, 1996; Bourbon et al., 199; Pavloski et al., 1990; Powers, 1978, 1989). However, studies that included a reference value parameter demonstrated that even when instructed to keep the cursor and target aligned, estimates of participants' reference values took non-zero values (Bourbon, 1996; Bourbon et al., 1990; Parker et al., 2017; Powers, 1978, 1989). Whilst models often only included a single position control unit, the theory posits that this unit is situated within a hierarchy of control units (Powers, 1973; Powers et al., 1960a, 1960b). Based on the theory, the reference value should be dynamically altered by units above. Therefore, it is a key limitation to assume a zero valued reference, particularly given that PCT attempts to make predictions of individual performance and the reference makes a unique contribution to model fit and differs between individuals (Parker et al., 2017). It may be more theoretically accurate to use a dynamic reference value in such tasks. One example of this is in Martin Taylor's velocity position model, in which the position controller assumes that the reference signal to the position controller is coming from a unit above that integrates target velocity (Taylor, 1995). Thus whilst this unit is not included in the diagram, a velocity input signal is combined with a constant position reference value and multiplied by a gain such that this produces a dynamic reference signal to the position controller below.

Individual specificity

The PCM has been shown to demonstrate individual specificity of predictions for pseudorandom targets with similar parameters (Parker et al., 2017). As is the case in the PCT literature, this has not been shown for any other types of target. Moreover, the extent to which an individual's model parameters would generalise across different target waveforms is unknown. It's likely that altering the properties of the waveform would have an effect upon the parameter estimates. However, it is not obvious whether individual differences scale such that someone who exhibits low gain relative to the norm would exhibit lower gain than their peers when tested on a faster signal. Model parameters would be altered during learning, with higher variance at the start of training toward the end; performance likely follows this pattern also. It could be the case that the authors inadvertently modelled differential learning rates and that individuals converge on an optimum parameter set.

Simultaneous control of multiple degrees of freedom and embodied simulation

The included studies have made an attempt to demonstrate how PCT could be applied to more complex control problems such as simultaneous control of two degrees of freedom in action (Marken & Powers, 1989; Marken, 1991; Powers, 1978). These give some insight into how parallel perceptual controllers can produce independent outputs whilst coordinated by hierarchical control units. These are very limited cases. Software simulations simplify the control problem as they assume that the lower level systems organise themselves to produce the behaviour, and they ignore any dynamical constraints and interactions between degrees of freedom that occur in physically realised movements. For example, with a single level PCM the position vector is directly translated to cursor position in the task (Powers, 2008). In humans, this signal must be translated to torque at joints at lowest levels of the hierarchy, and account for interaction forces between limb segments, this likely requires many transformations (Feldman et al., 2007; Todorov & Jordan, 2002; Wolpert, 1997). Synergistic movements requiring multiple joints must be produced through parallel and hierarchical control. Indeed, Powers produced a model of a virtual model of a three DoF human arm (Powers, 1999). This model has been implemented in a three DoF robotic arm that can compensate for visual and pressure disturbances to maintain endpoint position[4].

The environmental function in the software simulation considers that the output has a one-to-one relationship with the cursor position that it determines. The physical environment operates within a set of physical laws. These, in combination with a limb and body with inherent constraints, and the dynamical properties of the tracking apparatus, must determine how this control law manifests in the measured behavioural output and consequent perceptual input. Making inferences about the mechanism from the cursor movement is consequently a tricky business. How much of the overshoot after the reversal in direction of the target is a result of the CNS delays, and how much is due to inertial forces at the limb during movement execution? Consider that the handle or joystick has certain dynamical properties and may exhibit stickiness; this may produce noise in measured output such as high frequency behaviour which is not encoded in the motor command to the limb. Behaviour may be over-fit by models if these processes are aggregated into the output function at the PCM.

An additional simplification occurs at the input function. The input function in PCT models assumes a one-to-one matching of input signal and perceptual signal. This ignores the myriad of bottom up processes inherent in extracting and processing retinal and proprioceptive inputs hierarchically in the sensory cortices to ascertain complex perceptions such as the relative difference in position between the cursor and target. One way to address these assumptions is to build robotic devices with sensors and effectors which actually transform visual inputs into movements and interact with the tracking apparatus in real time. This may enable researchers to ascertain which processes operate at which hierarchical levels and better understand these functions.

Motor learning: reorganisation

Motor learning has not been elucidated within PCT tracking experiments. Whilst 'reorganisation' is PCT's explanation for motor learning (Powers, 1973; Powers et al., 1960a, 1960b), this has not been implemented in tracking models as an optimisation procedure. In contrast, other theoretical models can exhibit learning, for example via Bayesian inference (Adams et al., 2012). Whilst these show how existing control units can

[4] https://www.youtube.com/watch?v=wQ6FGeSjN9c

be optimised adaptively, they do not describe the developmental process of producing hierarchies in the absence of an existing control mechanism for a specific motor skill. In PCT, the reorganisation system is said to have inputs that are genetically determined intrinsic references (Powers et al., 1960a). The reorganisation system projects to the control units within a hierarchy and samples the error at those units, and is able to alter their functions if intrinsic error rises beyond a threshold (Powers, 1973). This way, learning in any particular unit may not be taking place if there is no intrinsic error. When the intrinsic error reaches some threshold, the reorganisation system kicks in and begins to alter the properties of the hierarchy in a trial-and-error fashion. This may involve acquiring new control units or reconnecting, via downstream references, existing control units within the hierarchy to produce a new functional pathway (Powers et al., 1960b). Thus, different theories make alternate hypotheses about the role of prediction and motor learning. Model comparisons could provide valuable insights; the tracking environment is a good test bed for such comparisons.

The reorganisation algorithm has not been investigated in much detail in these tracking experiments, and has never been explicitly modelled within the tracking task. Outside the tracking literature, models of reorganisation have been implemented, for example, for the optimisation of the three DoF virtual arm model mentioned previously (Powers, 2008). In this model, the hierarchical organisation was fixed. The reorganisation procedure altered the parameters and references for the control units. A reorganisation model has not been developed which actively produces perceptual hierarchies for any task.

Generalisability

The theory has been evaluated through models in a variety of different tracking tasks, which demonstrates the generalisability of the principles of perceptual control across task constraints. Some notable examples of differing task constraints are disturbance speed (Marken & Horth, 2011), dimension of tracking (horizontal or vertical), multiple tracking dimensions (Marken, 1986; Marken, 1991), and multiple different tracking apparatus including handles, joysticks, game paddles and computerised mice. One study utilised two apparatus simultaneously (Marken, 1986). Tracking is an ecologically valid activity requiring sensory integration, timing and multi-joint dynamics. The ability of humans to accurately track stimuli in these different conditions, despite disturbances, shows the robustness and adaptiveness of the human body and CNS. Similarly, the propensity for

PCT models to accurately simulate the behaviour of participants across these task constraints, even though the required movements change between targets, tasks and apparatus, is strong evidence that negative feedback perceptual control underpins human performance. However, no PCT models have been constructed of tracking predictable environments with delays, such as tracking of sinusoids, triangular waves or circles or ellipses in two dimensions, as mentioned previously in the article.

The PCT model does generalise to other perceptuo-motor tasks. For example, tracking experiments in the auditory domain demonstrate the same principles of negative feedback in perceptual control[5]. In three dimensions, perceptual control systems have been applied to catching and the outfielder problem (Marken, 2001; Marken, 2005; Shaffer, Marken, Dolgov, & Maynor, 2015). The TCV was applied to determine the controlled visual field variables in catching through head mounted camera footage (Marken, 2005). These hypothesised controlled optical variables are lateral angle and vertical angular velocity. A PCT computer model was developed which would simulate catching a ball in a three dimensional space by controlling these variables at constant values by moving across the virtual field (Marken, 2001). This resulted in the model being in the right position to catch the ball and showed running trajectories that look visually similar to those produced by humans catching real balls. This model was demonstrated to fit behaviour when participants caught objects thrown to themselves (Shaffer et al., 2015), and moved in unpredictable trajectories (Shaffer, Marken, Dolgov, & Maynor, 2013). There are other domains to which tracking models could be usefully applied, such as in driving, and flying with steering wheels and joysticks respectively.

Other than analysis and modelling of human data, perceptual control has been demonstrated in animals and can be used to control robotic devices. Heather Bell and colleagues conducted a behavioural analysis of food protection behaviour in rats (Bell & Pellis, 2011). These animals are observed to engage in complex dodging and bobbing behaviour when attempting to avoid other rats from stealing food pellets. The animals attempted to keep a constant inter-animal distance by altering their behavioural outputs. This is reflected by no correlation between the distance between the attacking rat and the food pellet (controlled variable) and the behaviour of the attacking rat (disturbance), yet a correlation between the disturbance and the behaviour of the rat (compensatory

[5] http://www.mindreadings.com/ControlDemo/AudioControl.html

movements). This of course is the same pattern of correlations found in tracking. The disturbance in a compensatory task is negatively correlated with output whilst the perception is not correlated with the disturbance (Powers, 1978). PCT also demonstrates promise as a control algorithm for robotic devices (Young, 2017). This adds additional complexity than in the software models. Sensor data has to be filtered for noise and movements must compensate for physical disturbances that affect movement coordination.

4.5.3 Conclusions

In the current article we conducted a narrative systematic review of the tracking literature in PCT to establish the state-of-the-evidence for the theory and identify future research directions. The review established that a large body of evidence exists, over multiple studies, that human tracking involves control of perceptual variables in intended states against possible disturbances. Preliminary evidence exists that PCT models can make individual-specific predictions. Despite assertions that negative feedback is sufficient to explain tracking behaviour, the model has not been adequately compared with a contemporary hybrid motor control theory including a feedforward element. Thus feedforward control cannot be excluded as a possibility, particularly as no PCT tracking studies have investigated tracking behaviour in predictable conditions. PCT is just beginning to test how the well-defined computer models can control multiple DoF devices in physical environments. Key to successful implementation in this regard will be powerful development and optimisation tools; reorganisation may provide an avenue for constructing complex working hierarchies.

Chapter 5: Perceptual Control Models of Pursuit Manual Tracking Demonstrate Individual Specificity and Parameter Consistency

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Maximilian G. Parker[1], Sarah F. Tyson[2], Andrew P. Weightman[3], Bruce Abbott[4], Richard Emsley[5] & Warren Mansell[1]

Author Affiliations:
[1]Division of Psychology and Mental Health, School of Psychological Sciences, University of Manchester
[2]Division of Nursing, Midwifery and Social Work, University of Manchester
[3]School of Mechanical, Aerospace and Civil Engineering, University of Manchester
[4]Psychology Department, Indiana University – Purdue University Port Wayne
[5]Centre for Biostatistics, School of Health Sciences, University of Manchester, Manchester Academic Health Science Centre

5.1 Abstract

Computational models that simulate individuals' movements in pursuit tracking tasks have been used to elucidate human motor control. Whilst there is evidence that individuals' demonstrate idiosyncratic control tracking strategies it remains to be established whether models can be sensitive to these idiosyncrasies. Perceptual control theory (PCT; Powers, 1973) provides a unique model architecture with an internally set reference value parameter, and can be optimised to fit an individual's tracking behaviour. The current study investigated whether a PCT Position Control Model (PCM) could show temporal stability and individual-specificity over time. Twenty adults completed three blocks of 15 one minute pursuit tracking trials; two blocks (training and post-training) were completed in one session and the third was completed after one week (follow-up). The target moved in a one dimensional pseudorandom pattern. The PCM was optimised to the training data using a least-squares algorithm, and validated with data from post-training and follow-up. We found significant inter-individual variability (partial η^2: .464-.697) and intra-individual consistency (Cronbach's α: .880-.976) in parameter estimates. Polynomial regression revealed that all model parameters, including the reference value parameter, contribute to simulation accuracy. Participants' tracking performances were significantly more accurately simulated by models developed from their own tracking data than by models developed from other participants' data. We conclude that the PCM can be optimised to simulate the performance of an individual and that the test-retest reliability of individual models is a necessary criterion for evaluating computational models of human performance.

5.2 Introduction

The ability to control visual and proprioceptive variables underpins all human manual skills. Tracking tasks, in which an end-effector (joystick or handle) is used to keep a cursor aligned with a target that changes position over time (Poulton, 1952; Poulton, 1974), have thus figured prominently in research studies of motor control and human-computer interaction. System identification approaches, applied to tracking behaviour, have led to the development of general computational models of the human operator (Levison, Baron, & Kleinman, 1969; McRuer & Jex, 1967). However, it has been established that humans display idiosyncratic invariants in some movement parameters (Morasso, 1981). These characteristic individual 'traits' should be evident between individual's manual tracking behaviour that show temporal stability within individuals. Below we review the evidence for such idiosyncrasies in individual tracking performance and outline a model, derived from perceptual control theory (Powers, 1973), which is capable of capturing these idiosyncrasies. The current study explores the potential for this computational model to individually characterise twenty individual's control strategies and differentially simulate their performance.

Time-series and frequency analysis of individual performance in pursuit tracking indicates that manual tracking performance is dependent on a number of factors. In the first instance, tracking strategies are partly determined by task constraints such as the frequency of the target signal (Neilson, Neilson, & O'Dwyer, 1993) and the motion pattern of the target; for instance whether targets move in sinusoidal or pseudorandom patterns (Notterman & Tufano, 1980; Viviani & Mounoud, 1990). Individuals also demonstrate large individual differences in tracking strategies and performance due to user-related factors including the volume of task practice (Notterman & Tufano, 1980), previous joystick experience (Joseph & Willingham, 2000), and age (Jagacinski, Liao, & Fayyad, 1995; Liao, Jagacinski, & Greenberg, 1997). Differences are even more evident in the tracking behaviour of individuals with motor deficits, such as the characteristic impairments of people with Parkinson's disease (PD). People with PD tend to undershoot the target peaks and demonstrate increased pursuit latencies relative to control participants (Abdel-Malek, Markham, Marmarelis, & Marmarelis, 1988; Flowers, 1978). Constructing dynamical models of pursuit tracking performance in healthy and atypical populations have helped to elucidate the nature of individual differences in tracking.

In healthy populations, dynamical models optimised to the data of individual participants demonstrate that idiosyncrasies in tracking performance can be reflected in estimated model gains and time constants (Abdel-Malek & Marmarelis, 1988; Viviani, Campadelli, & Mounoud, 1987; Viviani & Mounoud, 1990). Computational models of pursuit performance in people with Parkinson's Disease have shown that patterns of parameter estimates reflect their specific impairments in motor planning and execution. The characteristic target undershoot is quantified in the model by overdamped output (Abdel-Malek et al., 1988; Au et al., 2010) relative to control participants, and timing issues are evident in delays and velocity control gains (Viviani, Burkhard, Chiuvé, Dell'Acqua, & Vindras, 2009). Analysis of these parameters (gains, delays and damping constants), optimised to individual performance enable discrimination between samples of people with Parkinson's in receipt of medication, those who are non-medicated, and controls, despite the absence of a difference overall task accuracy between the groups (Au et al., 2010; Oishi et al., 2010). Whilst many studies found that models accurately simulated the tracking behaviour of individuals in model validation tests in both typical (Abdel-Malek & Marmarelis, 1988; Aiman Abdel-Malek & Marmarelis, 1990; Marken, 1991; Powers, 1978; Viviani et al., 1987; Viviani & Mounoud, 1990), and Parkinson's (Aiman Abdel-Malek et al., 1988; Au et al., 2010; Oishi et al., 2010; Oishi, Talebifard, & McKeown, 2011; Viviani et al., 2009) samples, there is a paucity of research studies that validate models with data collected at a later time point. This is problematic because the accuracy, and therefore usefulness, of a model must be dependent on the individual's control strategy remaining stable over time in a well-practiced individual. Whilst this has not been specifically modelled in tracking studies, there is some indication from studies of motor performance that control strategies might show temporal stability.

It has been established that there exist movement parameters that are invariant over repeated movement performances within participants, despite overall variability in produced movements and individual differences between participants; such as velocity profiles and hand tangential velocity in reaching movements (Morasso, 1981) and movement trajectories in pointing and joint angle-velocity ratios in pointing (Soechting & Lacquaniti, 1981). However there have been few studies testing whether this is the case in tracking experiments over repeated occasions. In one study, participants tracked a sinusoidal signal at a single frequency over ten days, the variability in their pursuit velocity profiles reduced as the variability in their error decreased, assessed by correlation coefficient between trials each day (Franks, Wilberg, & Fishburne, 1982), indicating that participants learned a particular control strategy. Another study showed that participants produced individual, characteristic direction-velocity distribution ‘ensembles’ in tracking of two dimensional sinusoidal targets, that persisted over a range of target frequencies (Miyake, Loslever, & Hancock, 2001); participants could be differentiated by these ensembles. While these studies suggest that intra-individual consistencies in tracking strategies may exist, we found only two studies that explicitly that optimised models to participants’ behaviour at one time point, and validated the model with data collected at a second time point (Bourbon, 1996b; Bourbon et al., 1990b). These studies found strong correlations (r = .98) between the model-simulated cursor movements and the participants own cursor movements. These studies had small sample sizes; five participants over one year (Bourbon et al., 1990b), and a single case (the author) over five years (Bourbon, 1996b). Whilst models accurately simulated the participant from which they were developed over this time period, the authors did not measure intra-individual consistency or individual differences in parameter estimates over the repeated testing sessions. These studies used a computational architecture, derived from perceptual control theory (Powers, 1973), which purports to have the potential to differentially simulate individual performance in healthy participants (Bourbon, 1996b).

Perceptual control theory (PCT; Powers, 1973) derived from conceptual principles and therefore the functions of model parameters on which individuals should differ are pre-specified and relate to specific aspects of the individual’s control strategy, in contrast to other models identified via system identification. The tracking model comprises the gains, delays and damping parameters common to other theories, in addition to another, unique parameter; the reference value. This parameter represents the goal specification for the control system and in PCT is set within the controlling system rather than from outside it (Mansell & Marken, 2015), as PCT provides a model of a purposeful system (W. T. Powers, 1978). Whilst other theories would assume this goal specification would be zero within the constraints of the tracking task as participants are instructed to keep the cursor and target aligned, this is not the case when models including a reference value parameter are optimised to individual performance (Mansell & Marken, 2015). In fact, estimated reference parameters frequently hold a non-zero value (Powers, 1978, 1989). The addition of this control parameter may improve the simulation accuracy of models to individual’s validation data and allow discrimination between individuals as their specific goal specification must be a core feature of their control strategy. Whilst PCMs have been frequently demonstrated to simulate individual performance to a high degree of accuracy in well-practised participants (Bourbon, 1996b; Bourbon et al., 1990; Powers, 1978, 1989), the nature of the relationship between PCM parameters and performance remains to be elucidated. Moreover, whilst the findings of Bourbon et al. (Bourbon, 1996b; Bourbon et al., 1990b) suggest that individuals might show differing and consistent patterns of control parameters over time, this has not been directly tested. It remains to be demonstrated whether PCT can be used to differentially simulate individual performance.

The current study aimed to examine the estimated control parameters of a PCM optimised to individual's performance over one week, and elucidate the relationship between individual parameters and model simulation accuracy. We trained a PCM on each participant's pursuit movements during a tracking task and examined the reliability of estimated parameter values for each participant and individual differences between participant's models over one week, and investigated the nature of the relationship between estimated control parameter values and model accuracy. To determine whether models were individual-specific, we additionally tested whether these models could make idiographic predictions of a participant's own pursuit movements after one week (validation) and whether these 'self' simulations were superior in accuracy to the predictions of general, aggregate model, that had not been optimised to the participant's data. We hypothesised: 1) Parameter estimates of an individual's computational model will remain stable over time (one week). 2) There will be differences in parameter estimates between individuals. 3) Estimated parameters are suspected to hold quadratic relationship with model simulation error as the participants are presumed to converge on optimal parameters in the task. The reference value parameter will increase the variance explained by the regression model when added to the model consisting of the other parameters. 4) The models generated from an individual's parameter estimates during training will accurately simulate that individual's tracking movements even after one week has elapsed. 5) A participant's tracking data will be more accurately simulated by the participant's own model than by other participants' models. We expect that the difference will be small but consistent given that we would expect participants to converge on an optimal control strategy for this task.

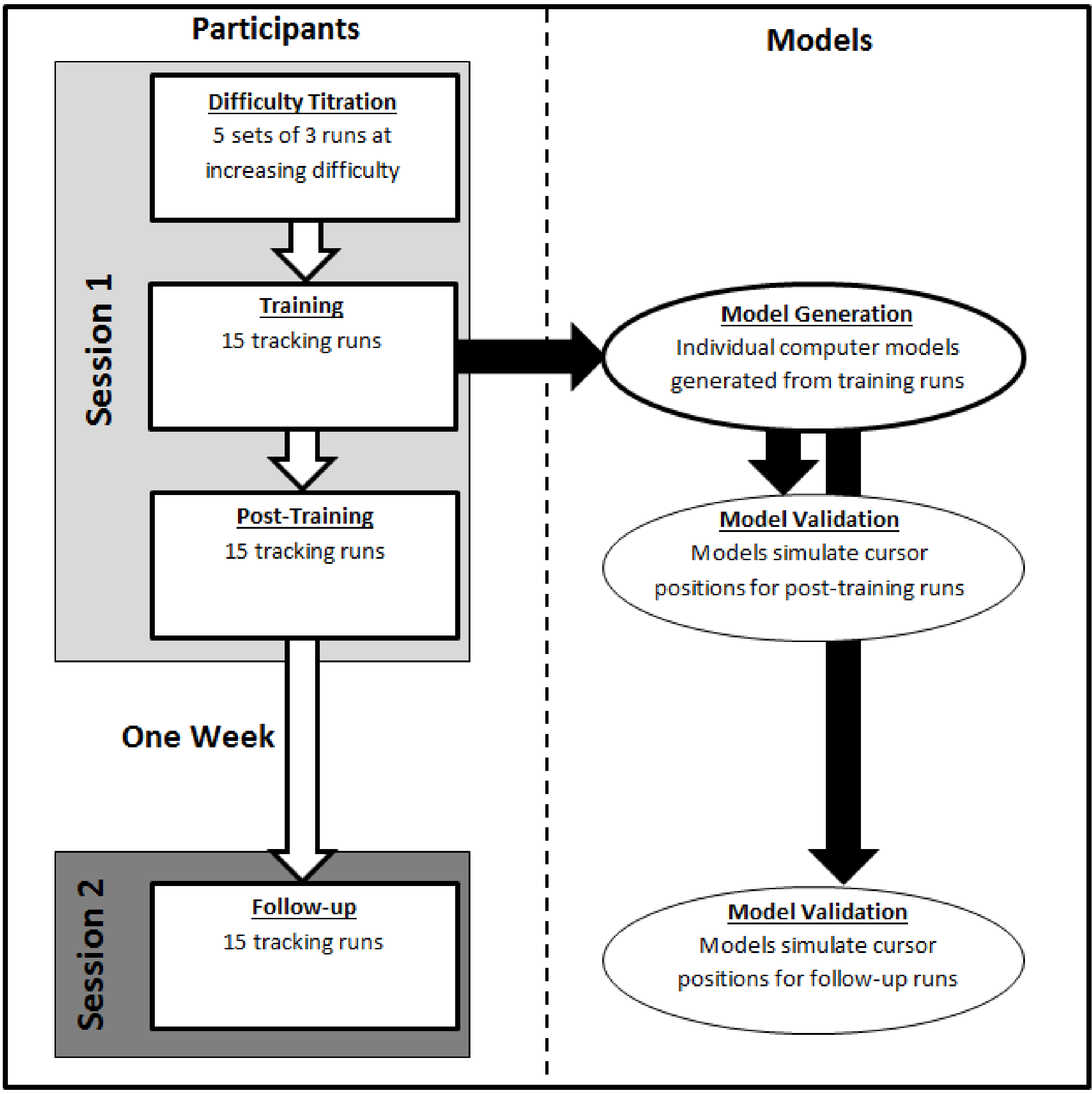
5.3 Method

5.3.1 Design

The experiment required twenty participants to complete ‘runs’ of a pursuit tracking task (Figure 5.2, panel B). For each ‘run’, the participant continuously tracked a target moving in a pseudorandom pattern for one minute. Target and cursor positions were recorded every 16.7 ms. Participants completed three blocks of pursuit tracking runs over two sessions, separated by one week (Figure 1). The first session consisted of a difficulty titration procedure (explained in full in the procedure section below), followed by the first block of 15 ‘training runs’ (from which the model was derived) and the second block of 15 ‘post-training runs’ (which were the benchmark for model validation). In the second session, at least one week after the first, participants completed the third block of 15 ‘follow-up runs’ (second validation).

Each participant’s training runs were used to generate an individual model, which simulated their cursor movements during the post-training and follow-up runs (Figure 5.1). The participants’ tracking accuracy was assessed by root mean square error (RMSE) between the target and cursor movements over the one minute run, expressed as a percentage of the total target excursion range (track RMSE). A second RMSE value quantified the accuracy of the fit of the model-simulated cursor movements to the participant’s actual cursor movements for each run; this was also expressed as a percentage of total target excursion range (model RMSE).

Figure 5.1 Flow diagram of experiment design



5.3.2 Participants

Twenty healthy volunteers were recruited through the University of Manchester volunteer database. Participants were excluded if they had impaired, uncorrected vision or any diagnosis of neurological problems of motor control. Participants were financially reimbursed or, if students, awarded course credits for their participation. Ethical approval was granted by the university research ethics committee. We only identified one study with a comparable analysis to ours. They confirmed the individual differences in parameter estimates of a model in a sample of 10 participants (Viviani et al., 1987). This article did not provide sufficient methodological detail for a power analysis. More recent studies of idiosyncrasies in pursuit tracking used 12 participants (Miyake et al., 2001), or groups of 20 or fewer participants (Oishi et al., 2010; Viviani et al., 2009) but did not conduct a similar analysis. As our primary aim in this article was to determine whether parameter estimates and simulation accuracy were temporally stable within individuals, it was crucial that we collect enough data from each participant. Therefore we selected a sample size of 20 participants based on previous studies of this kind, and collected tracking data from 45 runs for each participant (though participants completed 62 runs in total) over two sessions.

5.3.3 Apparatus

TrackAnalyze

The pursuit tracking task used was the TrackAnalyze program, part of the Living Control Systems III: The Fact of Control suite (Powers, 2008). In the task, the participant uses a Microsoft Sidewinder Force Feedback 2 joystick (*J*) to keep a cursor (*C*) aligned with a moving target (*T*) in one dimension (Figure 5.2, B). The cursor is a green horizontal bar (black in Figure 5.2) and the target marks are two red horizontal bars (grey in Figure 5.2). The participant was asked to keep the green cursor positioned between the red bars. Both the target and cursor could move only in the vertical dimension. The joystick positions were sampled and scaled such that joystick position and cursor position had a directly proportional relationship (*C* proportional to *J*). A computer algorithm used a pseudo-random number generator and smoothing routine to produce the pseudorandom target time series. The algorithm generates values in the time series by multiplying a random number (rectangular distribution with mean 0 and range ±0.5), by 20,000 yielding a number between ±10,000. Each number is divided one of five smoothing factors (64, 32, 16, 8 and 4, respectively) and added to the previous value. Thus each successive value is a weighted sum of all previous values. The resultant time series is smoothed a further two times using the same smoothing factor. Finally, target time series were rescaled to the excursion permitted for the target in screen pixels. The five smoothing factors determined the rate of change of the target time-series; targets with a higher rate of change were more difficult to track, and therefore as smoothing factor value decreased (64, 32, 16, 8, and 4), the assigned difficulty level of a run increased (1, 2, 3, 4, and 5). The values of the smoothing factor were derived through results from an experimental pilot in which these values gave a large range of error rates centred on 3% error. This error threshold was chosen to be low because high tracking performance is desirable for model fitting, but the task should not be so easy that participants reach a performance ceiling. Each run completed by each participant used a new pseudorandom time-series generated at the difficulty level specified by the experimenter.

The PCM used in this program is adapted from Perceptual Control Theory (PCT; Powers, 1973; Powers et al., 1960; Powers et al., 1960). PCT is a biologically plausible theory of behaviour, with roots in control systems theory. It states that organisms control their perceptions at referent goal states by varying their motor behaviour. This is implemented by a negative-feedback architecture comprising the organism, the environmental variable that it desires to control (the controlled variable), and the feedback path (Marken, 2014). These are encapsulated in the four functions of the control architecture: the input function, the comparator function and the output function and the environment (feedback) function. These functions have associated parameters, such as delays and gains, which are pre-specified in PCT.

These parameters are the key to individual differences as parameter values are optimised as an individual learns. One parameter, the reference value, represents the desired state of the controlled variable, which is compared to the current perception of the controlled variable. These parameters, embedded in functions, determine the dynamic relationship between input and output, and due to feedback, the effect of this output on system input. Thus motor output is a purposeful effort to reduce any difference between the perceived current state of the controlled environmental variable (such as the distance between a held cup of tea and one's mouth when drinking), and the desired perceptual state of that variable (the cup to one's lips) (Powers, 1973). In pursuit tracking, a participant senses the discrepancy between the cursor and the target, and compares this difference to a desired perceptual relationship (target-cursor alignment), acting to eliminate this error through varying joystick movements.

In the PCM of the participant in the tracking task (Figure 5.2, A) the input function (*i*) senses the controlled variable (target-cursor distance) and translates this to a perceptual signal (*p;* the perceived difference between the target (*T)* and cursor (*C*); see equation 1 below:

(5.1) $$p = C - T$$

The comparator function (*co*) compares this perceptual signal (*p*) to the reference signal (*r*), the desired state of the controlled variable, and results in an error signal (*e*); see equation 2:

(5.2) $$e = r - p$$

The error signal (e) drives the output at the output function (*o*). This output, in the model, is the simulated joystick position, which determines the cursor position. Calculation of the new output *o(t)* of the control unit is determined in the program by the following formula, which contains a leaky integrator to counteract the accumulation of output over successive iterations (equation 3):

(5.3) $$o(t) = o(t-1) + (K_o \times e(t-\tau) - K_d \times o(t-1)) \times \Delta t$$

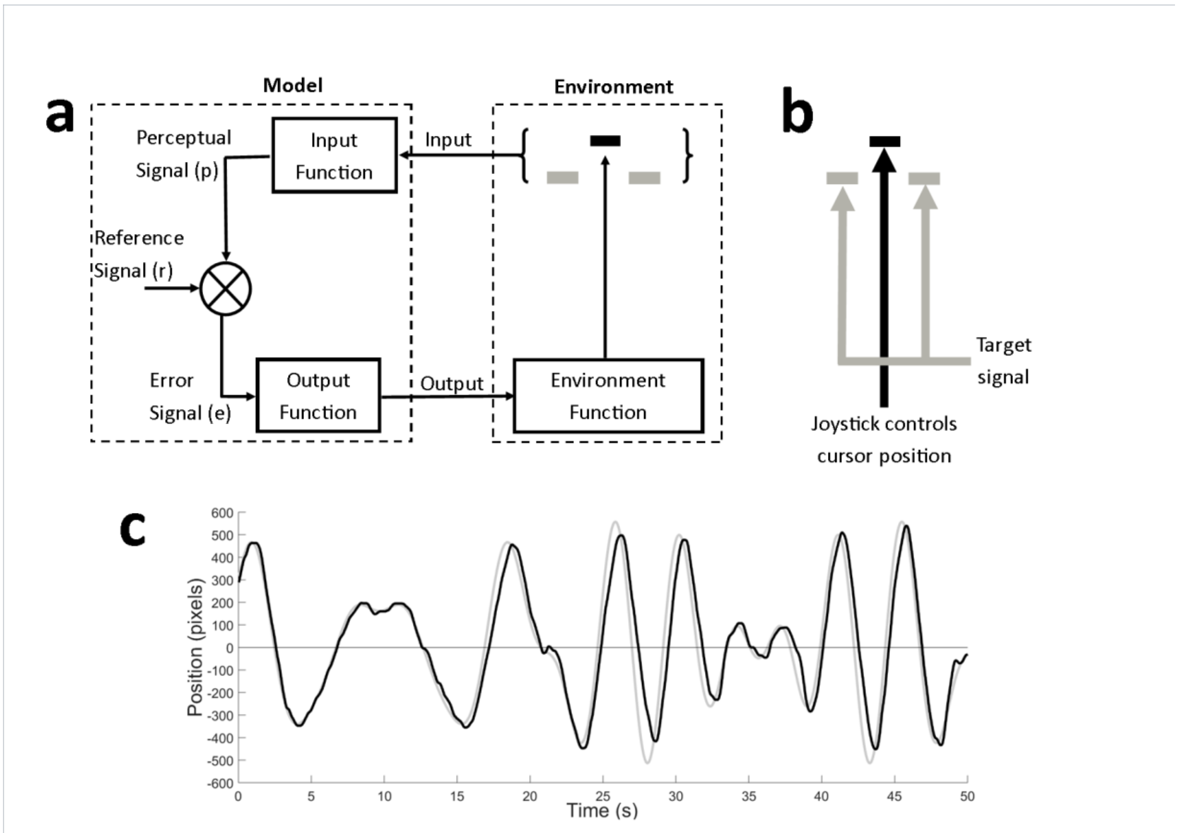
Where Δt is the time increment on each iteration (0.017 ms), *o(t-1)* is the value of the output at the previous iteration and $e(t - \tau)$ is the error with loop delay (τ) samples. The model has four alterable parameters: the reference value (*r*), loop delay (τ), output gain (K_o), and damping constant (K_d). The reference value specifies the desired distance between cursor and the target that the model is aiming to achieve. It is a positive or negative integer, expressed in pixels. The loop delay parameter is an estimate of the lag, in samples, of the cursor behind the target over the run. The output gain is a constant that proportionally amplifies the output, estimated from the velocity at which *e* is cancelled. The damping constant sets the leakage rate of the leaky integrator. It is therefore a constant that multiplies the previous output reduce its effect in the calculation of the current output, damping the response of the model. Whilst in the organic controller the input function (*i*), output function (*o*) and environment function (*f*) would have also have associated gains; the model simplifies these by setting both input and environment function gains to the integer 1. Therefore the output gain represents the total loop gain for the system, and the equation for the environment function is:

(5.4) $$C(t) = o(t)/1$$

A simulation of a PCM with adaptable gains for all three functions can be found in Living Control Systems III: The fact of control (Powers, 2008).

Parameters are estimated via an optimisation routine in which each parameter in turn is varied recursively to increase the goodness of fit between model-simulated cursor and actual cursor positions, assessed by a least-squares procedure repeated 20 times or until a minimum root-mean-square error (RMSE) change is achieved. Parameters are each fitted in this way in the order: output gain (K_o), reference value (r), loop delay (τ), then damping constant (K_d). This order is replicated five times with the latest estimations for each parameter used as initial values for the next recursive loop. The order in which the parameters are fitted was arrived at empirically (Powers, 2008). Further details of the PCM and TrackAnalyze program can be found in the appendices of Living Control Systems III: The Fact of Control (Powers, 2008).

Figure 5.2 Experimental set up and typical tracking trial



***A** shows how the computational model takes feedback of cursor-target positional error as an input and compares this distance to the desired reference distance (r) between target (T) and cursor (C), producing a positional error term (e) that drives an output response determined by the computational model parameters and previous outputs which determines cursor position via the environment function. As the gain value for the environment function is set to 1, the output wholly determines cursor position (C). **B** shows the experimental set up from the perspective of the participant. Joystick position is altered to move the cursor (C) in the vertical dimension and target marks (T) move according to a pseudorandom pattern. **C** shows typical results of a one minute run completed by a participant. Target (T): grey line, cursor (C): black line.*

Edinburgh handedness inventory

For completeness in characterising the demographics of our sample, we collected data on the handedness of participants. For this the Edinburgh Handedness Inventory short form (Veale, 2014; Appendix B) was used. It is a four-item questionnaire in which participants indicate which hand they would usually use to complete everyday activities on a five point Likert type scale ranging from always left to always right. A global score indicates whether the individual is left handed, mixed handed or right handed.

5.3.4 Procedure

In the first session, participants read the instruction sheet explaining the pursuit tracking task, and gave informed consent to take part. Then they completed the Edinburgh Handedness Inventory and performed two practice runs to familiarise themselves with the pursuit tracking task. Participants completed a difficulty titration procedure, the purpose of which was to ensure that each participant was well practiced at the task, and to standardise the tracking error rate across the sample of participants. The latter was necessary because the accuracy in the fit of the simulated cursor movements to the actual cursor movements (model RMSE) was affected by the accuracy of the fit in actual cursor movements to the target pattern (tracking RMSE) for the run being modelled. Thus the variability in task performance was reduced by standardising the error rate which enabled greater comparability of model simulation accuracy between individuals. Participants completed sets of three runs over the five different target difficulty levels (determined by the smoothing factors). The highest difficulty level at which the participant produced a tracking RMSE error below 3% on all three runs was selected for the duration of that participant's experiment. This procedure ensured that the task was equally difficult for each participant despite individual differences in participants' performances. The threshold 3% scaled tracking RMSE was decided as this was a typical error rate in pursuit tracking (Powers, 1978, 2008).

Following difficulty titration, participants started the 15 training runs, and after these, the 15 post-training runs. One week later, at the start of Session 2, participants received task instructions again and completed 15 follow-up runs. The design is summarised in Figure 5.1. For each run in each of the three blocks, a new pseudorandom target time-series was generated. Participants were thus administered different target time series from one another, and no participant completed the same target time series more than once.

5.3.5 Analyses

Prior to analysis, outliers were excluded from the dataset. This was necessary to control for tracking error as model fitting accuracy is extremely sensitive to participants' initial tracking errors. *A priori*, we planned to exclude participants if the mean tracking error for each participant was higher than three standard deviations above the mean tracking error of the participant sample. All analyses were conducted using data analysis package IBM SPSS 22.

Analyses of intra-individual consistency and inter-individual differences

We conducted Cronbach's alpha tests (Cronbach, 1951) for each parameter to determine whether participants' parameter estimates were stable trial-to-trial, and over one week. Parameter estimates were generated for each run in all three blocks, totalling 45 estimates of each parameter for each participant. In addition, a mean measurement, absolute-agreement, two-way mixed effects model was used to calculate the intra-class correlation coefficient for each parameter. The analysis was replicated in the subgroup of 13 participants that completed the task at difficulty level 2.

We conducted a factorial ANOVA for each of the four parameters (τ, K_o, K_d, r) to determine whether the parameter estimates differed between participants, replicating a previous analysis which tested the individual differences in parameter estimates of a model in a sample of 10 participants (Viviani et al., 1987). In our factorial design, participant was an independent group factor with 20 levels (as there were 20 participants). Block was a repeated measures factor with three levels; training, post-training and follow-up. To determine whether any inter-individual differences in parameters were due to participants tracking targets at different difficulty levels (due to the difficulty titration procedure) we conducted a subgroup analysis on the data from the participants that completed the task at the most common difficulty level (difficulty 2, n = 13).

Contribution of parameters to model accuracy

To investigate the nature of the relationship between the estimated parameter values and the accuracy of that model in simulating the participant's movements (across runs, blocks and individuals), we conducted a polynomial regression analysis with each of the model parameters as the predictor variables and model RMSE as the outcome variable. This stepwise analysis aimed to reveal whether the relationship followed a linear, quadratic or cubic pattern. The most appropriate model would be indicated by whether the R^2 change significantly improved as the polynomial order increased.

Following selection of an appropriate regression model order (quadratic), a second stepwise regression was conducted to determine the contribution of each parameter to the quadratic model. Parameters were added in a stepwise fashion; parameters were added in descending order of occurrence in tracking control models: output gain, loop delay, damping constant, and finally reference value. We opted to add the reference value last because we wished to test whether this parameter is essential to accurate model performance. In PCT, in contrast to other theories, this parameter is set from within the system and can take non-zero values (Mansell & Marken, 2015). Adding this parameter to the regression model last would determine whether it contributed significantly to model accuracy after all other parameters had been added, and therefore whether this parameter improved the control model.

It was thought that as participants completed the task at different difficulty levels this might confound the regressions as the different task constraints may influence parameter optima and show different distributions. Consequently we repeated the above analyses within the subgroup.

Accuracy of individual computational models

An individual model was developed for each participant by taking the mean of the estimates for each parameter across the 15 runs of the training block. To test whether these individual models accurately simulated the participant's tracking movements at post-training and follow-up (validation), we compared each participant's cursor positions as simulated by the model during the post-training and follow-up runs to the same participant's actual cursor positions during these blocks; the model RMSE.

Individual specificity of the computational models

To test the hypothesis that a participant's tracking data would be more accurately simulated by the participant's individual model than by other participants' models we analysed and compared the simulation accuracy of each individual computational model to the tracking data of all individuals. For each participant, a model (generated during the training runs) simulated that participant's tracking movements during the post-training and follow-up runs, resulting in an average model RMSE value for each time point ('self'). To generate the 'aggregate' data, all 19 other models simulated the participant's tracking runs in the post-training and follow-up blocks. Within each block, this yielded a mean error rate (model RMSE) fit for each of the 19 models to the tracking data in each block, and a standard deviation of the error around this mean. For each tracking dataset in both the post-training and follow-up blocks, the weighted mean of all other models to that participant's tracking data was calculated, resulting in an aggregate model RMSE for each block ('aggregate').

For each block, the mean RMSE fit for each 'aggregate' model was weighted according to the reciprocal of the standard deviation of each 'aggregate' model fit to the 15 tracking runs. Larger standard deviations in model fits were therefore assigned smaller weights. This measure was taken to control for large standard deviations in simulation error relative to mean error rates across the 15 simulated runs which would likely be the case where participants' tracking performance across the 15 runs were highly variable, resulting in highly variable accuracy in model fits. The weighted averages were calculated with the following equation 4:

$$x_{weighted} = \frac{\sum_{i=1}^{n}(x_i \times w_i)}{\sum_{i=1}^{n} w_i} \quad (5.5)$$

Where $x_{weighted}$ is the aggregate RMSE to each individual's tracking runs in each block, x is the mean RMSE when each model simulated the 15 tracking runs in that block, and w is the weight allocated to each mean as a function of the standard deviation around the mean RMSE within each block.

To compare the simulation accuracy of self and aggregate models, we conducted a 2x2 repeated measures ANOVA. The first repeated factor was model type: self (average model RMSE for participants own models against their own behavioural data) vs. aggregate (aggregate weighted average model RMSE for all other participants to the behavioural data of the individual being tested). The second repeated measures factor was block and had two levels: post-training and follow-up.

The same analysis was conducted with the sample subgroup that included only participants tested on the most common difficulty level (difficulty 2, 13 participants), to determine whether any differences between 'self' and 'aggregate' model fits were an artefact of the participants tracking at different difficulty levels.

5.4 Results

Complete data were collected from 20 participants, five of who were male and fifteen female. Sixteen participants were right handed, four were mixed handed. Mean age was 23.8 years (SD = 6.59 years).

There were no outliers among participant data; all participants' data were included in the analysis. Tracking and model RMSE were positively skewed. Following a log transformation a normal distribution was observed in participant tracking and model RMSE. The number of participants that completed the experiment at each difficulty level was as follows: difficulty 1, four participants; difficulty 2, 13 participants; difficulty 3, three participants.

5.4.1 Analyses of intra-individual consistency and inter-individual differences

Cronbach's Alpha coefficients for consistency in estimated parameter values were 0.921 (subgroup: 0.858) for loop delay, 0.976 (subgroup 0.886) for output gain, 0.880 (subgroup 0.852) for damping constant and 0.920 (subgroup 0.810) for reference value, indicating that all parameter estimates were highly consistent within individuals over the course of the experiment. Results of the intra-class correlations can be found in Table 5.1. Examination of lower bounds of the confidence interval for each parameter, following the interpretation guidelines of McGraw and Wong (McGraw & Wong, 1996) indicated output gain showed good reliability, whilst loop delay, damping constant and reference value showed moderate reliability, the same pattern of results were observed in the subgroup intra-class correlation analysis.

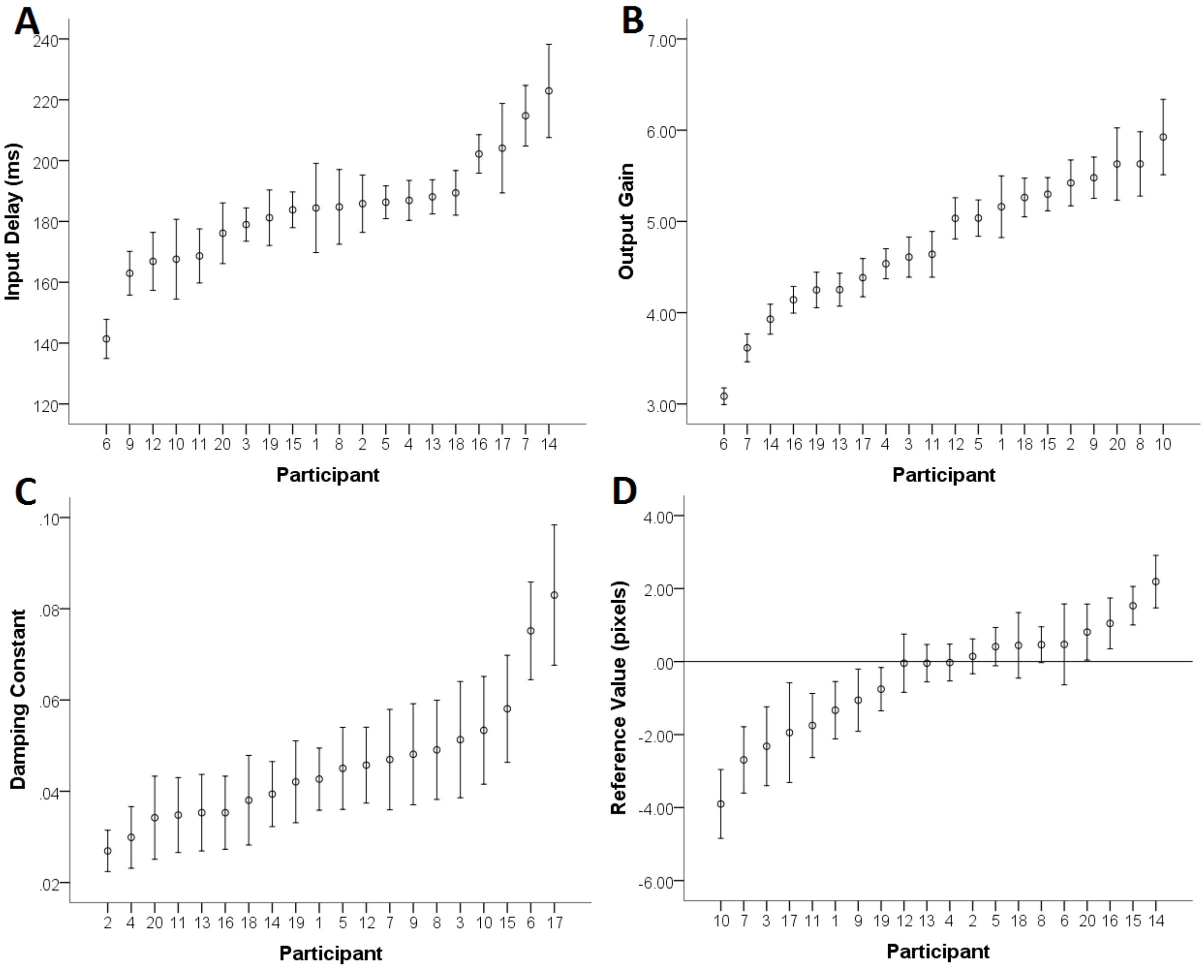
Table 5.1 Intra-Class correlation coefficients for each of the parameters

Average measures	Intraclass Correlation	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	*F*	df1	df2	*p*
Loop delay	.881	.751	.949	8.34	19	38	<.001
Output Gain	.914	.820	.963	11.75	19	38	<.001
Damping Constant	.866	.717	.943	8.34	19	38	<.001
Reference Value	.824	.628	.925	5.50	19	38	<.001

Note Intra-class correlation used average-rating, absolute-agreement, two-way mixed-effects model

The ANOVAs indicated significant differences in all parameters between participants across blocks. In the sub-analysis this was also found to be the case. Interactions between the factors of participant and block were also significant (Table 5.2). Post-hoc one-way ANOVAs within each block revealed individual differences in parameter estimates between participants within each block for all parameters. Inspection of effect sizes in Table 5.2 revealed that the largest individual differences between participants were in estimates of output gain (K_o). Figure 5.3 shows four graphs; each showing the mean and 95% confidence interval of parameter estimates of the loop delay (τ) and output gain (K_o), damping constant (K_d) and reference value (r) for each participant. Both inter-individual variability and intra-individual consistency can be observed, this pattern is pronounced in the output gain condition where both intra-individual consistency, and inter-individual variability are highest.

Figure 5.3 Error bar plots showing the mean value and standard deviations of parameter estimates across all trials for each participant.



***A** Loop delay (τ), **B** Output gain (K_o), **C** Damping constant (K_d) and **D** Reference value (r).*

Table 5.2 Results of the 2 x 3 factorial analyses and associated post-hoc ANOVAs for each parameter

Factor	***df1***	***df2***	***F***	***p***	**Partial η^2**
Loop delay (τ)					
Participant	19	277	12.62	< .001*	.464
Block	2	554	1.29	0.277	.005
Interaction	38	554	1.98	< .001*	.120
Post-hoc: training					
Participant	19	299	8.77	<.001*	
Post-hoc: post-training					
Participant	19	298	3.46	<.001*	
Post-hoc: follow-up					
Participant	19	297	7.75	<.001*	
Output Gain (K_o)					
Participant	19	277	33.6	< .001*	.697
Block	2	554	5.63	.004*	.020
Interaction	38	554	4.18	<.001*	.223
Post-hoc: training					
Participant	19	299	18.47	<.001*	
Post-hoc: post-training					
Participant	19	298	11.75	<.001*	
Post-hoc: follow-up					
Participant	19	297	20.15	<.001*	

Factor	***df1***	***df2***	***F***	***P***	**Partial η^2**
Damping Constant (K_d)					
Participant	19	277	21.39	< .001*	.595
Block	2	554	6.26	.002*	.022
Interaction	38	554	1.48	.036*	.092
Post-hoc: training					
Participant	19	299	5.3	<.001*	
Post-hoc: post-training					
Participant	19	298	5.86	<.001*	
Post-hoc: follow-up					
Participant	19	297	7.9	<.001*	
Reference Value (*r*)					
Participant	19	277	15.71	< .001*	.519
Block	2	554	0.44	0.645	.002
Interaction	38	554	2.85	<.001*	.163
Post-hoc: training					
Participant	19	299	8.99	<.001*	
Post-hoc: post-training					
Participant	19	298	6.06	<.001*	
Post-hoc: follow-up					
Participant	19	297	6.61	<.001*	

5.4.2 Contributions of parameters to model accuracy

Stepwise regressions were conducted to determine whether a linear, quadratic or cubic model best fit the available data. The results of the model fit can be found in Table 5.3. Examination of the R^2 change values associated with the models revealed that the quadratic equation accounted for a significantly more of the variance in accuracy than did the linear model. The cubic equation also made a significant contribution to the regression fit. However the R^2 change was very small and the F value was reduced relative to the quadratic model and inspection of the data plots (not reproduced in this article) showed that the third order curves did not deviate from the general path of the second order curves. We therefore opted to use a quadratic model for the stepwise regression to determine parameter contributions.

Table 5.3 Comparison of polynomial regression models where parameters predict model accuracy

					Change statistics	
Model	*F*	*P*	R	R^2	R^2 Change	*p*
1 Linear	44.18	>.001	.407	0.165	-	-
2 Quadratic	75.11	>.001	.635	0.404	.238	>.001
3 Cubic	51.75	>.001	.642	0.413	.009	.009

Note. All model parameters were used as predictors.

Investigation of the contribution of each parameter to the quadratic model revealed that the addition of each parameter as a predictor of model performance increased the R^2 fit significantly (Table 5.4); this was also the case if we conducted the analysis as a cubic regression. Tests of multicollinearity revealed that parameters fell within the acceptable range; with guidelines stating a variance inflation factor (VIF) threshold of 5-10 as a cut-off (Craney & Surles, 2002). VIF: Output gain, 1.081; Loop delay, 1.086; Damping constant, 1.087, Reference value 1.099.

Both analyses were repeated in the subgroup of 13 individuals that completed the experiment at difficulty level 2. This yielded the same pattern of findings: significant R^2 change for cubic over quadratic over linear models, and parameters contributed significantly to regression model accuracy for both quadratic and cubic models.

Table 5.4 Stepwise regression to determine parameter contribution to model accuracy

Model Predictors	*F*	*P*	R	R^2	Change Statistics R^2 Change	*P*
Output Gain	23.91	<.001	.273	.074	.074	<.001
Output Gain, Loop delay	34.87	<.001	.436	.190	.116	<.001
Output Gain, Loop delay, Damping Constant	56.53	<.001	.604	.365	.174	<.001
Output Gain, Loop delay, Damping Constant, Reference Value	51.75	<.001	.642	.413	.048	<.001

5.4.3 Accuracy of individual computational models

The average simulation error (model RMSE) when the 20 models generated from data at training simulated the cursor movements of the participant from which they were derived ('self') at post-training was 2.05% (SD = 0.37), 95%CI [1.88 – 2.22]; and 1.82% (SD = 0.38), 95%CI [1.64 – 1.99] at follow up. These values were in the same range as the error rate as that when models simulated the tracking runs on which the models were trained; the mean model RMSE when training models simulated training data was 1.85% (SD = 0.48%).

5.4.4 Individual specificity of the computational models

We hypothesised that models would be individual specific, that is, a model of a participant's performance would simulate that participant's tracking movements more accurately than models generated from other participant's tracking. The mean model RMSE of aggregate models to participants actual tracking data at post-training was 2.11% (SD = 0.35), 95%CI [1.94 – 2.27]; and 1.91% (SD = 0.42), 95%CI [1.71 – 2.11] at follow-up.

The 2 x 2 repeated measures ANOVA revealed that the main effect of model was significant $F_{(1, 19)} = 5.76$, $p = .027$, partial $\eta 2 = .232$; self-model fits were more accurate than the aggregate model fits. The main effect of block was also significant $F_{(1, 19)} = 8.45$, *p*

= .009, partial η^2 = .308; models generated during training more accurately fit the follow-up data than the post-training data. There was no interaction between model and block.

Within the subgroup, the mean simulation accuracy when 13 models fit to self-tracking data was 1.92% (SD = 0.29), 95%CI [1.76 – 2.10] at post-training; and 1.71% (SD = 0.25), 95%CI [1.55 – 1.87] at follow-up. The mean accuracy when the aggregate models fit tracking data was 2.01% (SD = 0.30), 95%CI [1.82 – 2.19] at post-training; and 1.77% (SD = 0.23), 95%CI [1.62 – 1.91] at follow-up. The subgroup 2 x 2 repeated measures ANOVA (13 participants) resulted in the same pattern of findings; firstly, a significant main effect of model $F_{(1,12)}$ = 25.59, p < .001, partial η2 = .681, self-models showed reduced error relative to aggregate models. The effect of block was also significant $F_{(1,12)}$ = 11.19, p = .006, partial η2 = .483. Models more accurately fit follow-up than post-training data. There was no interaction between model and block.

5.5 Discussion

We found that when model parameters were estimated directly from participant pursuit tracking of pseudorandom targets, these estimated parameter values were consistent over time within individuals but varied between individuals. These parameters accounted for a large proportion of the variance in model simulation accuracy and shared a curvilinear relationship. Moreover, when models generated from a participant’s pursuit tracking data at one time point simulated their performance at a later time point (model validation), these simulations were highly accurate, even after one week. Finally we demonstrated that a model produced from an individual’s performance more accurately simulated the cursor movements of that participant than did aggregate models.

5.5.1 Analyses of intra-individual consistency and inter-individual differences

The results support our hypothesis that parameter estimates would be consistent over time within participants. This was demonstrated by the high internal consistency in parameter estimates over the training, post-training and follow-up blocks within participants according to Cronbach’s Alpha coefficients, and moderate to high intra-class correlation coefficients. This indicated that control parameters remained stable over one week for each participant. Factorial analyses conducted in this study found individual differences in parameter estimates. These findings support similar findings of individual differences in estimated model parameters between individuals (Viviani et al., 1987) that constitute robust idiosyncratic pursuit tracking strategies (Franks et al., 1982; Miyake et al., 2001). The current study demonstrated that such differences persisted even when data were collected over one week, evidence that control parameters remain stable over time within an individual. A model architecture could be parameterised to characterise individual's strategies in the pursuit tracking task, even though the movements required for tracking the pseudorandom target varied between trials. Interestingly, output gain was the most variable parameter between individuals, and had the highest consistency within individuals. Consequently, it had the most discriminatory power and was the strongest indicator of an individual's control strategy. It is unclear from this experiment alone whether this is a task-specific parameter or alternatively whether a higher estimated output gain in tracking tasks would be associated with a higher output gain in other task paradigms.

5.5.2 Contribution of parameters to model accuracy

We hypothesised that estimated parameters for each run would share a quadratic relationship with the model simulation error when those parameters were used to fit the tracking data. Investigation of the nature of the relationship revealed that the parameters did share a curvilinear relationship with model simulation error. Both the addition of quadratic (second order), and cubic (third order) regression parameters improved the fit to the data significantly; the second order regression model resulted in a large improvement over the fit of the linear regression model and whilst third order regression model only negligibly (though significantly) increased in fit to the data over the second order regression model. The presence of such curvilinear peaks in simulation accuracy for each parameter indicates that there may be an optimal control strategy in the task on which skilled trackers are converging, thus these optima in parameter space are identified by the reorganisation algorithm when control models are optimised to the tracking data.

When each of the parameters were added in a stepwise fashion to determine their individual contribution to performance, each addition improved the fit to the model fit to tracking performance. The addition of damping constant provided the largest improvement to model fit. The addition of the reference value parameter to the regression model after all other parameters had been entered yielded a significant increase in the proportion of variance in simulation accuracy explained by the regression model. This indicates that the unique PCT reference parameter made an individual contribution to explaining the variance in performance. Whilst the reference value might be assumed to be zero as the task requires participants to minimise position error between the target and cursor, it remains a key parameter in the control model and demonstrates that referent perceptual goals are fundamental in motor performance and should be included within control models.

5.5.3 Accuracy of individual computational models

Model simulation error was very low at both post-training and follow-up. In fact, simulation error was lower when models simulated follow-up data than post-training data, despite the temporal proximity of training and post-training data collection. As participant tracking error was also increased at post-training relative to follow-up we suggest that this increase in error might be due to participant fatigue as they had to complete more than 30 one minute runs in succession, and that this increased tracking error reduced the model simulation accuracy as a consequence. Notwithstanding this difference in model simulation accuracy between post-training and follow-up, we might reasonably expect that the model would have been most accurate in simulating the tracking data on which it was trained as when simulating the cursor movements of participants in the post-training and follow-up blocks models encountered new target patterns. However, in this study the simulation error rate across training, post-training and follow-up were virtually the same. This would appear to provide strong evidence that the parameters are trait-like features of the individual independent of target movements. This supports the hypothesis that models generated from an individual's performance during training highly accurately simulated their later tracking movements. These findings are consistent with previous reports that dynamical models accurately simulate human control movements in pursuit tracking tasks (Abdel-Malek & Marmarelis, 1988; Powers, 1978, 1989; Viviani et al., 1987), even when models are validated with data from a later testing session (Bourbon, 1996b; Bourbon et al., 1990b).

5.5.4 Tests of individual specificity of the models

To establish whether models were individual-specific, we tested each model's simulation accuracy to participants own data and the data of other individuals. We found that, although the difference was small in magnitude, participants' own models consistently simulated their own data more accurately than did aggregate models. This difference was maintained and in fact increased when the analysis was repeated in the subgroup of participants who completed the task at the same difficulty level, indicating that the difference in simulation accuracy by self and aggregate models was not as a result of participants tracking under different task constraints. Thus model parameters optimised from participants' data at one time point can be used to simulate that individual's performance one week later, with higher accuracy than a model not optimised to that individual. This is an impressive feat when considering the robustness of the model to differences in human tracking and is, to our knowledge, the first formal test of individual model specificity.

Whilst previous studies have highlighted the individual differences between control strategies utilised by individuals in tracking tasks, the current study demonstrates that models optimised to individual tracking data can characterise these idiosyncratic strategies that persist over time in individuals practiced in such tasks. Tests of replicability within an individual should be a benchmark validity criterion evaluating models of human behaviour (Smith & Conrey, 2007), as it is in other fields of psychology in which trait-level constructs are measured. In such cases, it is recognised that in order for hypothesised task- and individual-specific factors to be valid they must demonstrate test-retest reliability (Chaplin, John, & Goldberg, 1988; Oppenheim & Oppenheim, 1992).

Individual models of pursuit tracking performance may find applications in the assessment and treatment of motor deficits following neurologic injury. The pioneering research in analysis of estimated model parameters for people with Parkinson's (Abdel-Malek et al., 1988; Au et al., 2010; Oishi et al., 2010, 2011) indicates that models might be used to assess bradykinesia and other deficits in this group (Allen et al., 2007). In therapeutic settings, upper-limb assistive robotic devices provide force assistance in upper limb movements to those with neurological motor impairments, often during virtual-reality pursuit tracking tasks (Maciejasz et al., 2014). Whilst assistive robotics often collect kinematic data which may help to assess symptom severity, individual models may be critical for delivering idiosyncratic rehabilitation regimes to people with neurological conditions. These individuals exhibit heterogeneous symptoms and outcomes (Kwakkel et al., 2004; Reinkensmeyer, Emken, & Cramer, 2004) and may use different motor strategies at different points in the recovery process (Fitts, 1964). Individual models may be useful to identify and treat specific deficits through tailored assistance or resistance control regimes (Marchal-Crespo & Reinkensmeyer, 2009).

5.5.5 Strengths and limitations

This first formal test of individual-specificity over time has found that PCMs could provide idiographic simulations of human behaviour in pursuit tracking tasks. However, the magnitude of the difference between idiographic and general models was small. The most likely explanation for this is that the parameter estimates are affected by the task constraints, and so participants converged on an optimum strategy in this task. This is supported by the finding that different target motion patterns and different target frequencies elicit characteristic tracking profiles and estimated model parameters in participants (Abdel-Malek & Marmarelis, 1988; Poulton, 1952b; Viviani & Mounoud, 1990). We used a limited range of low target velocities in this experiment, and this resulted in participants achieving a near-ceiling performance. Higher velocity target movements would be necessary to comprehensively test individuals' transient dynamics (Abdel-Malek & Marmarelis, 1990), which might expose further individual differences. The frequency content of targets could be controlled in future experiments by summation of sinusoids of different frequencies to ensure a sufficiently wide bandwidth within each pursuit run in future studies (Roth, Zhuang, Stamper, Fortune, & Cowan, 2011). In the current study, we manipulated of the rate of change of the target to be tracked between different participants in order to be sure that the difference between model simulation performances was not a result of their different levels of ability and therefore tracking accuracy. However, this introduced a potential confound; participants completing the task under different task constraints (difficulty levels) could account for differences in parameter estimates, as has been reported in previous studies (Neilson et al., 1993; Notterman & Tufano, 1980; Viviani & Mounoud, 1990). We therefore undertook repeated our analyses with a subgroup of 13 participants who completed tracking runs at a similar accuracy level to one another *and* under the same task constraints (difficulty level 2). All main hypotheses were confirmed in the analyses of subgroup data providing evidence that the pattern of results attained was not a consequence of either potential confound.

The model architecture used in this study was a simple first-order PCM with state delay, a single PCT control unit (Powers, 1973, 1978, 2008). This was chosen because it had been previously shown to accurately simulate motor perceptuo-motor behaviour during a tracking task (Bourbon, 1996; Bourbon et al., 1990; Marken, 1991; Powers, 1978, 1989, 2008) and had a biologically feasible conceptual foundation (Powers, 1973). However, it is by no means a comprehensive model of human motor control. Rather it attempts to demonstrate that parameterisation of such control architectures is useful to discriminate and simulate individual performance, regardless of whether they accurately specify how this would be achieved within human sensory and motor systems. It therefore goes without saying that other model architectures may be more appropriate or accurate in simulating both neurologically atypical and healthy individuals. System identification can be used to find the best-fitting model, for example (Neilson et al., 1993; Oishi et al., 2010, 2011). In addition, there are known relationships between the non-independent parameters of the PCT control loop. For example loop delay and output gain are negatively correlated, at high values of delay, high output gain produces an oscillatory response. Damping constant and output gain share a positive relationship; higher output gains require higher damping constants to avoid oscillatory behaviour. Whilst beyond the focus of this article, these relationships have implications for model fitting as different optimisation routines (order and method, number of iterations) might affect the efficiency of the search of the parameter space and consequently result in different parameter value combinations.

Critically, whilst we investigated pursuit tracking in one-dimension, application to assistive robotics for neurorehabilitation would require extension to two- and three-dimensional tracking tasks and different target movement patterns (Engel & Soechting, 2000; Marken, 1991; Viviani et al., 1987; Viviani & Mounoud, 1990). Moreover, control of other perceptual variables may increase simulation accuracy, such as target-cursor angle (Marken, 2014) or target-cursor velocity difference (Johnson, Howe, & Chang, 2013; Proteau & Masson, 1997; Viviani et al., 1987; Viviani & Mounoud, 1990). Future studies should aim to elucidate individual control strategies under different task constraints, and their stability over time, particularly in populations with neurological conditions.

5.5.6 Conclusions

In summary, we demonstrated that a negative-feedback computational model architecture can be optimised to characterise and accurately simulate an individual's tracking data over time. Estimated control parameters were highly consistent over time, whilst individual differences in control strategies were discriminated by the computational model. All model parameters contributed to the accuracy of PCMs to fit human tracking data. Moreover, even when the target patterns differ from trial to trial, individual computational models very accurately simulate the movements of the individual from which they were derived. We argue that establishing the test-retest reliability in parameter estimates and simulation accuracy should be an essential criterion for computational models of human performance.

Chapter 6: Sensorimotor delay compensation during manual tracking of predictable and unpredictable targets

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Maximilian G. Parker[1], Andrew P. Weightman[2], Sarah F. Tyson[3], Bruce Abbott[4], & Warren Mansell[1]

Author Affiliations:

[1]Division of Psychology and Mental Health, School of Psychological Sciences, University of Manchester

[2]School of Mechanical, Aerospace and Civil Engineering, University of Manchester

[3]Division of Nursing, Midwifery and Social Work, University of Manchester

[4]Psychology Department, Indiana University – Purdue University Fort Wayne, Fort Wayne, IN, USA

6.1 Abstract

The existence of intrinsic sensorimotor delays dictates that humans act on outdated sensory inputs. Models of action control must account for delay compensation in anticipatory behaviour. The current study evaluates four models to determine whether this can be achieved through negative feedback and sensory integration. Twenty-nine participants completed two blocks of 15 trials of a pursuit tracking task. The predictability of the target signals was either high (sinusoid) or limited (pseudorandom). Four models were compared fit to the tracking data when the loop delay parameter, representing sensorimotor delay in the participants, was constrained to values between 17 ms and 500 ms.

Participants tracked pseudorandom targets with phase delays of approximately 150 ms. The models simulated pseudorandom tracking performance equally well, with optima around a loop delay of 150 - 250 ms; a feasible value given estimates of sensorimotor delays. For sinusoid targets participants displayed a shorter phase delay relative to the target (~50 ms), indicating anticipatory tracking. Two of the models (PCM and HCM) simulated sinusoid tracking fit most accurately when loop delays were unfeasibly short; accuracy decreased as a function of increasing delay. In contrast, models that extrapolated the future target position (PEM and HEM) maintained accuracy across the full range of loop delay values without clear optima. Extrapolating target position may enable feedback models to compensate for detrimental effects of sensory delays on performance.

We conclude that when tracking continuous signals, humans may integrate position and velocity information. This may then be used to compensate for delays in action control and engage in anticipatory behaviour.

6.2 Introduction

Sensorimotor delays accumulate as a result of delays in afferent and efferent signal transmission, and central processing (Carlton, 1981; Smith & Bowen, 1980; Smith, McCrary, & Smith, 1960). In action control, visual and proprioceptive signals must be integrated in the cortex (Crevecoeur, Munoz, & Scott, 2016; Pizzella et al., 1999). Efferent signals must compensate for the longer feedback delays associated with distal motor responses by generating appropriate muscle forces and accounting for limb inertia (Desmurget et al., 1999). Consequently, humans act on outdated sensory inputs (Carlton, 1981; Stepp, 2009; Wolpert, Ghahramani, & Flanagan, 2001). This may pose a significant issue for feedback in action control, for '*if the system is changing rapidly, then by the time a feedback signal has been used to modify the motor commands, the system will have evolved to a new state for which the corrective signal is inappropriate*' (Hollerbach, 1982). The CNS must therefore compensate sensorimotor delays in order to produce well-timed anticipatory movements such as in object interception and avoidance (Brenner & Smeets, 2015; Dessing, Oostwoud Wijdenes, Peper, & Beek, 2009).

An ongoing reaching movement can be altered based on delayed visual feedback within 100 ms to 150 ms (Brenner & Smeets, 2015; Day & Lyon, 2000; Foulkes & Miall, 2000; Franklin & Wolpert, 2008; Saunders & Knill, 2005). However, measured delays when arm movements are generated from standstill may be considerably longer than this. For example, in manual tracking experiments, an input consisting of series of steps of irregular amplitude and timing evoke transient responses that are initiated only after a 'pure' delay of 200 ms-450 ms. These movements reach steady-state after approximately one second (Abdel-Malek & Marmarelis, 1990; Navas & Stark, 1968). For these target signals, the target position change is both unpredictable and instantaneous. Therefore visual and proprioceptive feedback information provide the only sensory basis for action (Kreifeldt, 1965). It is highly likely that the visual-sensory aspect of the sensorimotor delay is the same across both discrete reaching-type movements and manual tracking tasks. However, in manual tracking, the requirement of generating movement from standstill may add to this pure sensorimotor delay, thus resulting in the longer 200 ms lower estimate. In contrast to transient manual tracking, tracking in the steady-state with smoothly time-varying signals, there may be a smaller contribution of motor coordination delays because the limb is already moving.

During manual pursuit of a smoothly varying target signal, participants exhibit a phase delay relative to the target signal. For pseudorandom or sum-of-sines inputs, this phase delay is observed to be in the region of 180 - 200 ms (Khoramshahi, Shukla, & Billard, 2014; Parker et al., 2017; Viviani & Mounoud, 1987; Yu, Gillespie, Freudenberg, & Cook, 2014), but increases as a function of increasing input bandwidth (Abdel-Malek & Marmarelis, 1988; Neilson, Neilson, & O'Dwyer, 1993). This indicates a reduction in ability to utilise visual feedback information at high frequencies. Within the range of frequencies that participants track accurately (0 - 0.7 Hz) tracking behaviour can be simulated with a PCM. In the PCM calculates output based on the positional difference between the cursor and target (Abdel-Malek & Marmarelis, 1990; Levison et al., 1969; Viviani et al., 1987). Models have been demonstrated to characterise individual performance (Bourbon, 1996b; Bourbon et al., 1990b; Parker et al., 2017), and compensate for disturbances on-line (Marken, 1991; Powers, 1978, 1989). Critically, the constant phase delay in tracking movements can be simulated by including a loop delay parameter (Gerisch et al., 2013; Khoramshahi et al., 2014; Parker et al., 2017; Viviani et al., 1987). This parameter specifies the theoretical sensorimotor delay within the model. However, a model controlling target cursor distance includes no method to mitigate the effect of this sensorimotor delay to simulate anticipatory tracking behaviour.

Anticipatory manual tracking behaviour is observed when participants track target signals that are periodic (Poulton, 1952a, 1952b), such as simple sinusoid signals or periodic step signals. When participants track these signals, phase delay is attenuated almost entirely (Poulton, 1952b; Stark, Iida, & Willis, 1961; Stepp, 2009; Stepp & Turvey, 2017; Viviani & Mounoud, 1990). This is termed tracking with *zero phase delay*. However, it should be noted that participants may not exhibit constant zero-phase tracking but alternating, small, phase advances and phase delays relative to the target signal, that average around zero (Inoue & Sakaguchi, 2014; Neilson, Neilson, & O'Dwyer, 1988; Vercher & Gauthier, 1992; Gollee, Gawthrop, Lakie, & Loram, 2017). When tracking in zero-phase, the contribution of the sensorimotor delay to phase delay is evidently attenuated. It might be expected that this attenuation should not be possible to simulate with a PCM, as this would produce a phase delay at least the length of the loop delay parameter. A plausible model of how humans produce zero-phase tracking for sinusoid targets would indicate that the CNS compensates sensorimotor delays by utilising additional sensory information, either by perceptual integration or prediction (Miall, Weir,

& Stein, 1993; Stepp, 2009; Viviani & Mounoud, 1990; Voss, McCandliss, Ghajar, & Suh, 2007).

In addition to target and cursor position, delayed visual motion information is also present during tracking and is likely used alongside position information. During smooth pursuit eye tracking, the extra-striate Middle Temporal (MT) and Medial Superior Temporal (MST) cortical brain areas actively encode local motion information from the visual field and integrate this into global motion patterns (Averbeck, 2004; Lisberger, Morris, & Tychsen, 1987). This may be integrated with position information to extrapolate current inputs at specific position-velocity integrated sites (Buneo & Andersen, 2006). In MT and MST, velocity information is extracted within 100 - 200 ms following stimulus presentation (Bennett, Orban de Xivry, Barnes, & Lefèvre, 2007) a feedback delay comparable to the extraction of visual position information. No populations of neurons have been found that systematically encode acceleration information (Lisberger & Movshon, 1999). Target acceleration may be derived mathematically from the rate velocity across a population of neurons sensitive to target velocity (Lisberger & Movshon, 1999). However, this cognitive process may add substantially to the central processing delay (Bennett et al., 2007), so the sensorimotor delay for control of acceleration may be longer than for velocity or position. This is supported by the finding of a higher discrimination threshold for target acceleration than for target velocity, which results in reduced sensitivity to acceleration in visual smooth pursuit (Watamaniuk & Heinen, 2003). Velocity may be used for extrapolation as the feedback delay for acceleration may be too long to be used for sensorimotor delay compensation.

Target extrapolation from velocity signals would require delayed target position and velocity signals to be integrated into a single control variable: extrapolated position. The difference between this extrapolated target position and the cursor position would be the controlled variable within a feedback controller. There are many indications that humans use an extrapolation in a range of different object tracking situations, in both eye tracking (Barnes & Collins, 2008; Bennett et al., 2007; Khoei, Masson, & Perrinet, 2013; Lisberger & Movshon, 1999; Mrotek & Soechting, 2007) and manual interception (Brenner & Smeets, 2015; Brouwer, Brenner, & Smeets, 2002; Dessing et al., 2009). In manual tracking, if the target is occluded for a short duration (less than 200 ms), participants seem to use delayed feedback of velocity and position from prior to the occlusion to extrapolate the target trajectory in the absence of visual feedback (Fine et al., 2014). It is therefore expected that individuals may extrapolate target position during tracking non-occluded targets as this information is available and may be used to compensate for sensorimotor delays. It should be possible to construct computational feedback control models that utilise both target velocity and position information to track predictable targets with zero latency. Alternatively, target-cursor velocity difference could form a separate error signal to be controlled simultaneously to target-cursor position. Support for this hypothesis comes from studies that indicate that target position, velocity and even acceleration may be controlled independently (Krauzlis & Lisberger, 1994). In such a model, two systems could work in parallel where the output signal is a weighted sum of the two system outputs or in a hierarchical fashion where one system outputs the reference value (set point) for the subordinate control system (Marken, 1986; Marken & Powers, 1989; Powers, 1999). Delayed visual feedback regarding target and cursor velocity may be used as a control signal available and used to compensate for delays when tracking predictable stimuli (Viviani et al., 1987; Viviani & Mounoud, 1990). These models may result in improved accuracy and emulation of zero phase delay tracking for periodic signals whilst using only delayed sensory input.

In the current experiment, we aimed to characterise tracking performance for two different target types - sinusoid and pseudorandom - and to develop and compare the fit of four computational models to individual tracking performance. The first model, used as a baseline comparison, was a Position Control Model (PCM; Parker et al., 2017; Powers, 2008). The second was a Hierarchical Control Model (HCM) which utilised controlled target-cursor position and target-cursor velocity simultaneously. The third model was a Position Extrapolation Model (PEM). This controlled for the difference between a position extrapolation estimate and the cursor. The final model comprised both simultaneous hierarchical control and position extrapolation - the Hierarchical Extrapolation Model (HEM). Model parameters were optimised at 11 delay values that ranged between 17 ms and 500 ms. Regarding tracking performance, we expected that participants would track sinusoids with a higher accuracy, and lower phase delay than pseudorandom targets. We made the following hypotheses:

1) Sinusoid targets would be tracked more accurately than pseudorandom targets, and low difficulty targets more accurately than high difficulty targets
2) The PCM would most accurately fit pseudorandom tracking at around 200 ms as this was the estimated delay for pseudorandom targets in previous studies

(Abdel-Malek & Marmarelis, 1990; Khoramshahi et al., 2014; Parker et al., 2017; Viviani et al., 1987).

3) The PCM would most accurately simulate sinusoid tracking at 17 ms, relative to longer delays, as it would not compensate for the model loop delay.
4) Regarding the HCM, PEM and HEM, we did not expect the simulation accuracy to differ from that of the PCM model for pseudorandom targets. However, we expected that these other models (not PCM) may simulate sinusoid tracking more accurately than the PCM, particularly at longer loop delays.

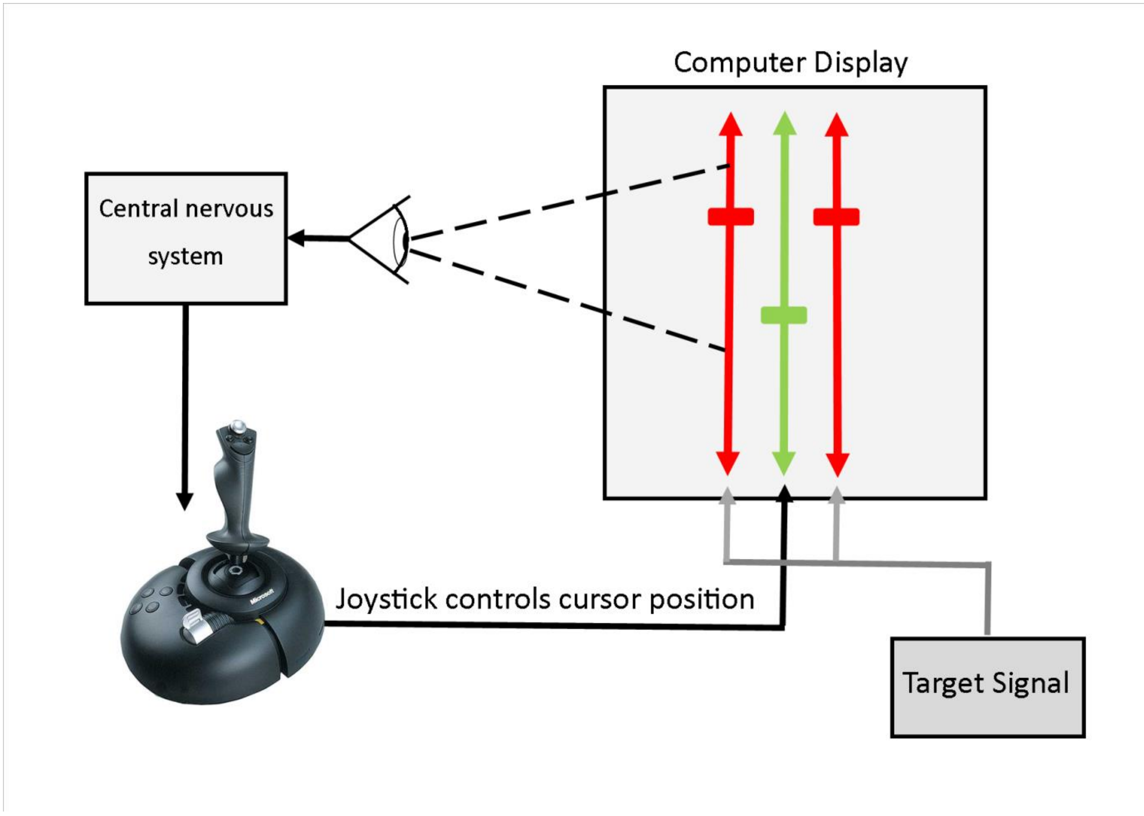
6.3 Method

6.3.1 Design

In the experiment, participants completed three blocks of 15 trials of a computerised visuo-manual pursuit tracking task (Figure 6.1). In Block 1 was for practice, block 2 and 3 were test blocks. Each trial required the participant to move a cursor to track a target that moved continuously in the vertical dimension on a computer screen. Each trial lasted for one minute. All three blocks were completed in a single experimental session. Participants were randomly allocated to one of two conditions. In the first condition Pseudorandom-Sinusoid (PS), participants tracked pseudorandom movements of the targets in blocks one and two, and tracked sinusoidal targets in block three. In the second condition, Sinusoid-Pseudorandom (SP), participants tracked sinusoidal targets in blocks one and two, and pseudorandom targets in block three.

For each trial, the accuracy of each participant’s tracking was assessed by the Root Mean Square Error (RMSE) between the target positions and actual cursor positions over the one minute trial. Block 1 trials were practice trials to ensure that participants had reached asymptote performance. Participants completed 15 practice trials on the target type they would be tracking in the first test block; pseudorandom for participants in the PS condition and sinusoidal for those in the SP condition. In the two test blocks, trials 1-5 were considered additional practice trials. Trials 6-15 were analysed (and later used to optimise and validate models). Even-numbered trials (6, 8, 10, 12, and 14) were optimisation trials while odd-numbered trials (7, 9, 11, 13, and 15) were validation trials.

Figure 6.1 Computerised pursuit manual tracking task set up



The participant is instructed to keep the Target marks (red) and Cursor marks (green) aligned during a one minute trial. The Participant controls the joystick to affect cursor position. The target marks move according to a target signal. The target signal is either sinusoidal or pseudorandom

6.3.2 Participants

Thirty adult volunteers were recruited through the university volunteer database and were reimbursed monetarily or with course credits for their participation in the experiment. On the basis of our exclusion criteria, individuals were unable to participate if they had been formerly diagnosed neurological motor control impairments, or uncorrected visual impairments. However no recruited individuals fulfilled these criteria and as such all recruited individuals participated in the study. Ethical approval was granted by the university ethics committee. Informed consent was mandatory for participation in the experiment.

Participant data were collected within the same recruitment cycle as a previous study (Parker et al., 2017). This data collection cycle recruited 80 participants to four experimental conditions. The previous study analysed data from one condition (20 participants). The current study used a portion of data from two other conditions (40 participants). Of these 40 participants, 30 fit the criteria to be involved within this experiment as all must have completed the practice trials at the same difficulty level. Due to this split in the experimental data between two separate research articles with different hypotheses, no power analysis was conducted for the current article. However, the sample size for the current experiment is substantially larger than comparable and recently published manual tracking and modelling studies which used between 10 and 22 participants (Gollee, Gawthrop, Lakie, & Loram, 2017; Inoue & Sakaguchi, 2014; Stepp & Turvey, 2017; Viviani et al., 1987).

6.3.3 Apparatus

Visuo-manual pursuit tracking task

The manual tracking data were collected in the TrackAnalyze software application (Powers, 2008). In the experiment, the participant was asked to track a target that moved vertically on a computer screen using a joystick to keep a cursor aligned with a target. In the task, targets moved in a smoothly varying pseudorandom or sinusoidal target pattern.

Pseudorandom target time series were generated by a computer algorithm. The algorithm initialised three variables (D1, D2 and D3) to 0. Random numbers were generated between 0 and 1 (Rand), normalised around zero. These pseudorandom numbers were smoothed by dividing each component number by one of five smoothing factors (64, 32, 16, 8, and 4, respectively). These smoothing factors determine the difficulty of the task by altering the rate of change of the target. This process is displayed in Equation 1:

(1) $D1_t = D1_{t-1} + (Rand - 0.5)/Smooth$

This process was repeated a further twice:

(2) $D2_t = D2_{(t-1)} + (D1_t - D2_{(t-1)})/Smooth$

(3) $D3_t = D3_{(t-1)} + (D2_t - D3_{(t-1)})/Smooth$

The D3 values were then scaled to have a range of -500 to 500 and mean 0. The purpose of this was to rescale the numbers to screen size in pixels. Sinusoid targets required no smoothing. Difficulty was manipulated by changing the frequency of the sinusoid. This is computed in the following manner:

(4) $D_t = \sin(t*2*pi/Slowing)$

(5) $D_t = D_t * Range/2$

The slowing factors were 120, 240, 480, 960, and 1920, or 2, 4, 8, 16, and 32 cycles per minute. Equation 5 normalised the sinewave to vary between -500 and 500 screen pixels, similar to the pseudorandom targets. This range of 1000 pixels accounted for 19 cm of on screen displacement.

The cursor and target positions were sampled every $1/60^{th}$ of a second (~16.67 ms). At the end of each one minute trial the sampled cursor and target positions were saved to a tab delimited text file.

Joystick

The joystick that the participants controlled was a Microsoft Sidewinder Force Feedback 2 computerised joystick. The force feedback functionality was turned off such that participants tracked without force cantering. Performing across the full range of motion of the joystick did not require large trunk movements to be made but mostly shoulder and elbow movements. The angle of the joystick determined the position of the cursor on the screen, the full range of movement of the joystick was scaled the maximum displacement of the cursor on the screen.

6.3.4 Procedure

Participants first completed the Edinburgh Handedness Inventory (Veale, 2014). Participants read the written instructions for the manual tracking task and were given the opportunity to ask questions. Participants completed one practice trial on each of the target patterns, following which they completed 15 practice tracking runs according to the condition to which they were assigned (Block 1). Participants then completed the first test block using the same type of target that they had tracked in practice (Block 2). A five minute break followed the end of Block 2. The second test block was then completed (Block 3). This involved 15 tracking trials of the target type that was not tracked in the previous two blocks. The pseudorandom pattern differed for each trial for each participant.

6.3.5 Analysis: Tracking

The key tracking accuracy criterion used was Root Mean Square Error (RMSE). This measured the average deviation of the participant's cursor from the target during the one minute trial; lower scores represented more accurate fits. We compared participants' tracking accuracy on the two target types across the two conditions. A mixed-measures ANOVA was conducted in which average target-cursor RMSE across ten trials of each test block was the dependent variable. These ten trials consisted of the five optimisation trials and the five validation trials. The repeated measures variable was target type and had two levels: pseudorandom and sinusoid. The independent group factor was participant condition, and had two levels: Pseudorandom-Sinusoid and Sinusoid-Pseudorandom.

RMSE values do not enable the discrimination of errors due to timing and those due to reproduced signal magnitude. As we aimed to investigate the role of sensorimotor delays on phase delays this would be essential. We therefore calculated phase delay: the average delay of the cursor relative to the target across the trial. In addition, we calculated the amplitude ratio between the target and cursor, alongside signal coherence. Coherence is the correlation coefficient of the two signals in the frequency domain. All three measures were calculated by spectral analysis of the target and cursor signals.

The spectral analysis was conducted according to the procedure of a previous paper (Cofré Lizama et al., 2013), with several minor adaptations. We designed custom software for this purpose within Mathworks Matlab v2018a. This software used the Welch algorithm with a window length of .25 times the length of the signal, and an overlap of .9 times the window length. Signals were zero-padded to achieve a bin resolution in the frequency domain of .02Hz. In practice this required a scaling factor of 1.25 times the original target signal length, an effective change in the sampling rate from 1/60 to 1/75. As sinusoid targets comprised a single frequency (.062435 Hz) measures were calculated at this frequency only. For pseudorandom targets, the three largest power values in the frequency domain were averaged for each measure. The value of .75 times this mean determined the lower cut-off frequency, and therefore defined the band of frequencies over which the measures were calculated. Any values between the mean of maximum scores and the frequency cut-off were averaged to determine the value of that measure for the trials (Cofré Lizama et al., 2013).

True zero phase delay tracking would give a phase delay value of zero. A positive value would show that the cursor is, in general, advanced of the target in time. A negative value would represent a phase delay; the cursor lagging the target in time. Perfect alignment in signal magnitude would give an amplitude ratio of 1. Values above one show an increase in cursor amplitude relative to the target. Coherence estimates are bounded (maximum correlation coefficient =1). Amplitude ratios and coherence values are not affected by phase delay.

The phase delay, amplitude ratio and coherence measures were each evaluated in a paired t-test in which the independent variable was target (pseudorandom or sinusoid).

All data manipulation and analyses were completed in Mathworks MatLab and IBM SPSS 22.

6.4 Data Modelling

Four computational models were developed. These models were trained on the optimisation trial data and fit to the validation trial data.

6.4.1 Model architectures

Position control model (PCM)

The standard computational model used for comparison in this experiment was the standard tracking model proposed by Perceptual Control Theory (PCT; Powers, 1973, 2008). An identical PCM was reported in our previous study (Parker et al., 2017). This model iteratively computed outputs every sample. The current sample in the equations is denoted by (*t*). A diagram of the model can be seen in Figure 6.2.

The model input was the difference in position of the target (*T*) and cursor (*C*), this is the input signal (*iD*), Equation 1:

(6.1) $iD = T - C$

As the input gain was set to 1, the perceptual signal (*pD*) to the system remained equivalent to the input signal, though was sampled with a loop delay (τ samples). Equation 6.2:

(6.2) $pD = T(t-\tau) - C(t-\tau)$

The perceptual signal was compared to the reference signal (*r*), which represents the intended difference to be kept between the target and cursor. It might be expected that the value of the reference signal was zero as participants were instructed to maintain a distance of zero. The comparison yields the error term e (Equation 6.3):

(6.3) $eD = rD - pD$

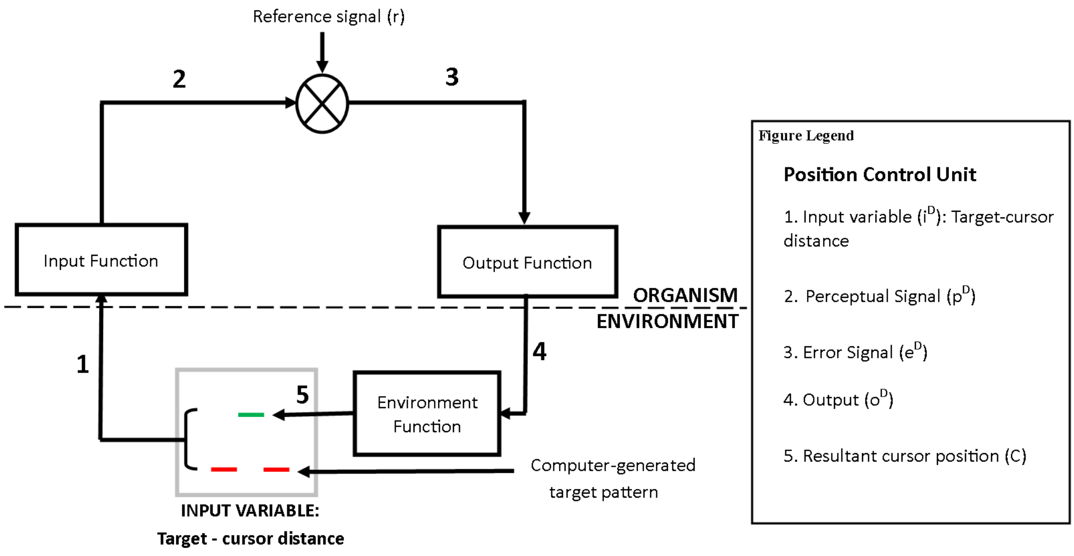
This error signal was fed into the output function where the output (*o*) was computed via the following equation:

(6.4) $o(t) = o(t-1) + (KoD * eD - Kd * o(t-1)) * dt$

In this equation *o(t)* is the current output and *o(t-1)* is the output at the previous iteration of the model. *KoD* is the output gain which represents a factor that the difference e is scaled to amplify the response. Given that the input and environment function gains are set to the integer 1, the loop gain represents the total loop gain for the control unit. *Kd* is the damping constant which is the gain for the leaky integrator and determines the proportion of the response that is lost per iteration. The sample rate, *dt* was 1/60 seconds ~ 17 ms. The loop delay parameter (τ) determined the input sampling delay in number of samples. This parameter was specified manually and thus was not a free parameter for optimisation. The output of the system determined cursor position (*C(t)*) directly as the environment function gain is unity:

(6.5) $C(t) = o(t)/1$

Figure 6.2 Diagram of the PCM



Position Extrapolation Model (PEM)

The PEM was identical to the position control except that the controlled variable was not the distance between the delayed target position and the delayed cursor position. In this model, the perceptual signal was the difference between an extrapolated target position and the delayed cursor position. The extrapolated target position was calculated at the input function by computing a delayed estimate of the target velocity, and multiplying this with an additional gain parameter (*Kx*). Finally, this product was summed with the delayed measured target position. Optimisation of the gain parameter (*Kx*) would scale the velocity estimate such that it counteracted the delay in measurement of the target signal, estimating a target position that approximated the current or immediate future target position.

Decomposing the PEM as was done for the PCM in Experiment 1, the input to the PEM was therefore:

(6.6) $iD = T\text{-}C$

The perceptual signal added the estimated target velocity, multiplied by the parameter *Kx*, to the target position, and subtracted the cursor position. Thus the perceptual signal (*pV*) was:

(6.7) $pD = ((T\,(t - \tau)) + (Kx*((T\,(t - \tau) - T\,(t\text{-}\ (\tau + s))/\ s))) - C\,(t - \tau)$

All the further equations of the PEM were identical to those in the PCM. The error signal (eD) of the parallel model is given by Equation 6.8:

(6.8) $eD = rD - pD$

The output was determined by the error signal and the output function. The latter transformed the error signal (eD) into the output signal (oD), by Equation 6.9:

(6.9) $oD = (o(t\text{-}1) + ((KoD*\ eD) - (o(t\text{-}1) * Kd)) * dt$

The output determined the cursor position via the environment function, which had a gain of 1:

(6.10) $C(t) = o(t)/1$

Hierarchical control model (HCM)

The hierarchical model was formed of two PCT control units, one controlling visual target-cursor position, and one controlling target-cursor velocity. However the output is computed in a serial manner where the position control unit is the superordinate unit and the subordinate unit controls velocity. Therefore the output of the position control unit is the reference value for the velocity control unit below it, and the output of the velocity control unit is the output of the integrated system (cursor position). Consequently, the velocity reference value (*rV*) is not a free parameter for optimisation and instead changes dynamically throughout control system operation. The equation for computation of the distance reference (*rV*).

The superordinate position unit simply comprised an output gain (*KoD*) and this multiplied the error signal (*eD*) which was calculated by the difference between the position reference (*rD*) and the perceptual signal (*pD*):

(6.11) $eD = rD – pD$

Thus the velocity reference (*rV*) is computed:

(6.12) $rV = KoD * eD$

The velocity unit had two free parameters: velocity output gain (K_{oV}), and damping constant (K_d). The value of loop delay parameter (τ) was constrained experimentally and always took the same value for both the position and velocity control units.

As target-cursor velocity was the controlled variable of the latter control unit, the inputs to the velocity unit were the target and cursor velocities. The input function determined that these were calculated as the change in position between the position measurement at the given loop delay (τ), and at the loop delay plus a constant (s) The constant had to be low enough not to confound the effect of loop delay, but high enough to smooth velocity calculation for the cursor output (which was noisy). Piloting determined that when s was set to the integer three for all velocity equations for all participants, this provided suitable stability.

The equation for the input to the velocity control unit (*iV*) was therefore:

(6.13) $iV = TV – CV$

The perceptual signal (*pV*) was:

(6.14) $pV = ((T\ (t - \tau) – T\ (t- (\tau + s))/ s) - ((C\ (t - \tau) – C(t- (\tau + s))/ s)$

The error signal (*eV*) of the parallel model is given by Equation 6.15.

(6.15) $eV = rV - pV$

The output is determined by the error signal and the output function. The latter transformed the error signal (*eV*) into the output signal (*oV*) of the hierarchical model.

(6.16) $oV = o(t\text{-}1) + (KoV * eV - o(t\text{-}1) * Kd) * dt$

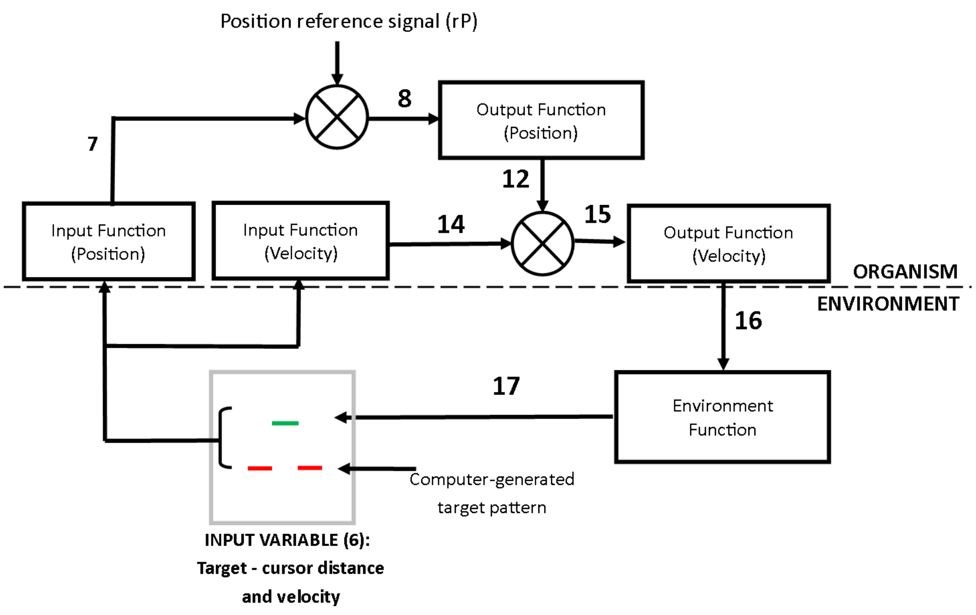
This determined the simulated cursor position (*C(t)*), via the environment function.

(6.17) $C(t) = o(t)/1$

Hierarchical Extrapolation Model (HEM)

The final model architecture incorporated both position extrapolation and hierarchical control of position and velocity (Figure 5). The HEM thus follows Equations 6.6 through 6.8, and 6.12 through 6.17. The model contained five free parameters: One extrapolation gain (K_X), position reference value (*rD*), output gains for the position and velocity controllers (*KoD* and *KoV* respectively), and a damping constant (*Kd*). Figure 5 graphically depicts the HEM. Figure 6.3 depicts the HEM architecture.

Figure 6.3 Diagram of the HEM architecture



6.4.2 Model delays

We aimed to test the model robustly over a range of loop delay values. Thus, loop delay values were selected with reference to estimates of central processing latencies, identified by Event Related Potentials (ERPs) in response to the presentation of visual stimuli in humans. The delay values were selected that covered a range durations cantering on estimates of peak activation in brain areas that have been identified as critical to spatial processing, and sensorimotor areas implicated in planning, preparation and execution of movement.

We wished the shortest loop delay to be below the biologically plausible threshold for perceptual feedback regarding visual stimuli, 17 ms was selected as this represented one sample; the minimum delay to which the model could be constrained in the program. This is substantially shorter than the time taken for the stimulus to be registered in the visual cortex. Signals arrive from the optical nerve at the Lateral Geniculate Nucleus (LGN) and are projected to the primary visual cortex, where extra-retinal processing of the visual information takes place. Onset of activation in areas V1, V2 and V3 of the visual cortex occurs at approximately 30 ms (Foxe & Simpson, 2002). Cells in the Middle Temporal (MT) and Medial Superior Temporal (MST) areas of the primary visual cortex respond to and code the direction and velocity of stimulus movement (Lisberger & Movshon, 1999). Onset of activation in these follows V1 activation by approximately 10 ms in humans and monkeys (Foxe & Simpson, 2002; Schmolesky et al., 1998). Activation in the visual cortex peaks around 60 ms following stimulus onset (Kruse, Dannenberg, Kleiser, & Hoffmann, 2002), MT and MST represent the gateway to the dorsal stream (sometimes called the ‘where’ pathway), which continues processing of spatial and motion information thus 50 ms was selected as our second loop delay value.

In the dorsal stream, the MT and MST areas project to the Posterior Parietal Cortex (PPC) and frontal areas, and subsequently premotor and motor areas. The frontal areas are implicated mostly in attention and executive control (onset latencies 60 ms, peaks 60 ms to 90 ms; (Di Russo, Martínez, Sereno, Pitzalis, & Hillyard, 2002; Martínez et al., 1999). The function of the PPC is the integration of spatial and motion information (Hill & Raab, 2005). The PPC is the most likely candidate for the brain location where relative position and velocity judgements concerning the target and cursor might take place during manual tracking (Hill & Raab, 2005).The PPC has been implicated in coding feedback-dependent computations of movement error which are used to correct movement trajectories online

(Desmurget et al., 1999; Gréa et al., 2002). Activation onset occurs at approximately 80 ms and peaks after 100 ms. Therefore 100 ms was selected as the third loop delay value.

The PPC projects to the Supplementary Motor Area (SMA) and to the motor cortices. Recurrent activations throughout the dorsal stream occur during movement preparation and execution such that "*100–400 ms is commonly needed for information processing prior to response output in humans.*" (Foxe & Simpson, 2002). Pure sensorimotor delays in movement to an unexpected stimulus from static are typically in the region of 180-200 ms, whilst response times for continuous stimuli are often much shorter, in the region of 180 ms (Hill & Raab, 2005; Parker et al., 2017). Consequently, we selected equally-spaced values between 100 ms and a liberal high end loop delay value of 500 ms.

Thus the selected loop delay (τ) values were 17 ms, 50 ms, 100 ms, 150 ms, 200 ms, 250 ms, 300 ms, 350 ms, 400 ms, 450 ms, and 500 ms. The model was optimised to participant tracking data at each of these separate loop delay values.

6.4.3 Model optimisation and selection

Excepting the loop delay value (τ), all other model parameters were free parameters for optimisation. The parameters of the model were optimised with the MatLab function 'lsqnonlin', a non-linear least squares algorithm. The maximum number of iterations was set to 2000, and the function tolerance to 1 x 10^{-8}. The initial conditions and boundaries for parameter optimisation were: Position and velocity output gains (*KoD*, *KoV*), 1 [1, 500]; position and velocity damping constants (*Kd*), 0 [0, 1]; reference values (*rD*), 0 [-500, 500]; and extrapolation gains (*Kx*), 0 [0, 50].

For optimisation trials, the parameters of the computational model were optimised to each trial at each of 11 delay values. The set of model parameter values that resulted in the best fit to the cursor movements was selected as the individual model for that specific delay value for each participant. These 11 parameter combinations were used for model validation at each of the delay values.

6.4.4 Model validation

Validation trial data were simulated and the accuracy of fit to the individual's movements was assessed at each of the loop delay values. Statistical outliers in model fit were identified as RMSE values for a validation trial being three or more standard deviations above the mean error rate for that participant at that loop delay value. For any outlying data, the next best-fitting model parameters from optimisation would be selected and used to simulate the validation data again. This process would continue till model fit statistics were no longer outlying. In practice, outliers occurred infrequently and in all the second best parameter combination did not produce outliers.

6.4.5 Model analysis

Model simulation accuracy was assessed by RMSE between the simulated cursor signal and the participant's actual cursor signal.

For each target type, a mixed model regression analysis was conducted. The outcome variable was model-simulated cursor RMSE and loop delay was the predictor variable. We included Participant as a random effect (both slope and intercept). This analysis enabled modelling of the whole dataset rather than the average model simulation error value for each individual across the five trials for each target. Both linear and quadratic mixed models were tested for their fit to the data.

Following regression analysis, ten comparison t-tests were conducted to compare across delays within targets, and between targets at specific constrained delay values. For each target type, the model simulation error at loop delays of 17 ms, and 200 ms were compared. The loop delay of 17 ms was chosen because it represented the minimum tested loop delay and it was considered an implausible value for the sensorimotor delay in manual tracking. The second loop delay value, 200 ms, was chosen because it was the closest delay value to the estimates of sensorimotor delays in manual pursuit (Abdel-Malek & Marmarelis, 1988; Khoramshahi et al., 2014; Parker et al., 2017; Viviani et al., 1987; Yu et al., 2014)

Model simulation error was also compared *between* models at these loop delay values 200 ms to establish whether differences existed in the pattern of tracking results. A Bonferroni correction was applied for ten comparisons; $p < .005$ for significance.

Using the same spectral analysis methods applied to tracking performance, we calculated the amplitude ratio, phase delay and coherence between the simulated cursor and target, and the simulated cursor and participant cursor. The statistics were calculated at a loop delay of 200 ms. These statistics were used to determine whether the model-simulated cursor differed significantly from participants' cursors in its phase delay, amplitude ratio and coherence. One-sample t-tests were run with each statistic. For amplitude ratio and coherence, the test value was 1, which represents a perfect match of amplitude and coherence. For phase delay, the test value was 0, representing perfect match to the cursor signal in time (no phase delay or advance). For each set of four one-sample t-tests the bonferonni-corrected criterion value was $p = .013$.

The same analyses were conducted for both optimisation data and validation data. Only results for validation data are presented in this article because validation trials provide a more robust test of the models as target signals are not identical to those that the model was trained on (Oberkampf et al., 2004).

6.5 Results

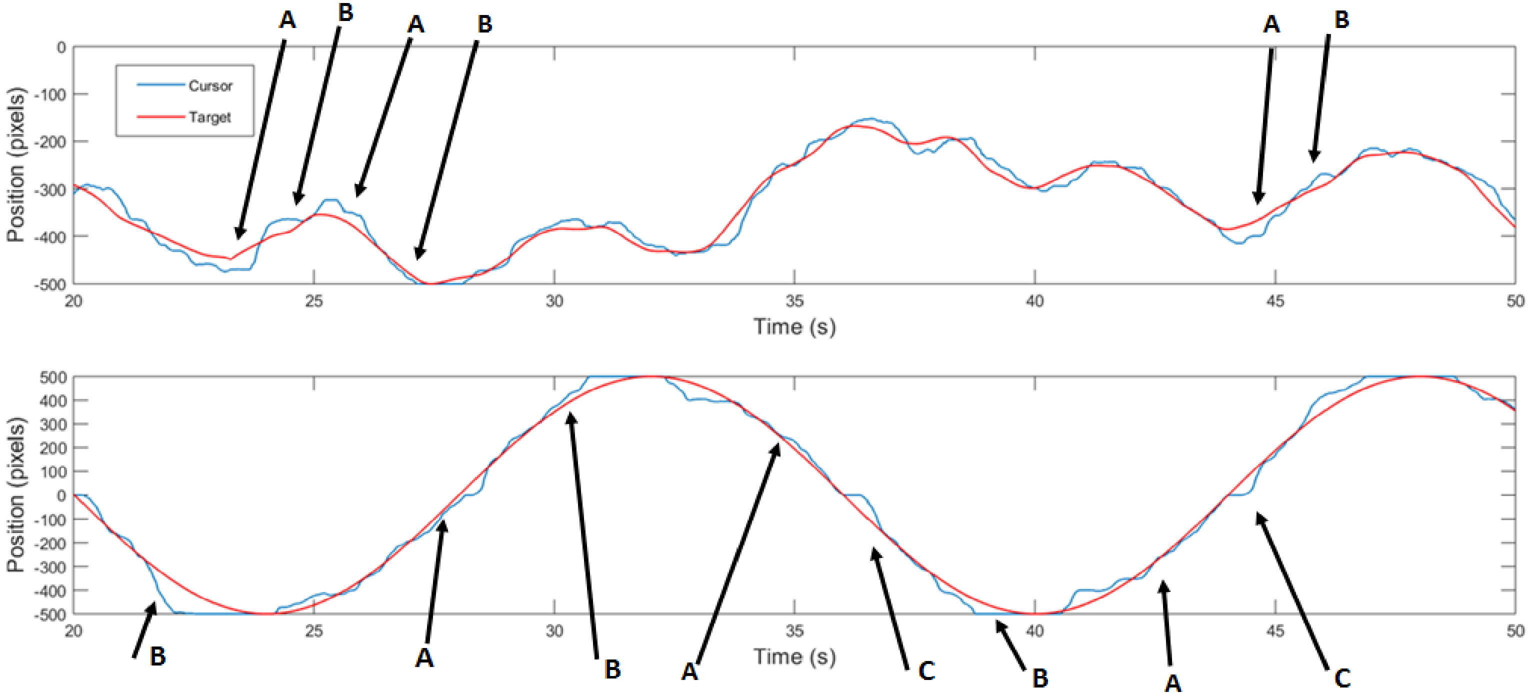
6.5.1 Tracking performance

One participant was excluded from the analysis as their target to cursor RMSE was larger than three standard deviations above the mean when tracking both pseudorandom and sinusoid targets. Twenty-nine participants' data were analysed. Participant cursor-target RMSE, optimal model cursor-target RMSE and participant model cursor-participant cursor RMSE were positively skewed. Log transformations were applied to mean statistics. Demographic and tracking error statistics are displayed alongside tracking accuracy statistics in Table 6.1. Figure 6.4 displays time series graphs of typical pseudorandom and sinusoid tracking trials.

Table 6.1 Descriptive statistics of participant demographic and tracking data

		Age	Sex	Handedness	Track RMSE	
Condition	N	Mean (SD)	Male/ Female	Right/Mixed/ Left	Pseudorandom Mean (SD)	Sinusoid Mean (SD)
Pseudorandom-Sinusoid	14	22.21 (3.72)	5/9	13/1/1	28.86 (6.99)	27.85 (4.95)
Sinusoid-Pseudorandom	15	21.34 (2.44)	2/13	13/0/2	29.57 (6.77)	27.67 (6.99)

Figure 6.4 Example segments of tracking trials for a pseudorandom target (top) and sinusoid target (bottom) from the same participant



Note the different y axis scales. The sinusoid's displacement is 1000 pixels. This is not usually the case for pseudorandom targets. Note also the longer phase delay for pseudorandom targets. Finally, note the alternating pattern of phase delay during target acceleration (A in diagram) and phase advance during target deceleration (B in diagram), which may be indicative of velocity-based extrapolation. C indicates where joystick stickiness in the centre may cause a small displacement when tracking across the centreline.

The 2*2 mixed ANOVA of tracking accuracy (RMSE) revealed no difference in tracking error between sinusoid and pseudorandom targets; $F_{(1,27)} = 0.99$, $p = 0.328$, partial eta^2 = .035. The main effect of condition was not significant; $F_{(1,26)} = 0.19$, $p = .892$, partial eta^2 = .001. There was no interaction between condition and target type, $F_{(1,27)} = .093$, $p = .762$, partial eta^2 =.003. Therefore practice with only one target type did not later tracking accuracy on either target type in the test phase. The condition variable was thus excluded from further analyses of performance.

Table 6.2 displays the means and standard deviations for the measures derived by spectral analysis: Phase delay, amplitude ratio, and coherence. Participants tracked pseudorandom targets with a significantly longer phase delay than sinusoid targets; $t_{(28)} = 9.50$, $p < .001$. The amplitude ratio during tracking of pseudorandom signals was higher than that of sinusoid targets; $t_{(28)} = 3.03$, $p = .005$. Target and cursor signals were equally coherent for both target types; $t_{(28)} = 1.53$, $p = .138$.

Table 6.2 Spectral analysis statistics

	Phase Delay	Amplitude Ratio	Coherence
Target Type	Mean (SD)	Mean (SD)	Mean (SD)
Pseudorandom	-159.40 (59.82)	0.99 (0.01)	.986 (.006)
Sinusoid	-53.31 (37.35)	0.97 (0.02)	.992 (.010)

Note that amplitude ratio cannot exceed the value 1 in this experiment as the maximum cursor displacement is equal to amplitude of the sinusoid

6.5.2 Model validation

Model validation trials were almost all simulated without outliers. There were several exceptions. Following optimisation and model selection, only one participant's PCM produced outlying model fit data for any validation trials. This occurred at a loop delay of 400 ms for all five of the validation trials. The HCM generated outlying model simulation error statistics for four participants for all five validation trials. Three of these at the loop delay 350 ms, and one was at 400 ms. One participant's model generated outlying model simulation error statistics for the HEM at 400 ms. All outliers were adequately replaced by simulation with the next best fitting model parameters from optimisation for that participant.

Pseudorandom targets

Figure 6.5 displays a 15 s segment of a pseudorandom tracking trial, the PCM and HEM simulated cursors shown for comparison. The simulations displayed were those with a loop delay of 200 ms. Optimal model parameters for pseudorandom targets at each loop delay value are shown in Appendix C.

All regression models showed a quadratic relationship between loop delay and model simulation error (Figure 6.6). The regression statistics can be found in Appendix E. Delay was a significant predictor of model simulation error in all models. The optima of the quadratic functions were approximately 150 ms for the PCM model, and 200 ms for the HCM, PEM, and HEM models. The mean data demonstrated optima at 200 ms for the PCM and HCM, and 250 ms for the PEM and HEM models. The gradient of increase in model simulation error after these optima was steepest for the PCM, then the PEM, then the HCM, and finally the HEM.

For all models, model simulation error was lower at a loop delay of 200 ms than it was at 17 ms. For the PCM, $t_{(28)} = 5.51$, $p < .001$; for the HCM, $t_{(28)} = 10.51$, $p < .001$; for the PEM, $t_{(28)} = 13.58$, $p < .001$; for the HEM model, $t_{(28)} = 13.69$, $p < .001$. Thus the loop delay value of 200 ms gave a better fit to manual tracking data than shorter one.

Model simulation error was evaluated between the models when loop delays were constrained to 200 ms. There was no difference in model simulation error for pseudorandom targets: PCM vs. HCM, $t_{(28)} = 1.50$, $p = .144$; PCM vs. PEM, $t_{(28)} = 0.94$, $p = .354$; PCM vs. HEM, $t_{(28)} = 2.05$, $p = .050$; HCM vs. PEM, $t_{(28)} = 0.81$, $p = .426$; HCM vs. HEM, $t_{(28)} = 1.89$, $p = .069$; PEM vs. HEM, $t_{(28)} = 1.34$, $p = .193$

Figure 6.5 Time series graph showing 15 s of a typical pseudorandom tracking trial and the model-simulated cursor positions for the PCM and HEM models (at 200 ms loop delay).

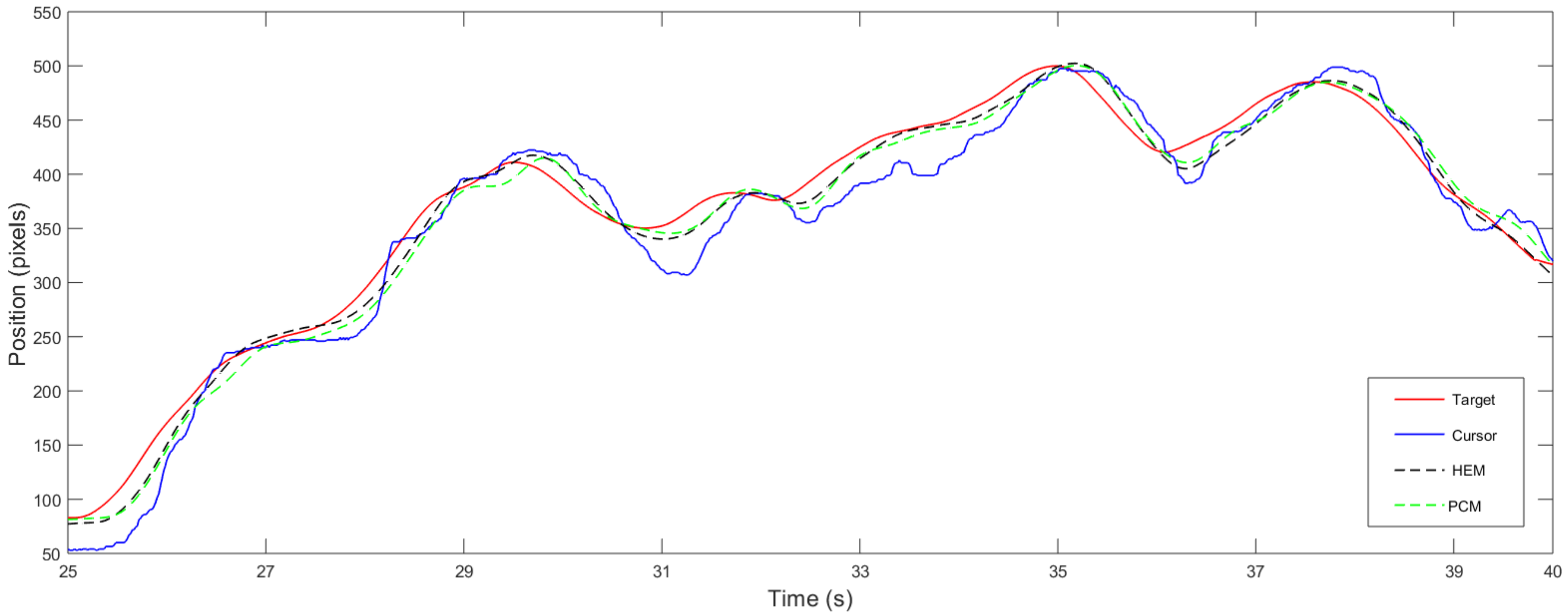
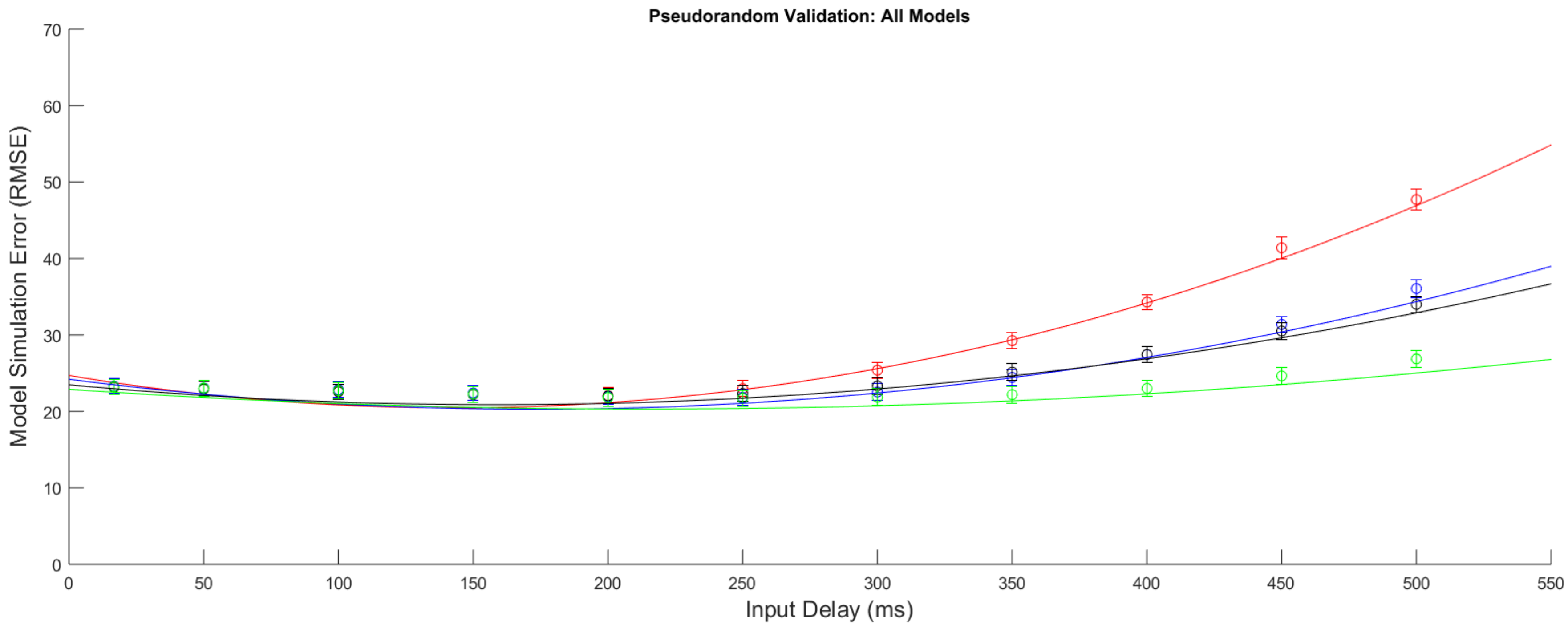


Figure 6.6 Mean model simulation error and standard error, and quadratic functions for model fits to validation data: Pseudorandom targets



Note: The colours of the regression line and error bars indicates the model they represent: Red: PCM, Black: HCM, Green: PCM, and Blue: HEM.

For both the PCM and HCM, there was no significant phase delay or advance of the simulated cursors relative to the participant cursors; PCM, $t_{(28)} = 0.79$, $p = .436$; HCM, $t_{(28)} = 0.62$, $p = .539$. In contrast, the PEM and HEM simulated cursors were significantly phase advanced when compared with the participant cursors; PEM, $t_{(28)} = 4.04$, $p = .001$; HEM, $t_{(28)} = 3.76$, $p = .001$.

The amplitude ratio was not significantly different from 1 for any model; PCM, $t_{(28)} = 0.23$, $p = .823$; PEM, $t_{(28)} = 0.90$, $p = .378$; HCM, $t_{(28)} = 0.18$, $p = .860$; HEM, $t_{(28)} = 1.15$, $p = .259$. In contrast, coherence was significantly lower than zero for all models; PCM, $t_{(28)} = 3.76$, $p = .001$; PEM, $t_{(28)} = 3.82$, $p = .001$; HCM; $t_{(28)} = 3.66$, $p = .001$; HEM, $t_{(28)} = 3.66$, $p = .001$. Table 6.6 displays the means and standard deviations in the phase delay, amplitude ratio and coherence statistics for pseudorandom targets

Table 6.6 Amplitude ratios, phase delays and coherence coefficients for the model-simulated cursors for pseudorandom targets.

	Simulated Cursor – Target						**Simulated Cursor - Participant Cursor**					
	Phase Delay		**Amplitude Ratio**		**Coherence**		**Phase Delay**		**Amplitude Ratio**		**Coherence**	
Model	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
PCM	-165.77	35.80	0.97	0.03	1.000	.000	-5.74	39.10	1.00	0.03	1.000	0.001
PEM	-114.98	69.04	0.97	0.03	1.000	.000	43.48	58.02	1.00	0.03	1.000	0.001
HCM	-162.61	36.89	0.97	0.02	1.000	.000	-4.24	36.68	1.00	0.02	1.000	0.001
HEM	-117.46	70.39	0.97	0.03	1.000	.000	39.29	58.05	0.99	0.03	1.000	0.001

Sinusoid targets

Figure 6.7 displays a 15 s segment of a typical sinusoid trial, and PCM and HEM model-simulated cursors. These models were those optimised with a loop delay of 200 ms. The optimal parameters for each delay value can be found in Appendix D.

For sinusoid targets, model simulation error increased as a function of loop delay in a quadratic relationship from zero milliseconds for both the PCM and HCM. The PEM and HEM regression models were not significant in either linear or quadratic form (quadratics shown in Figure 6.8). Thus increases in loop delay did not reduce the accuracy of the model fit to tracking data. The regression statistics can be found in Appendix F.

For the PCM, error was significantly lower at 17 ms than it was at 200 ms, $t_{(28)}$ = 3.83, p = .001. The same difference was observed in the HCM; though this did not reach significance when accounting for multiple comparisons; $t_{(28)}$ = 2.09, p =. 046. For the PEM and HEM there was no difference in simulation accuracy between 17 ms and 200 ms; $t_{(28)}$ = 1.41, p = .171, and $t_{(28)}$ = 1.43, p = .163 respectively.

Comparisons of model fit when models were constrained to a loop delay of 200 ms indicated no difference between the PCM and HCM; $t_{(28)}$ = 1.46, $p < .155$. However, both the PEM and HEM showed a reduction in error relative to the PCM; $t_{(28)}$ = 3.77, $p < .001$, and $t_{(28)}$ = 3.87, $p < .001$. Similarly, the PEM and HEM showed reduced error relative to the HCM; $t_{(28)}$ = 3.86, $p < .001$, and $t_{(28)}$ = 4.75, $p < .001$. No difference in model simulation error was observed between PEM and HEM; $t_{(28)}$ = 0.12, p = .908.

Figure 6.7 Time series graph showing 15 seconds of a typical sinusoid tracking trial and the model-simulated cursor positions for the PCM and HEM models (at 200 ms loop delay)

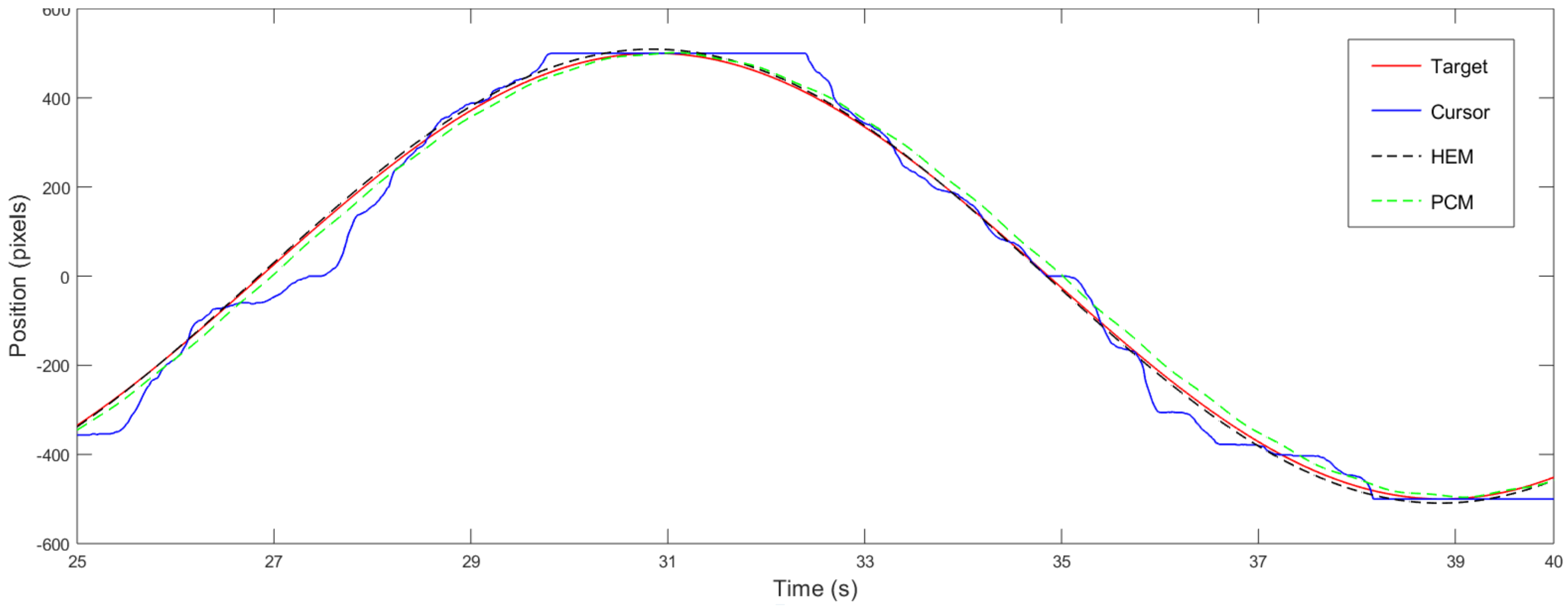
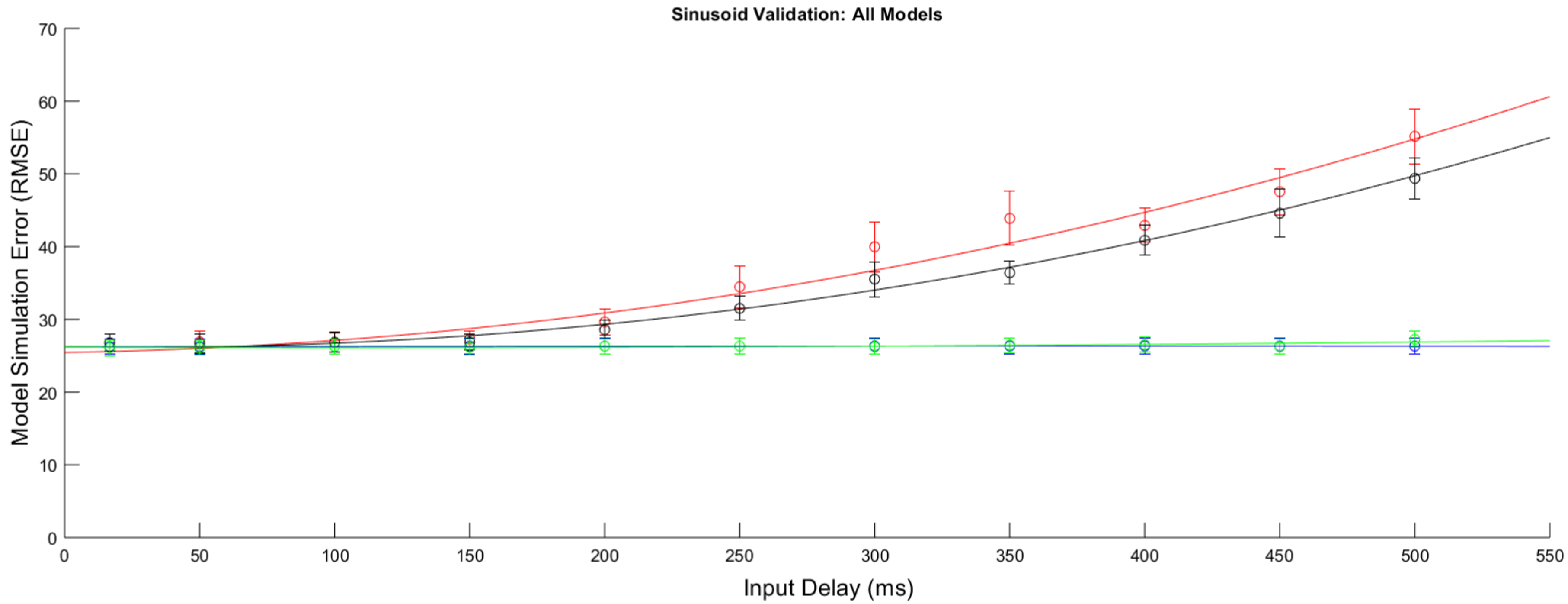


Figure 6.8 Mean model simulation error and standard error, and quadratic functions for model fits to participant tracking data on sinusoid targets



Note: The colours of the regression line and error bars indicates the model they represent: Red: PCM, Black: HCM, Green: PCM, and Blue: HEM.

The one-sample t-test of phase delay statistics showed that the PCM model and HCM simulated cursor was significantly delayed in phase relative to the participant cursor; PCM, $t_{(28)} = 9.54$, $p < .001$; HCM, $t_{(28)} = 9.72$, $p < .001$. In contrast, there was no difference in phase between the simulated and participant cursors for PEM and HEM models; PEM, $t_{(28)} = 0.42$, $p = .677$; HEM, $t_{(28)} = 0.92$, $p = .366$.

Amplitude ratios were not significantly different from 1 for the PCM and HCM models; $t_{(28)} = 0.76$, $p = .452$; HCM, $t_{(28)} = 1.20$, $p = .240$. Amplitude ratios were significantly above 1 for the PEM and HEM models; PEM, $t_{(28)} = 3.35$, $p = .002$; HEM, $t_{(28)} = 3.12$, $p = .004$. This indicated that PEM and HEM models produced higher amplitudes than the participants did.

Coherence between the simulated cursor and the participant's cursor was significantly lower than 1 for all models; PCM, $t_{(28)} = 3.39$, $p = .002$; PEM, 3.39, $p = .002$; HCM, $t_{(28)} = 3.39$, $p = .002$; HEM, $t_{(28)} = 3.39$, $p = .002$. Thus the simulated cursor was significantly different from a perfect linear correlation in the frequency domain for all models.

Table 6.7 reports the amplitude ratios, phase delays and coherence estimates for model-simulated cursors during sinusoid tracking.

Table 6.7 Amplitude ratios, phase delays and coherence coefficients for the model-simulated cursors for sinusoid targets

	Simulated Cursor – Target						Simulated Cursor - Participant Cursor					
	Phase Delay		Amplitude Ratio		Coherence		Phase Delay		Amplitude Ratio		Coherence	
Model	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
PCM	-111.80	11.33	0.97	0.12	1.000	.000	-58.49	35.58	0.98	0.12	0.999	0.001
PEM	-48.44	66.87	1.00	0.03	1.000	.000	4.87	62.18	1.02	0.03	0.999	0.001
HCM	-117.32	10.99	0.99	0.02	1.000	.000	-64.02	35.49	1.01	0.02	0.999	0.001
HEM	-58.45	40.07	1.00	0.02	1.000	.000	-5.14	30.12	1.01	0.02	0.999	0.001

6.6 Discussion

6.6.1 Tracking accuracy

Participants were able to track targets accurately that moved in both pseudorandom and sinusoid movement patterns. Additional practice did not improve nor hinder performance, indicating that the participants were reaching performance asymptote and thus no longer learning. Similarly, switching from one target type to another did not seem to interfere with performance on the second target type, though it may be that task switch and learning effects were flushed out by the end of the five practice trials at the start of the second test block.

Critically, participants were observed to exhibit reduced phase delays when tracking sinusoid targets relative to tracking pseudorandom target signals. This supports the interpretation that individuals engage in anticipation whilst tracking sinusoid target signals (Gollee et al., 2017; Inoue & Sakaguchi, 2014; Khoramshahi et al., 2014; Neilson et al., 1993; Parker et al., 2017; Poulton, 1952a, 1952b; Stepp & Turvey, 2017; Viviani & Mounoud, 1990). However, sinusoid tracking has been described as *zero*-phase delay tracking, this is not observed to be the case in our experiment. The average delay over trials for sinusoid targets was ~50 ms. However, as this phase delay is at least 30 - 50 ms shorter than the shortest sensorimotor and visual feedback processing time estimates (Brenner & Smeets, 2015; Day & Lyon, 2000; Foulkes & Miall, 2000; Franklin & Wolpert, 2008; Saunders & Knill, 2005) sinusoid tracking in this experiment is certainly anticipatory. In contrast, pseudorandom tracking performance was within the estimated sensorimotor delay range: approximately 150 ms; though was close to the minimum of the expected range of values (Khoramshahi, Shukla, & Billard, 2014; Viviani, Campadelli & Mounoud, 1987; Yu, Gillespie, Freudenberg, & Cook, 2014).

It was expected that participants would track sinusoids more accurately than pseudorandom target signals given the degree of predictability of the target signal. We did not find a significant difference in tracking performance (RMSE) between the two target types, though a trend in the hypothesised direction was observed. It is likely that the reduced sample size in this analysis (due to the between groups comparison) was underpowered to find all but large effects. There was no significant difference in coherence estimates, although there was a trend towards improved performance for sinusoid targets.

The spectral analysis statistics clarify the null difference between pseudorandom and sinusoid tracking performance. Firstly, although the maximum displacement of the target signals on-screen was equal (1000 pixels), the sinusoid always had this amplitude, whilst, in practice, the pseudorandom signal rarely made such large displacements. This may have contributed to amplitude errors for the sinusoid targets. This is supported by the finding of a higher amplitude ratio for pseudorandom targets than for sinusoid targets. Participants tracked with lower amplitude (undershoot) for sinusoid targets. This may have mitigated the improvement in overall fit conferred the reduced phase delay. In future experiments, pseudorandom and sinusoid target signals may be made to have equal average displacement (rather than maximum displacement). Alternatively, signal velocity or frequency may be altered.

Graphs of tracking data allow several of observations to be highlighted regarding trends in tracking data (Figure 6.4). Firstly, the phase delay can be seen to be observed to be longer, on average, for pseudorandom targets than for sinusoid targets. This is confirmed by the phase statistics discussed previously. Secondly, the phase relationship between the cursor and target typically alternates between phase advance particularly during target deceleration and phase delay during target acceleration for *both* targets. This is consistent with extrapolation based on delayed motion information. If, for example, the delayed estimate of target velocity is lower than the actual velocity (as is the case during target acceleration), the phase delay would increase as the cursor moves too slowly. The opposite would be the case for target deceleration, and would cause significant overshoot when the target stops or changes direction. Finally, the jump in cursor position around zero pixels may indicate centre stickiness in the joystick.

6.6.2 Model simulation accuracy

Pseudorandom targets

We had hypothesised that for all models, the simulation error for pseudorandom targets would be lowest when loop delays were in the region of 200 ms because estimates of the sensorimotor delay in manual tracking in previous experiments approximated this value (Khoramshahi, Shukla, & Billard, 2014; Parker et al., 2017; Viviani & Mounoud, 1987; Yu, Gillespie, Freudenberg, & Cook, 2014). The PCM did not support this, as the optimum model fit was produced at a loop delay of 150 ms. This indicated that sensorimotor delay may be shorter than 200 ms, consistent with estimates of sensorimotor delays in reaching experiments (Brenner & Smeets, 2015; Day & Lyon, 2000; Foulkes & Miall, 2000; Franklin & Wolpert, 2008; Saunders & Knill, 2005).

The three extended models fit pseudorandom tracking performance most accurately at loop delays of 200 ms or above. However, the PEM and HEM maintained low model simulation error at loop delay values longer than 200 ms, which indicates that extrapolation may mitigate the deleterious effect to performance associated with using longer loop delays in the other models. This maintained performance at longer delays may be due to phase delay compensation. This is supported by the finding of a significant phase advance for the simulated cursor of PEM and HEM models relative to the participant's cursor at 200 ms which indicates that the PEM and HEM models were over-compensating the loop delay. In contrast, no phase advance or delay was found for the PCM and HCM models. This is strong evidence that extrapolation can be used to compensate for sensorimotor delays. However, whether participants use extrapolation during pseudorandom tracking is difficult to determine given the equivalence of the model fits to pseudorandom targets at 200 ms loop delays.

It remains to be established whether participants use target extrapolation when tracking pseudorandom targets. However, it is clear that it is possible for models as the velocity of the target gives some indication of its future position. Despite this, the longer phase delay when participants track pseudorandom targets (~160 ms), relative to sinusoid targets (~50 ms) seems to indicate that participants do not compensate for phase delay to the same extent as they do when tracking sinusoid targets. In fact, even positional feedback control this may enable a small amount of sensorimotor delays compensation. This can be observed in the data as whilst participants tracked with a phase delay of 160 ms, the PCM and HCM reproduced this phase delay (no phase difference between simulated cursor and participant cursor) when the loop delay was 200 ms. This indicates that the models compensated approximately 40 ms of sensorimotor delay via positional feedback control only.

Sinusoid targets

For sinusoid targets, the lowest error in simulation was observed when PCM loop delays were minimal (17 ms). Simulation error increased as a function of increasing loop delay and thus was significantly higher when the model simulated tracking with a loop delay of 200 ms. This 17 ms optimum is substantially shorter than the shortest estimates of sensorimotor delay (Brenner & Smeets, 2015; Saunders & Knill, 2005). This may indicate that participants may use a mechanism other than position control when tracking sinusoid targets. The phase delay in PCM simulation relative to the participant cursor (~60 ms) provides further evidence to this conclusion. We hypothesised that utilising target or cursor velocity information in control schemes may enable models to compensate for 200 ms loop delays and simulate zero-phase delay tacking.

One model, the HCM, used the difference between target and cursor velocities as an additional control signal, within a hierarchical control structure. The HCM performed similarly to the PCM. It showed a similar decrease in simulation accuracy for sinusoids as loop delays increased. Like the position control strategy, hierarchical control of velocity and position does not seem provide sufficient compensation if the loop delay is 200 ms. However, it should be noted that at this loop delay the PCM and HCM both produced an approximate 120 ms phase delay behind the target and therefore compensated 80 ms of the loop delay. Position control and hierarchical position and velocity control may not account for anticipatory tracking of sinusoids if sensorimotor delays are in the region of 200 ms. However, models may better simulate sinusoid tracking data at 100 - 150 ms loop delays. Such reduced loop delays might be expected to reduce the phase delay difference between the simulated cursor and cursor.

The HCM controlled similar inputs to another architecture used in a two-dimensional tracking study (Viviani & Mounoud, 1990). In contrast to our findings, their model could emulate anticipatory tracking (zero-phase). However, Viviani's model did not use delayed inputs, but rather than inputs from imminent future target trajectory. This may explain why it could engage in anticipatory tracking behaviour. In order to elucidate the mechanism of anticipation in the task, models should use only delayed inputs.

The other two models developed in the current study were the PEM and HEM. These models integrated delayed target velocity information with delayed position information to estimate an extrapolated target position. This extrapolated position, minus the cursor position, was used as a control input. In contrast to the PCM and HCM, the simulated cursors of the extrapolation models did not exhibit a phase delay relative to the participant's cursor when loop delays were constrained to 200 ms. Moreover, these models maintained simulation accuracy across the full range of loop delay values with no clear optima. It might be considered therefore that position extrapolation is a potential mechanism that could underpin anticipatory sinusoid tracking. This interpretation adheres with suggestions that participants can extrapolate the target trajectory to account for feedback and central processing delays into the near future and use this as an input for the error correction (Brenner & Smeets, 2015; Brouwer, Brenner, & Smeets, 2002; Dessing et al., 2009; Lisberger et al., 1987; Mrotek & Soechting, 2007; Pavel, Cunningham, & Stone, 1992; Soechting, Rao, & Juveli, 2010).

It is also possible that participants use a different control strategy when tracking sinusoid targets. Participants may be able to change their control strategy to emulate the shape of target pattern in the sinusoid condition. This would not be possible in the pseudorandom condition as the target amplitude and frequency are irregular. Poulton called this course anticipation (Poulton, 1952a). There is some evidence that humans may do this, particularly when targets move very quickly. (Leist, Freund, & Cohen, 1987) found that in a sinusoid tracking task the eyes can only track smoothly up to a frequency of 1Hz and velocities of 60deg/s, but above 2Hz the eyes stop moving altogether. Participants cannot track the target at these speeds with their eyes and maintain a coherent visual image. Despite this, participants may be able to continue tracking with their arm by changing control strategy to simply match the frequency and amplitude of a periodic target.

6.6.3 General Discussion

It is unclear why participants tracking pseudorandom signals do not track with a phase delay as short in duration to the, though it appears that phase delays increase with both signal complexity (as in the current experiment), and with frequency (Neilson et al., 1993). In the current study, the acceleration and velocity of the target are reliable indicators of the future position of the target leading up until the target stops prior to potential directional switch. In addition, the direction the target takes following the switch point is predictable for the sinusoid target. However, for pseudorandom targets, the next target movement vector could be in either direction and cannot be determined by the participant in advance of the switch point. This may contribute to participants' inability to use of anticipatory strategies. This conclusion is supported by the findings of another study which found that when a change in target direction was predictable, participants showed an 'anticipatory' positive peak in SMA activity that averaged 170 ms before the target changed direction (Hill & Raab, 2005). However, when the change could not be determined from the target trajectory, this peak shifted to follow the change in direction and tracking latencies were increased (Hill, 2009). Whilst the tracking latencies cannot be directly compared with the current study (Hill and colleagues' studies used a two-dimensional tracking task with different parameters), it is apparent that as the target predictability increases, the processing of information relevant to the change in direction is shifted earlier and tracking latencies are reduced. This early positive ERP may represent early use of target velocity to estimate future target position or directional switch. Another possible explanation for the difference in phase delay between tracking of sinusoid and pseudorandom targets may be due to shorter average time between directional switches for pseudorandom targets than for sinusoids. For high frequencies this may be too short relative to the duration of the feedback delay to extrapolate position or use another anticipatory mechanism. When the target changes direction frequently or accelerates quickly, delayed velocity measurements would become unusable. Thus, it may be the case that velocity control could be utilised by humans when tracking pseudorandom targets that vary only at very low target velocities.

These possibilities could be tested by altering the characteristics of the input signal and observing changes in human and model behaviour; for instance by increasing or decreasing the velocity of the target, adding high frequency noise and increasing jerk, or altering the feedback function. The test for the controlled variable (TCV; Marken & Mansell, 2013; Marken, 2005, 2014) provides explicit instruction in how to manipulate environmental variables to determine which are under control. This could be applied to human control systems in the tracking task. Nevertheless, the existence of a single, generalisable solution to the tracking problem is unrealistic. More likely, healthy humans, with their array of sensory inputs, memory and cognitive abilities, can learn and adapt to perform accurately under different task demands. For very noisy signals for example, target extrapolation as conceived in this article would be of little use. However, averaging velocity inputs over 200 ms duration, for example, would have the effect of smoothing the noise, and thus reducing oscillations in output.

6.6.4 Limitations

In the current article we aimed to establish the effect of changing sensorimotor delay on model fit performance. To achieve this we altered the loop delay of the models and simulated performance at 50 ms intervals between 17 ms and 500 ms. Although this gave insight into how model accuracy evolves over a range of implausible and plausible delay values, we did not compare the fit of the models at all these points because this would require too large a number of statistical tests. We also did not characterise the phase delays reproduced by the models at each of these delays. Consequently, it is difficult to answer several key questions. Firstly, we were unable to establish whether the PCM (and HCM) could reproduce participants' sinusoid tracking latencies if delays were shorter than 200 ms but still within a biologically plausible range (100 ms and above). Secondly, we could not determine whether the PEM and HEM models simulate the tracking latency of pseudorandom targets more accurately if they were optimised to longer delays; above 200 ms. Finally, we cannot determine the true optima for model simulation accuracy as the loop delay interval was approximately 50 ms. In future it may be preferable to resample the data to a 1 ms resolution and find the true optimum for each model, and compare models at their optima.

The finding that the amplitude ratio of PEM and HEM simulated cursors to the participant cursor was higher than 1 indicates that the models overshot the targets at the point at which the target switches. It is likely that this is a statistical artefact of the experimental design as the maximum displacement of the cursor was the same as the amplitude of the sinusoid. This can be observed in Figure 6.2, where the cursor reaches 500 pixels above the target but does not exceed this value. This is an issue because if a participant's cursor had been moving with high velocity toward the switching point, it would have likely overshot the target due to inertia if they joystick. However, the upper limit on the displacement of the cursor (and joystick) precluded the possibility that participants' cursors overshot the target at the switch point. This would not have been observed so often in pseudorandom tracking because the amplitude of the target would not frequently reach the maximum displacement. Thus models do not have a higher amplitude ratio than the participant in the pseudorandom condition.

In a biological system, optimisation is ongoing and not discrete. Parameter values would never be stable and in fact would be dynamically varying, albeit slowly toward performance asymptote. In this study, optimisation operated over five single trials and the best fitting parameters were selected to form a static individual model of practised performance. These trials were non-consecutive such that any effect of trial order on participant performance and estimated model parameters was minimised. Furthermore, any software model is determinedly a simplification of the operation of the human controller. The models in this paper suggest a mechanism for a perceptual process, rather than specifying how control signals are translated to movement. In these models, the control signal directly specified cursor position. Other PCT models have been developed that control virtual joints (Kennaway, 2004; Powers, 1999), arms (Powers, 2008), and robotic arms via negative feedback processes, incurring the additional benefit of being resistant to perturbations. In a future study we intend to test whether the PCT reorganisation algorithm can be used to optimise the PCT models developed in these experiments to drive a force-feedback steering wheel in pursuit tracking.

In future, researchers should aim to produce models that can simulate human tracking during target occlusion (tracking in the absence of visual feedback) and unpredictable step input signals, to further differentiate between tracking strategies of predictable and unpredictable targets. In studies of occlusion, it is more likely that stored representations of the target are utilised to extrapolate the trajectory beyond that which is used when perceiving target velocity and controlling cursor velocity.

6.6.5 Conclusion

We aimed to test whether feedback control systems could adequately account for observed behaviour when humans track both predictable and unpredictable targets whilst maintaining biologically-feasible sensory feedback duration. We found that models that controlled both the position and velocity of a cursor using delayed target information could suitably account for both a) tracking of pseudorandom targets with delayed latencies, and b) tracking of sinusoid targets with zero phase delay.

Chapter 7: Temporal consistency in predictions of pursuit performance with a novel hierarchical controller

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Maximilian G. Parker[1], Sarah F. Tyson[2], Andrew P. Weightman[3], & Warren Mansell[1]

Author Affiliations:

[1]Division of Psychology and Mental Health, School of Psychological Sciences, University of

Manchester

[2]Division of Nursing, Midwifery and Social Work, University of Manchester

[3]School of Mechanical, Aerospace and Civil Engineering, University of Manchester

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7.1 Abstract

Due to intrinsic sensorimotor delays in the CNS, humans tend to exhibit movement delays in response to stimuli. However, when target movements are predictable, humans can often compensate for these sensorimotor delays and track without a delay. In a previous study, a computational model was developed that could simulate continuous manual tracking behaviour for both predictable and unpredictable targets while a model loop delay, characterising human sensorimotor delay, was constrained to 200 ms (Parker et al., in preparation). The current study aimed to conduct further evaluations of this model, the Hierarchical Extrapolation Model (HEM), using a Position Control Model (PCM) as a baseline comparison. Firstly, the models were tested across target types with different difficulty levels (determined by the fundamental frequency of the signal). Second, models were validated for temporal consistency with new targets tracked after one week. Third, a different apparatus was used; a steering wheel – altering the required movements and feedback path. Fourth, models were explicitly tested for the accuracy of their individual predictions, against a general model (aggregate of other individual models). Twenty-four neuro-typical adult participants completed three blocks of 16 one-minute trials over one week (two in one session, and a final block after one week). Each block comprised pseudorandom and sinusoid targets of high and low difficulty. Models were optimised to individual tracking performance in block one and validated with data from blocks two and three. The findings of the previous study were successfully replicated with the new apparatus. We found that models accurately simulated performance on all target types and difficulties, even after one week had elapsed (3.26 - 6.03% root mean square error, r = .969 - .996). Models showed individual specificity in their predictions: individual models fit significantly more accurately than aggregate models. The HEM model is a good candidate model of smooth pursuit manual tracking. Such individual models may find application in the rehabilitation domain.

7.2 Introduction

During task-oriented movement, humans display very low variance in task–relevant parameters, such as end-point hand position, whilst variability in non-task-critical parameters, such as shoulder and elbow joint angles, is much higher (Latash et al., 2002; Scholz & Schöner, 1999). This difference may be explained by control of task-critical perceptions. Conversely, non-task-critical parameters may be free to vary (Latash et al., 2002). This confers flexibility as these parameters can be altered continuously to consistently achieve stability in the task-critical perception across contexts, and compensate for disturbances. In well-practiced individuals this consistency can be observed in the parameters of perceptual control systems (Bourbon, 1996; Bourbon, Copeland, Dyer, Harman, & Mosley, 1990). Between individuals, differences in performance may arise due to differences in task goals, alongside physiological differences such as reductions in sensor acuity and reaction time with age (Krampe, 2002; Liao, Jagacinski, & Greenberg, 1997), and volume of relevant task practice (Noble et al., 1955; Notterman & Tufano, 1980). It might be expected that general models derived from averaging responses across multiple participants may not capture these idiosyncrasies. This method may impede progress in understanding and predicting individual functioning (Mansell & Huddy, 2018). An alternative, the functional modelling approach (Runkel, 2007), aims to construct and test mathematically-specified models of individual participants.

The functional modelling approach (Mansell & Huddy, 2018; Runkel, 2007) begins with an inference about which perceptual variables the individual is controlling in a task. A model is then constructed based on the inferred control process and optimised to an individual's task data. The model then simulates another dataset from that participant and the fit of the data to the individual's behaviour can be assessed. The approach has mostly been used to study motor control in visuo-manual tasks as these produce large quantities of continuous behavioural data for model fitting. Constructing models of individual performance may enable superior predictions of individual behaviour and performance in future trials than general models (Mansell & Huddy, 2018; Parker et al., 2017). Many such general computational models have been developed to specify task variables that are controlled and their mechanisms (Abdel-Malek & Marmarelis, 1988, 1990; Levison, Baron, & Kleinman, 1969; McRuer & Jex, 1967; Stepp & Turvey, 2017; Viviani, Campadelli, & Mounoud, 1987; Viviani & Mounoud, 1990). However, perceptual control theory (Powers, 1973; Powers et al., 1960; Powers et al., 1960), using the functional modelling approach, may be uniquely placed to produce accurate fits to *individual* human behaviour.

Perceptual control theory (PCT) proposes that individuals behave in order to achieve perceptual goals (Powers, 1973, 2008; Powers et al., 1960). The CNS is proposed to operate as a hierarchy of perceptual control units (Powers et al., 1960). Each control unit attempts to maintain a controlled perceptual variable at a reference (goal) value. The reference value is specified by the reference signal, a top-down projection linking the output of one control unit to the unit below. This reference value is compared to an incoming perceptual signal, yielding an error term. This error term drives output (and consequently the reference signal for the unit below). At the lowest level of the hierarchy, the output motivates an action. The action has an effect on the environment, which changes the inputs to the hierarchy (closed loop control). As individual humans differ in their motivations and goals, so do their references. That is, both the perceptual variables individuals control in a task as well as the reference values to which the same variable is controlled. The latter has been demonstrated in tracking studies where the model reference parameter shows individual differences and consistency (Bourbon, 1996b; Bourbon & Powers, 1999; Parker et al., 2017). The dynamic nature of the control system enables flexibility in tracking different targets, and accounting for disturbances. The parameters of models can be adjusted based on task demands.

In the tracking domain, PCT computational models have accurately simulated the behaviour of individual participants (Bourbon, 1996, 1999; Bourbon et al., 1990; Marken, 1991; Powers, 1978, 2008). In fact, models could still fit individual participant performance if tested on new data collected from that participant after one or five years (Bourbon, 1996b; Bourbon et al., 1990b). In a recent study we tested whether models, optimised to individual performance, would show individual-specificity in their predictions of tracking performance (Parker et al., 2017). Specifically, we hypothesised that each individual participant's tracking performance would be more accurately simulated by a model optimised to their data than by a general model derived from parameters averaged across all participants. This prediction was confirmed. This demonstrated that estimates of a participant's control parameters characterised their individual control strategy and could be used to predict their performance.

In the Parker et al. (2017) study, participants tracked only one type of target: pseudorandom input signals. There is evidence that tracking performance differs qualitatively between complex targets, such as pseudorandom targets, and those that move in periodic or regular patterns, like simple sinusoids. For example, individuals track pseudorandom targets with a phase delay of approximately 180 ms, which is presumed to arise from sensorimotor delays in processing of stimuli in the CNS (Abdel-Malek & Marmarelis, 1988, 1990; Bekey, 1962; Hill & Raab, 2005; Neilson et al., 1993; Viviani & Mounoud, 1990). However, no such tracking delay is exhibited with sinusoid targets delay (Neilson et al., 1993; Poulton, 1952b, 1952a; Stark et al., 1961; Vercher & Gauthier, 1992; Viviani & Mounoud, 1990). This has been described as zero-phase delay tracking (Inoue & Sakaguchi, 2014; Yu et al., 2014), in which the cursor may alternate between slight phase advance and phase delay (Inoue & Sakaguchi, 2014). The reduction in tracking delay for sinusoid targets is thought to be underpinned by anticipatory strategies which act to compensate for sensorimotor delays (Inoue & Sakaguchi, 2014; Khoramshahi et al., 2014; Poulton, 1952a, 1952b; Yu et al., 2014). The PCT Position Control Model (PCM), whilst showing individual specificity in predictions for pseudorandom targets, was not expected to accurately simulate performance for sinusoid signals.

In a second study, we extended the PCT control model to account for anticipatory tracking of sinusoid signals (Parker et al., in preparation).As we had expected, the PCM could not sufficiently compensate for delays when these were fixed within the model at biologically plausible duration. We adapted the PCM to enable it to extrapolate the target position from the target’s previous position and velocity (Khoei et al., 2013; Pavel et al., 1992; Zago et al., 2010). In contrast to the PCM, the adapted model could simulate zero phase delay tracking of sinusoid targets accurately in the presence of sensorimotor delays. It was concluded that control of extrapolated position is a plausible mechanism for compensating sensorimotor delay and may underpin anticipation in manual tracking. However, the study had a number of limitations.

Firstly, the adapted models were validated only with data collected in the same experimental session. This is unlike the first study in which the PCM was validated on new pseudorandom data collected one week later (Parker et al., 2017). Therefore it is unclear whether the adapted model shows individual specificity in parameters or predictions for tracking of sinusoid targets. Secondly, in both of the above studies each participant tracked a different set of randomly generated target signals. We could not directly compare between participants on the same target signals or compare individual model predictions on the same target patterns. Thirdly, substantial evidence exists that individual tracking characteristics are affected by target speed. In studies of tracking behaviour when individuals track sum-of-sinusoid targets of increasing bandwidth, the phase delay is reduced and the gain increases (Abdel-Malek & Marmarelis, 1988; Neilson et al., 1993). It is possible that the HEM is suitable for tracking target signals only of the specific bandwidth studied, but would not generalise to targets that moved more quickly. A robust model would accurately simulate human tracking performance across different task constraints.

The current study aimed to address these shortcomings and establish whether the model could generalise across different task constraints such as target difficulty (speed) and across apparatus, and produce accurate predictions of behaviour over time. Participants tracked sinusoid and pseudorandom targets in three blocks in two sessions separated by one week. The methodology was very similar to previous studies (Parker et al. 2017; in preparation) with a few critical differences. Firstly, the tracking apparatus was a steering wheel rather than a joystick, and the target moved horizontally rather than vertically. Second, both target types (sinusoid and pseudorandom) were tested at two difficulty levels (one faster, one slower). Third, participants each tracked the same combination of target signals (in a counterbalanced order) so that tracking performance and models could be directly compared across participants. Crucially, model simulation accuracy was assessed over one week to establish whether models robustly accounted for individual control characteristics. We hypothesised that participants would track sinusoids more accurately than pseudorandom targets, and low difficulty targets more accurately than high difficulty targets. We wished to test whether the PCT internal reference value would contribute unique variance to simulation accuracy for both models in all targets. With regards to model simulation accuracy, we hypothesised that there would be no difference in PCM and HEM simulation accuracy for pseudorandom targets. However, that the HEM would provide a superior fit to sinusoid tracking data than the PCM. Similarly, we predicted that the HEM would match the tracking phase delay and amplitude of participants' cursors more accurately than the PCM for sinusoid targets, but there would be no difference for pseudorandom targets. We hypothesised that each participant's tracking data (validation) would be more accurately simulated by their own optimised model than the general (aggregate) model. Finally, we expected that these models would generalise to the new apparatus, the steering wheel.

7.3 Method

7.3.1 Design

In the experiment, participants used a steering wheel to complete one-minute trials of a pursuit tracking task. In the task, participants had to control the position of a cursor to align it with a target signal that moved in a sinusoid or pseudorandom (sum-of-sines) pattern in the horizontal direction (Figure 7.1). Participants completed three blocks of 20 trials each. The first 16 trials of each block comprised four sinusoid trials at low difficulty, four trials sinusoid trials at a high difficulty, four pseudorandom trials at a low difficulty and four pseudorandom trials at a higher difficulty. The order of these sets was counterbalanced such that each of the 24 participants completed a different order. The counterbalancing order was randomly assigned to each participant in each block; thus participants didn't complete the set of sixteen runs in the same order each block.

The other four trials in each block consisted of two sinusoid trials - one each at high and one at low difficulty - with a period of target occlusion in the last 20% of the trial, and two step input signals. These final four trials will be analysed in a separate research article. These four runs were always completed after the 16 counterbalanced trials.

The first two blocks were completed in a single one-hour session. The first block was the training block. Two sets of 96 computer models (one for each target type for each participant) were optimised to the tracking data of participants in this block. Half of the 96 models were PCMs; the other half were HEMs (These models were developed and are outlined in the previous study; Parker et al. (in preparation). The second block comprised the first validation set; the optimised models tracked the target signals and these simulated cursor movements were compared to those of the participant from which the model was derived. The resultant fit was assessed by Root Mean Square Error (RMSE). This determined how accurately each model simulated the cursor movements of the participants. A third block was completed in a second session at least one week after the first session. This block was a second validation and was used to determine whether the models reliably simulated each individual's performance. Every trial that the participants completed was seeded with a different random number such that the pattern was differed (pseudorandom trials), or the starting direction of the target signal was randomised (simple sinusoid trials).

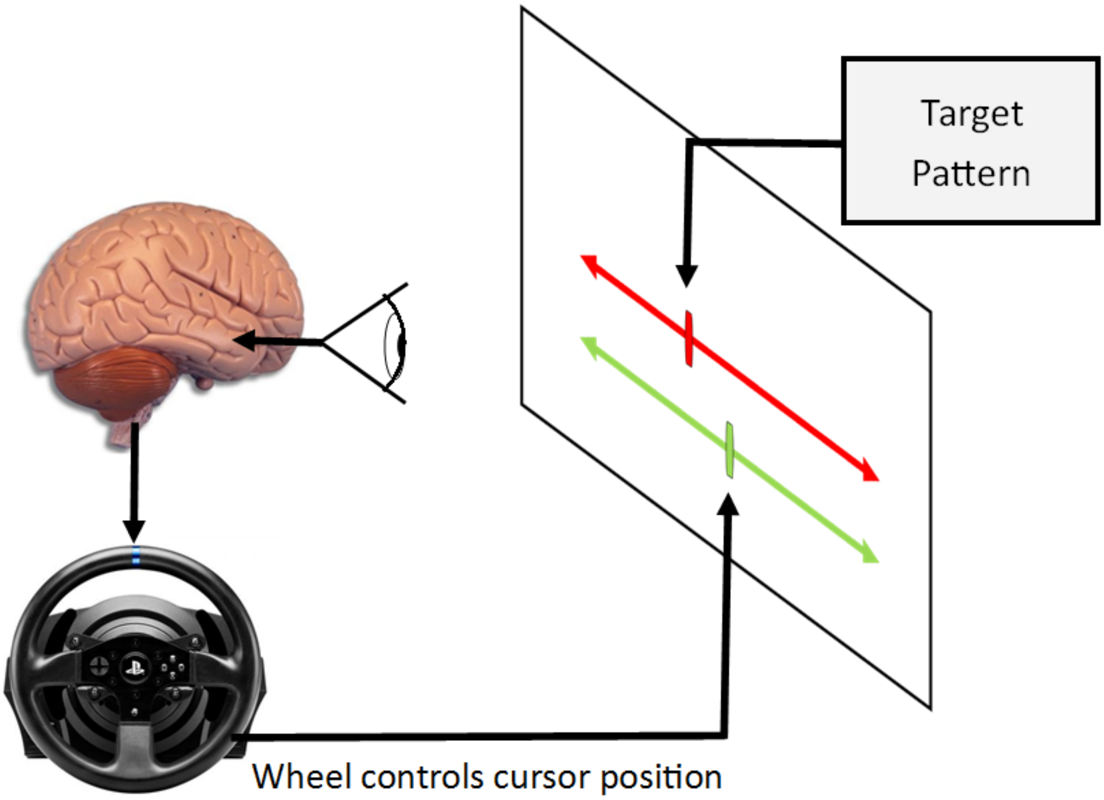
Participants tracked the same target signals though in a different order. This enabled direct comparisons of tracking accuracy.

7.3.2 Participants

Twenty-four healthy adult participants were recruited from the university. Ethical approval for the study was granted by the University ethics committee. Undergraduate student participants were compensated for their participation with course credits. Participants were excluded if they had any diagnosis of an uncorrected visual impairment or any diagnosed motor impairments.

In a previous study in which we investigated individual specificity of PCM with the same analysis as we intended in the current study (self-aggregate). In the previous study the sample size was 20 participants (Parker et al., 2017), and the analysis was a two–way repeated measures ANOVA with block and model (self-aggregate) as independent variables. The main effect of self-other was significant with an effect size (partial eta2) of .232, f=.550 (SPSS). We conducted an a priori power calculation with this effect size to determine the required sample size for sufficient power (.8) in the current experiment (G*Power 3.1.9.2). This indicated that a sample size of 24 participants was required. This was the number of possible variants of the order (four conditions), thus 24 participants were selected to perfectly counterbalance the order. This compares favourably to other similar studies which used between 12 and 20 participants (Soechting, Rao, & Juveli, 2010; Viviani et al., 1987; Viviani & Mounoud, 1990; Voss, McCandliss, Ghajar, & Suh, 2007).

Figure 7.1 Diagram of the task and hypothesised mechanism of control in the participant



7.3.3 Apparatus

Tracking task

The manual pursuit task was conducted in a custom software application. This was necessary to support the apparatus used (steering wheel). In the task, participants moved the steering wheel to control the visual position of a green cursor mark to align it with a red target mark as the target that moved horizontally across the screen in either a simple sinusoid or pseudorandom (sum-of-sines) pattern that lasted for one minute. The characteristics of the signal were altered by manipulating its fundamental frequency and the number of sine and cosine signals that were summed. Sinusoid signals comprised a constant term at zero and a single sine with a random coefficient, the number of cycles within the one minute run was determined by the frequency of the signal, either 0.0925 Hz (low difficulty) or 0.185 Hz (high difficulty). Pseudorandom signals were created by a Fourier transform, and comprised 10 sines and 10 cosines, each with a random coefficient, in addition to a constant (always zero). The difficulty of the signal was determined by the fundamental frequency of the transform. This was also either .0925 Hz (low difficulty) or .185 Hz (high difficulty). As the fundamental frequency was the lowest frequency component, the average frequency was higher for pseudorandom targets than sinusoid targets. The maximum displacement of the cursor on the screen was 30.5 cm. The maximum displacement of the target (and the amplitude of the sinusoid target) was 28.5 cm.

The positions of the target and cursor were sampled every 26 ms and recorded in an output comma separated file. Data were extracted and analysed in Mathworks Matlab, where all model optimisation and simulation was conducted. Statistical analyses were conducted in IBM SPSS 22.

Force-feedback steering wheel

The ThrustMaster T300RS is a force feedback steering wheel with 1080 degrees of rotation. This full rotational range was used, thus a full 540 degree movement from the centreline to either side would reach the maximum displacement of the cursor on the left or right of the screen (15.25 cm from centreline in either direction). The wheel had a 28 cm diameter and a brushless motor provided force-feedback capabilities (force centring).

7.3.4 Procedure

Participants were instructed to read the written instructions for the task and any questions regarding the apparatus and task were answered by the experimenter. Participants then completed a practice trial on each of the target types in the order; pseudorandom low difficulty, sinusoid low difficulty, pseudorandom high difficulty, sinusoid high difficulty. Participants then completed the first block of trials which consisted of four sets of four trials in a counterbalanced order. These four sets were pseudorandom low difficulty, pseudorandom high difficulty, sinusoid low difficulty and sinusoid high difficulty.

Participants then had a five minutes break in which they completed the Edinburgh Handedness Inventory short form (Veale, 2014) prior to completing the second block of trials. This was identical to the first block of trials. The first four sets of trials were again completed in a counterbalanced order. Following completion of these trials the first experimental session ended.

After at least one week, the participant returned for the second experimental session. The participant completed a final block of 20 trials (block 3). The block structure was identical to the previous two blocks except that the first four sets of trials (16 trials) were completed in a separate counterbalanced order. Trials in all three blocks were seeded with a different random number such that target signals followed a different pattern in each case for pseudorandom and step signal trials, and differed in the starting direction for sinusoid targets and occluded sinusoids. The seed numbers were the same for each participant such that each participant completed the same target patterns, but each participant encountered no two pseudorandom trials with the same pattern.

7.3.5 Modelling procedure

Computational models

Two computational model architectures were used, both adapted from previous experiments (Parker et al. 2017; in preparation). The first was a canonical PCT PCM, adapted from Living Control Systems III demo suite (Powers, 2008), which was adapted in Matlab in the previous experiments (Parker et al, 2017, Parker et al., in preparation). The second model was a previously developed Hierarchical model with a position extrapolation unit and a velocity control unit (HEM; Parker et al., in preparation). A diagram of the PCM can be found in Figure 7.2, and a diagram of the HEM in Figure 7.3.

Figure 7.2 Diagram of the PCM

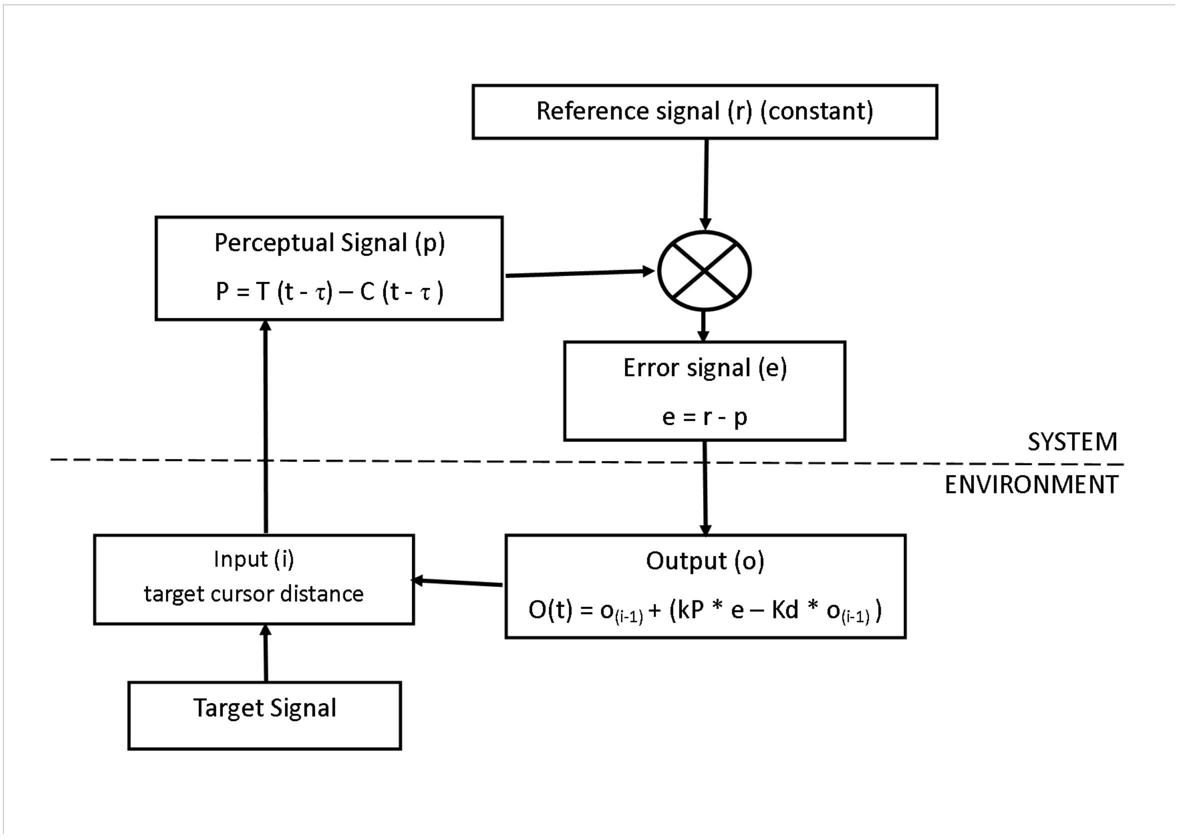
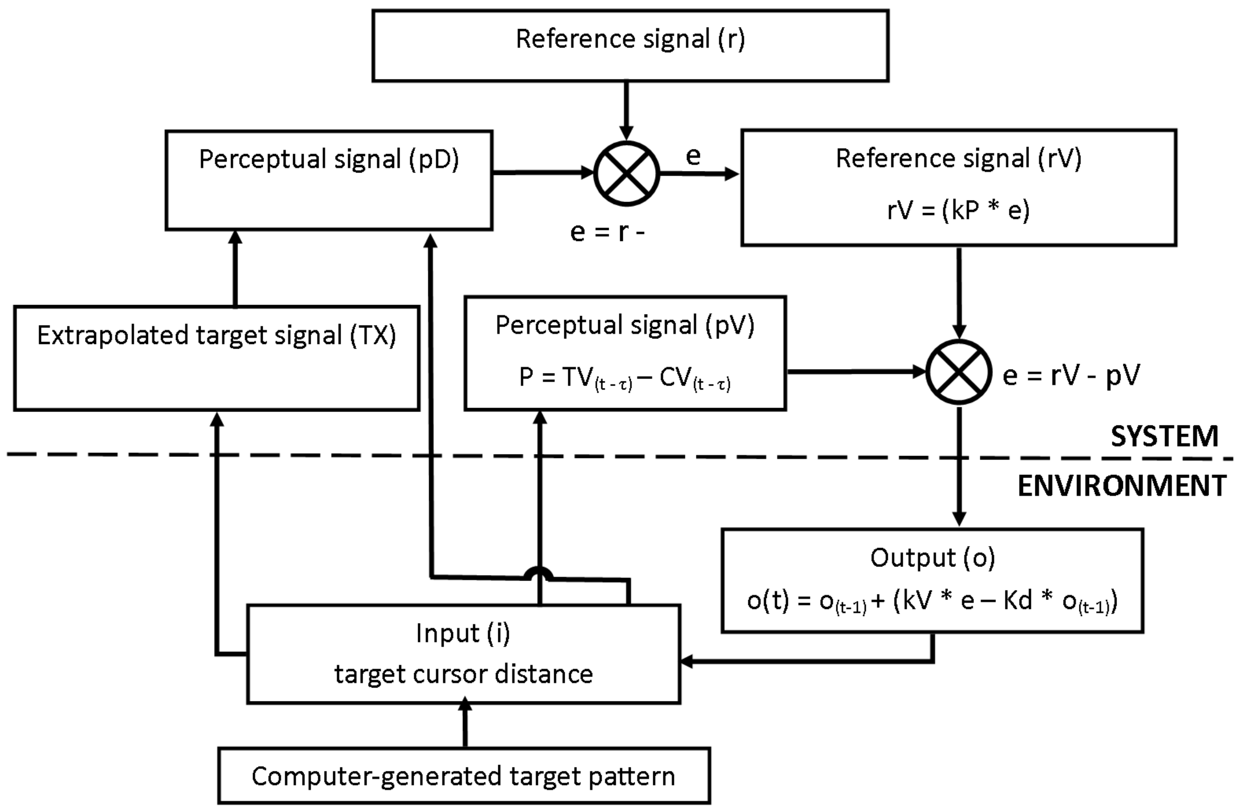


Figure 7.3 Diagram of the HEM



Model optimisation

Models were optimised using the non-linear least squares 'lsqnonlin' function in Matlab. The function tolerance was set to $1x10^{-8}$ and the maximum number of iterations performed was 2000. The initial conditions and boundaries for optimisation for each parameter were: output gains, 1 with boundaries [0, 500], damping constants 0 [0, 1], reference values 0 [-500, 500]. The loop delay could take only integer values in a number of samples and was optimised with a minimum of seven samples (182 ms), as this was the closest number of samples to the minimum biologically feasible estimate of the sensorimotor and central processing delays in tracking in previous modelling experiments (182 ms; Parker et al. 2017; in preparation). Model parameters were optimised for each trial, for each target and difficulty level (16 trials) for each participant. The optimal model for each target and difficulty level combination was selected by the lowest produced model simulation error value (RMSE).

Model validation

Optimal parameter combinations for each target and difficulty level combination were used to validate models in trials in blocks two and three (16 trials each, four for each target and difficulty combination). Any outliers were identified as model fit values more than three standard deviations above the mean for that participant, within that target type and difficulty level. Trials would then be simulated again with the second best fitting parameter combination from optimisation. This would be continued until no outlying data were produced.

7.3.6 Analyses

Tracking Accuracy

We conducted a repeated measures ANOVA to test the hypothesis that sinusoid targets were tracked more accurately than pseudorandom targets, low difficulty targets more accurately than high difficulty targets. The independent variables were block (three levels), target type (two levels; pseudorandom and sinusoid) and difficulty (two levels; low difficulty and high difficulty). We investigated any interactions by breaking down this ANOVA by block and investigating the effects of target and difficulty.

Amplitude ratio and phase delay

Spectral analysis was used to generate secondary statistics that characterised tracking performance. These statistics were: the average phase difference, in milliseconds, between the target signal and the participant cursor; and the amplitude ratio between the cursor and target displacement over the trial. The analysis replicated the analysis conducted in a previous article (Parker et al., in preparation) and was based on an analysis described in another article (Cofré Lizama et al., 2013). The analysis was conducted using custom software, designed in Matlab and adapted from the previous experiment (Parker et al., in preparation). The software used the cpsd and pwelch (Welch) functions which estimate the cross-power spectral density and power spectral density of a signal using the Welch method with overlapping segmentation (Hamming windows). The window length was .25 multiplied by the trial length (samples), and the overlap was 0.9 multiplied by the window length. Target and cursor signals were zero padded to attain a 0.02 Hz resolution. The procedure is documented in the previous paper (Parker et al. in preparation).

To characterise the errors made by participants when tracking the different targets, we employed one-sample t-tests. These aimed to determine whether there were significant amplitude and phase differences between the different target types and difficulty levels. If the cursor matched the amplitude of the target perfectly the amplitude would equal 1. In contrast, no phase delay of the cursor relative to the target would give a value of 0. Thus these values were determined to be the thresholds for the one-sample t-tests. Values of amplitude ratio and phase delay of the cursor were averaged across the three blocks.

Contributions of parameters to individual model fit

Each parameter of the model was assessed for its contribution to model simulation accuracy. Reference value was added last to establish whether the internally specified reference value would contribute uniquely to variance above the other model parameters. Thus regressions were conducted with the parameters from optimisation trials (block one) as predictor variables (coefficients), and model simulation error for that trial as the outcome variable. Based on a previous experiment (Parker et al., 2017), parameters were expected to hold a quadratic or cubic relationship with model simulation error so polynomial regression was performed. Quadratic regression statistics are reported for each of the target and difficulty level combinations. The change in r square value when reference value was added indicated whether the internally-set reference value parameter was key to the model fit (separate significant contribution to explained variance). Akaike Information Criterion values (AIC; Akaike, 1974) determined which model best accounted for the data when controlling for the number of coefficients in the regression model.

Model simulation accuracy

With regards to model accuracy in block one (optimisation), a repeated measures ANOVA was conducted to investigate whether models accurately simulated participant tracking data for the different targets across the difficulty levels. Thus, the repeated measures independent variables were model (two levels, position control and hierarchical), target type (two levels; pseudorandom and sinusoid), and difficulty (low and high).

For blocks 2 and 3 (model validation), the same analysis was conducted with 'block' as an additional repeated measures independent variable. Thus the ANOVA had four independent variables: block, model, target type and difficulty, each with two levels.

We collected phase delay, amplitude ratio and coherence data characterising the fit between the model and the participant cursor. A perfect match of amplitude would equal an amplitude ratio of 1. A perfect match to the phase delay that the participant produced would equal 0. Therefore we conducted a series of paired t-tests to determine whether the phase delay differed significantly between models. If a difference was found, and the models produced statistics the same direction from the threshold, this difference indicated that one model was matching the participant cursor more accurately.

Test of individual specificity of the model

An analysis of individual specificity was conducted. This required each individual model from the optimisation data to simulate each participant's tracking trials in validation blocks (blocks two and three). Each participant's individual model fit to their own validation data (self-fit) was compared to the aggregate of the fit of each of the other 23 individuals (aggregate fit). Thus an ANOVA was conducted with four repeated measures independent variables: Model type (two levels; self and aggregate), Block (two levels; blocks 2 and 3), target type (two levels; pseudorandom and sinusoid), and target difficulty (two levels; low difficulty and high difficulty). The dependent variable was model simulation error (RMSE).

7.4 Results

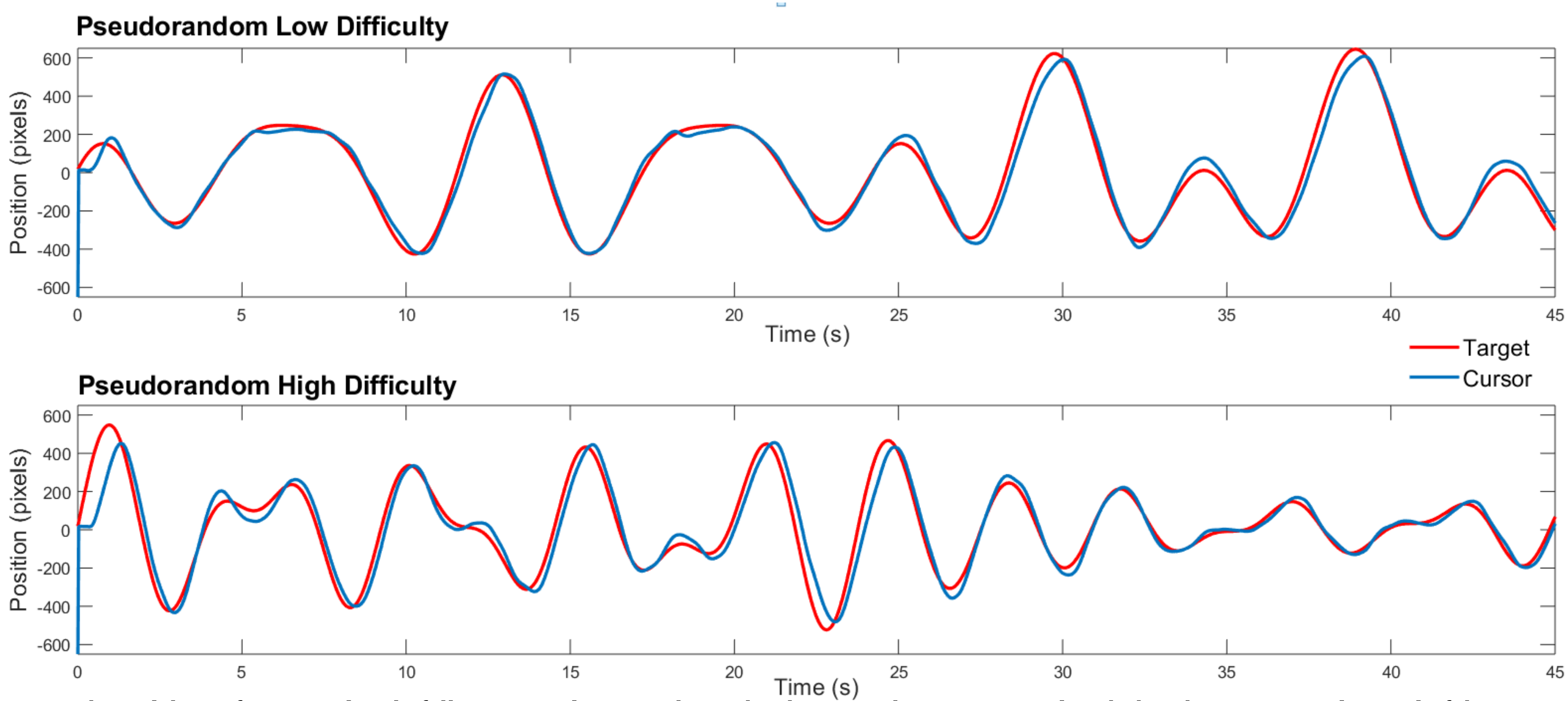
Twenty-four individuals participated. Their mean age was 20 (SD = 1.89). Twenty participants were female and four were male. Twenty-one participants were right-handed, two mixed-handed and one was left handed (assessed via Edinburgh Handedness Inventory). No outliers were found in tracking data and all were included in the analysis.

No outliers were found in model data and therefore no outlier procedure to simulate data with second-best parameters was conducted for any participant model data.

7.4.1 Tracking accuracy

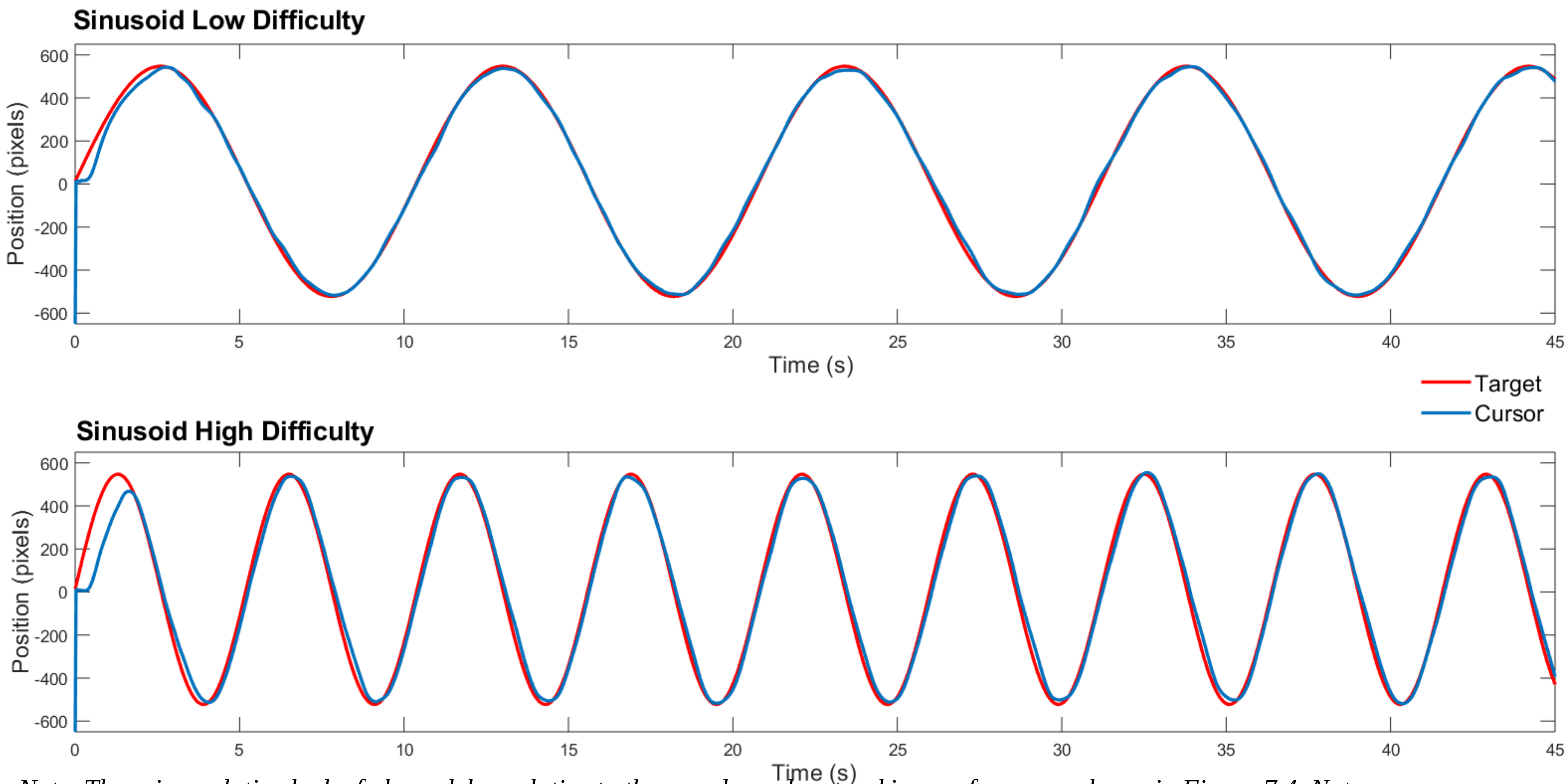
Figures 7.4 and 7.5 show typical tracking data for each of target. All tracking data were normally distributed.

Figure 7.4 Diagram displays 45 s of tracking of pseudorandom trials of low and high difficulty.



Note. *Phase delays often immediately follow target directional switch. These may be compensated such that the cursor is advanced of the target at the next switch point. This may indicate an extrapolation strategy. For large target displacements, the phase delay may increase toward the target directional switch. This may be the result of the experimental setup. The steering wheel required large angles of rotation to produce large movements. These may have required the participant to adjust their hands on the , causing a drop in cursor velocity*

Figure 7.5 Diagram displays 45 s of tracking of sinusoid trials of low and high difficulty



Note. There is a relative lack of phase delay relative to the pseudorandom tracking performance shown in Figure 7.4. Note also the consistent increase in phase delay between the centreline and the target switch point

In the thee-way ANOVA investigating differences in tracking accuracy, there was a three way interaction between block, target type and difficulty (Table 7.1). Table 7.2 displays the two-way ANOVAs following the three-way interaction. For the two-way ANOVA within pseudorandom targets, there was an interaction between block and difficulty and this was also the case within sinusoid targets. Therefore, for low difficulty targets of both target types, tracking error reduced across blocks. However, for high difficulty pseudorandom targets, tracking error increased between blocks 1 and 2, but decreased from 2 to 3. For high difficulty sinusoid targets, error decreased between blocks 1 and 2, but not significantly between blocks 2 and 3. These patterns can be observed in Figure 7.6, where the error bars indicate the repeated measures 95% confidence interval for the mean.

Table 7.1 Three-way ANOVA of tracking accuracy

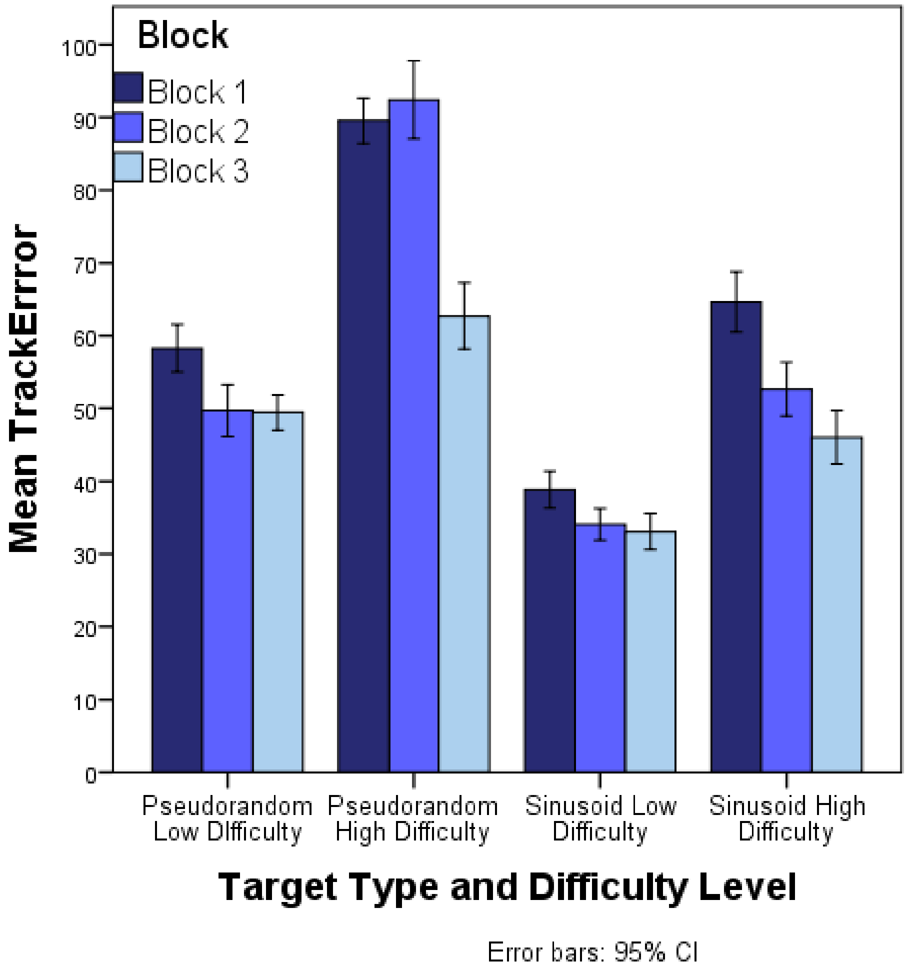
ANOVA	**Effect**	**Trend**	**DoF**	***F***	***P***	***partial η2***
Three-way	Block	Linear	2, 46	50.88	<.001	0.689
	Target		1, 23	142.05	<.001	0.861
	Difficulty		1, 23	166.92	<.001	0.879
	Block x Target		2, 46	6.24	0.004	0.213
	Block x Difficulty		2, 46	26.11	<.001	0.532
	Target x B41Difficulty		1, 23	11.52	<.001	0.334
	Black x Target x Difficulty		1, 23	8.79	0.001	0.276

Table 7.2 Two-way ANOVAs investigating tracking accuracy

ANOVA	**Effect (trend)**	**DoF**	***F***	***p***	***partial η2***
Two-way within Pseudorandom Targets	Block (Quadratic)	2, 46	31.68	<.001	.579
	Difficulty	1, 23	111.22	<.001	.829
	Block x Difficulty	2, 46	24.64	<.001	.517
Two-way within Sinusoid Targets	Block (Linear)	2, 46	20.81	<.001	.247
	Difficulty	1, 23	99.02	<.001	.812
	Block x Difficulty	2, 46	5.94	.005	.205
Two-way within Low Difficulty	Block (Quadratic)	2, 46	11.31	<.001	.330
	Target	1,23	103.20	<.001	.818
	Block x Difficulty	1, 23	0.78	.463	.033
Two-way within High Difficulty	Block (Quadratic)	2, 46	56.11	<.001	.709
	Target	1, 23	87.73	<.001	.792
	Block x Difficulty	1, 23	9.87	<.001	.300
Two-way within Block 1	Target	1, 23	88.67	<.001	.794
	Difficulty	1, 23	125.26	<.001	.845
	Target x Difficulty	1, 23	1.50	.234	.061
Two-way within Block 2	Target	1, 23	71.45	<.001	.756
	Difficulty	1, 23	134.55	<.001	.854
	Target x Difficulty	1, 23	21.08	<.001	.478
Two-way within Block 3	Target	1, 23	66.83	<.001	.744
	Difficulty	1, 23	42.99	<.001	.651
	Target x Difficulty	1, 23	0.01	.926	.001

Note. DoF refers to the degrees of freedom regarding each F value

Figure 7.6 Mean participant tracking error for different target types and difficulty levels for each block



Within low difficulty targets, there were main effects of block (quadratic) and target type, but no interaction. Tracking error was lower for sinusoid targets than for pseudorandom targets and decreased over consecutive blocks. Within high difficulty targets, there was a significant quadratic interaction between block and target. This indicated that for high difficulty targets, sinusoids were tracked more accurately than pseudorandom targets only in blocks 1 and 2, but not in block 3 (Figure 7.6).

When block 1 was considered separately, there were main effects of target type and difficulty on tracking performance, but no interaction. Thus, in the first block, sinusoid targets were tracked more accurately than pseudorandom targets and low difficulty targets were tracked more accurately than high difficulty targets.

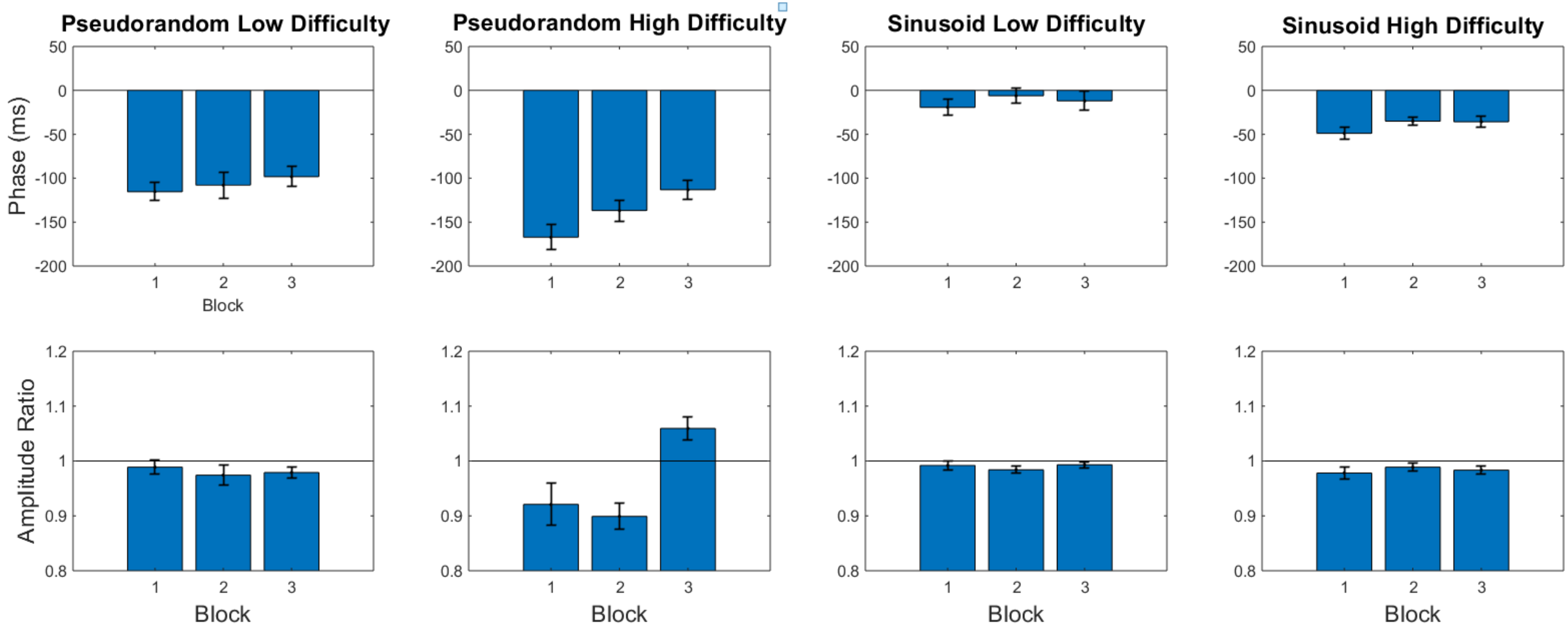
In block 2, there was a significant interaction between target type and difficulty. Sinusoids of low difficulty were tracked with lower error than pseudorandom targets of high difficulty, but there was no difference in tracking error between pseudorandom targets of low difficulty and sinusoids of high difficulty (Figure 7.6).

In block 3, there were main effects of target type and difficulty, and no interaction. Participants tracked sinusoid targets with less error than pseudorandom targets, and tracked targets of low difficulty with lower error than high difficulty targets.

Figure 7.7 displays means and standard errors of the amplitude ratio and phase delay between participant cursors and targets. For phase delay, participant cursors tracked low difficulty pseudorandom, high difficulty pseudorandom and high difficulty sinusoid targets with a significant phase delay; low difficulty pseudorandom, $t_{(23)} = 10.25$, $p < .001$; high difficulty pseudorandom, $t_{(23)} = 11.88$, $p < .001$; high difficulty sinusoid, $t_{(23)} = 7.46$, $p < .001$. Participant cursors did not exhibit phase delay for low difficulty sinusoid targets, $t_{(23)} = 1.36$, $p = .118$.

The amplitude of the cursors were significantly lower than the amplitude of the target for sinusoid targets, but not for pseudorandom targets; low difficulty sinusoid targets, $t_{(23)} = 2.20$, $p = .038$; high difficulty sinusoid targets, $t_{(23)} = 2.49$, $p = .020$; low difficulty pseudorandom targets $t_{(23)} = 1.78$, $p = .089$; high difficulty pseudorandom targets; $t_{(23)} = 1.57$, $p = .131$.

Figure 7.7 Mean phase, amplitude ratio estimates and their variability (standard error): Tracking performance



Note. For phase delay (top row) the line at zero indicates the threshold for zero-phase tracking (tracking without a phase delay relative to the target). Positive values indicate a phase advance whilst negative values indicate a phase delay. For amplitude ratios (bottom row), the horizontal line at 1 indicates the threshold for a perfect match between the amplitude of the target and the cursor. A Value larger than 1 indicates participants' cursors overshot the targets. A value smaller than 1 indicates participants' cursors undershot targets. Error bars show standard error.

7.4.2 Contribution of parameters to model fit

Table 7.3 and Table 7.4 provide summary statistics of the raw PCM and HEM model parameters at optimisation are for each target type and difficulty level combination

Table 7.3 Summary statistics for the parameters of the PCM model during optimisation

Target	Loop Delay (ms)		Position Gain		Position Damping		Position Reference	
	M	SD	M	SD	M	SD	M	SD
P1	201.23	36.23	11.16	2.64	0.50	0.50	0.64	0.45
P2	219.38	55.55	10.22	3.32	0.42	0.49	1.67	1.49
S1	182.27	2.67	13.26	1.46	0.47	0.48	0.27	0.34
S2	182.27	2.67	13.36	1.53	0.76	0.42	0.75	0.44

Note. Loop delay could take a minimum value of 182 ms based on previous estimates of sensorimotor delays in tracking (Section 7.3.5).

Table 7.4 Summary statistics for the parameters of the HEM model during optimisation

Target	Loop Delay (ms)		Position Gain		Position Reference		Velocity Gain		Velocity Damping		Extrapolation Gain	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
P1	282.48	82.96	128.11	221.08	4.68	6.32	15.13	15.81	0.38	0.30	24.53	14.87
P2	287.90	82.33	26.68	60.85	6.38	15.13	17.06	15.34	0.73	0.33	27.35	17.83
S1	465.29	76.90	27.47	66.08	4.04	5.91	8.66	11.44	0.29	0.11	37.09	13.55
S2	412.99	69.61	96.52	88.77	14.52	14.75	3.03	8.05	0.94	0.17	43.65	10.51

Note. Loop delay could take a minimum value of 182 ms based on previous estimates of sensorimotor delays in tracking (Section 7.3.5).

Inspection of the regression R^2 and *AIC* values showed that parameter values shared a quadratic relationship with model fit when quadratic and linear models were compared. Tables 7.5 and 7.6 display the respective statistics for the quadratic regression models. We predicted that reference value parameters would contribute uniquely to the variance in regression models. As hypothesised, for the PCM, the R^2 change was significant when reference value was finally added to the regression model for pseudorandom low difficulty targets, and sinusoid targets of both low and high difficulty (Table 7.5). For the HCM, this was the case for pseudorandom targets but not sinusoid targets (Table 7.6).

Table 7.5 Contributions of parameters to model simulation accuracy at optimisation: PCM

Target and Difficulty level	**Parameters**	***F***	***P***	***AIC***	***r***	***R^2***	**Change Statistics** ***R^2*** **Change**	***P***
Pseudorandom Low Difficulty	PG	8.00	.001	-676.49	.383	.147		
	PG, LD	4.49	.002	-670.55	.406	.165	.018	.382
	PG, LD, PD	3.34	.005	-664.48	.429	.184	.019	.361
	PG, LD, PD, PR	4.37	< .001	-647.74	.535	.286	.103	.003
Pseudorandom High Difficulty	PG	12.71	< .001	-757.66	.463	.215		
	PG, LD	8.44	< .001	-746.66	.520	.271	.056	.035
	PG, LD, PD	6.27	< .001	-739.25	.545	.297	.026	.194
	PG, LD, PD, PR	4.70	< .001	-734.76	.549	.302	.005	.738

							Change Statistics	
Target and Difficulty level	**Parameters**	***F***	***p***	***AIC***	***r***	R^2	R^2 **Change**	***p***
Sinusoid Low Difficulty	PG	20.92	< .001	-752.27	.557	.310		
	PG, LD	12.86	< .001	-741.02	.501	.361	.051	.031
	PG, LD, PD	8.47	< .001	-736.78	.603	.364	.002	.842
	PG, LD, PD, PR	17.35	< .001	-684.79	.784	.615	.251	< .001
Sinusoid High Difficulty	PG	12.66	< .001	-760.64	.465	.216		
	PG, LD	8.39	< .001	-756.56	.466	.217	.001	.739
	PG, LD, PD	5.02	< .001	-752.29	.469	.220	.003	.836
	PG, LD, PD, PR	6.80	< .001	-730.56	.595	.354	.134	< .001

Note. ***PG*** *– Position Gain,* ***LD*** *– Loop Delay,* ***PD*** *– Position Damping Constant,* ***PR*** *– Position Reference Value*

Table 7.6 Contributions of parameters to model simulation accuracy at optimisation: HCM

Target and Difficulty level	Parameters	*F*	*P*	*AIC*	*r*	R^2	Change Statistics: R^2 Change	Change Statistics: *P*
Pseudorandom	PG	0.06	.943	-692.89	.035	.001	.001	.943
Low Difficulty	PG, LD	0.38	.823	-687.51	.128	.016	.015	.500
	PG, LD, VD	2.71	.018	-669.14	.393	.154	.138	.001
	PG, LD, VD, XG	2.88	.007	- 658.874	.457	.209	.055	.054
	PG, LD, VD, XG, VG	2.32	.018	-654.52	.463	.214	.005	.771
	PG, LD, VD, XG, VG, PR	2.61	.005	-643.16	.524	.274	.060	.037
Pseudorandom	PG	0.21	.812	-778.89	.067	.004	.004	.812
High Difficulty	PG, LD	2.49	.049	-765.45	.314	.099	.094	.011
	PG, LD, VD	2.78	.016	-755.05	.397	.158	.059	.048
	PG, LD, VD, XG	2.63	.013	-746.95	.441	.195	.037	.143
	PG, LD, VD, XG, VG	2.39	.015	-740.18	.468	.219	.025	.265
	PG, LD, VD, XG, VG, PR	2.75	.003	-728.08	.534	.285	.065	.027

Target and Difficulty level	Parameters	*F*	*P*	*AIC*	*r*	R^2	Change Statistics: R^2 Change	Change Statistics: *P*
Sinusoid	PG	1.49	.231	-719.56	.176	.031	.031	.231
Low Difficulty	PG, LD	0.78	.543	-715.44	.182	.033	.002	.909
	PG, LD, VD	4.89	< .001	-687.46	.498	.248	.215	< .001
	PG, LD, VD, XG	8.57	< .001	-655.18	.664	.441	.193	< .001
	PG, LD, VD, XG, VG	10.49	< .001	-630.04	.743	.552	.112	< .001
	PG, LD, VD, XG, VG, PR	9.46	< .001	-620.75	.760	.578	.025	.090
Sinusoid	PG	27.90	< .001	-780.15	.614	.377	.377	< .001
High Difficulty	PG, LD	23.25	< .001	-753.85	.713	.508	.131	< .001
	PG, LD, VD	16.20	< .001	-746.72	.724	.525	.017	.220
	PG, LD, VD, XG	12.96	< .001	-738.46	.739	.547	.022	.134
	PG, LD, VD, XG, VG	12.29	< .001	-724.18	.771	.594	.048	.010
	PG, LD, VD, XG, VG, PR	15.13	< .001	-695.19	.830	.689	.095	< .001

***Note. PG** – Position Gain, **LD** – Loop Gain, **VD** – Velocity Damping, **XG** – Extrapolation Gain, **VG** – Velocity Gain, **PR** – Position Reference*

7.4.3 Model simulation accuracy

Optimisation: Block 1

Figure 7.8 presents the means and repeated measures error bars of the differences in model fit by target type and difficulty within block 1. There were significant main effects of model (position control or hierarchical), target type, and difficulty. There were significant interactions between model and target type, and target type and difficulty, but no other interactions. Thus the accuracy of the model fit was affected by the target type but not the difficulty level. Table 7.7 reports the three-way ANOVA of model simulation accuracy in Block 1, and the two-way ANOVA investigating the interaction in which difficulty levels were factored together. In this ANOVA, the main effects of model and target type were significant. There was no interaction. The HEM simulated both sinusoid and pseudorandom targets with lower error than the PCM. Sinusoid targets were fitted more accurately than pseudorandom targets by both models (Figure 7.8).

Figure 7.8 Model simulation errors at optimisation for the different targets and difficulty levels (block 1)

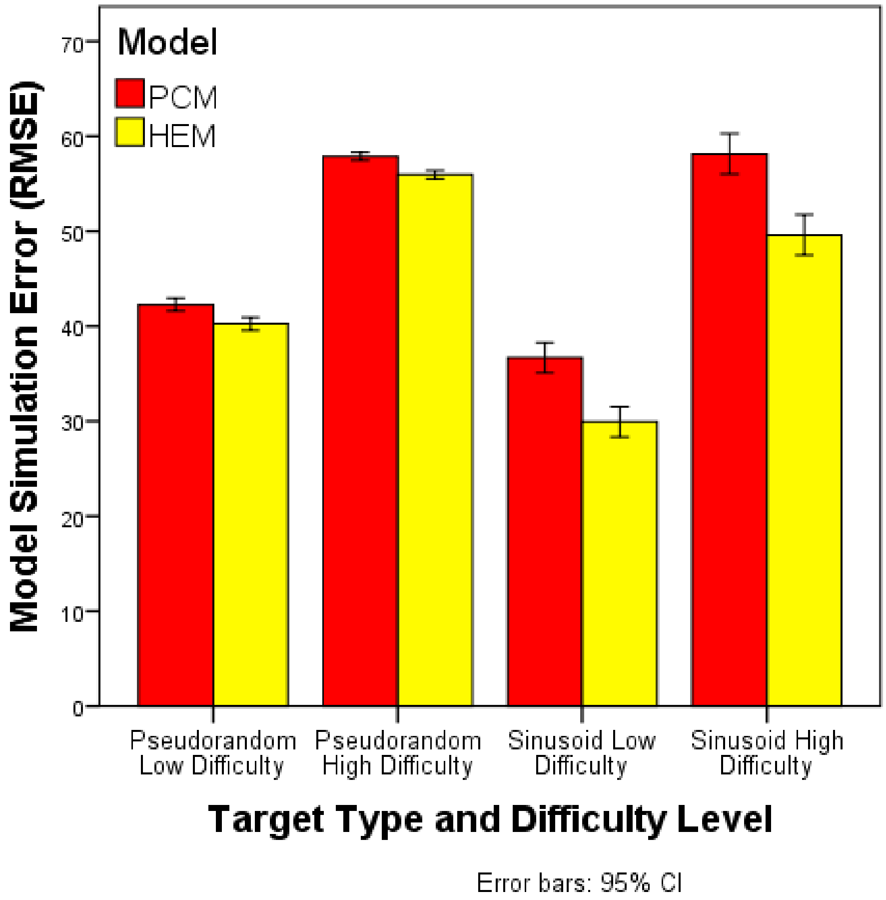


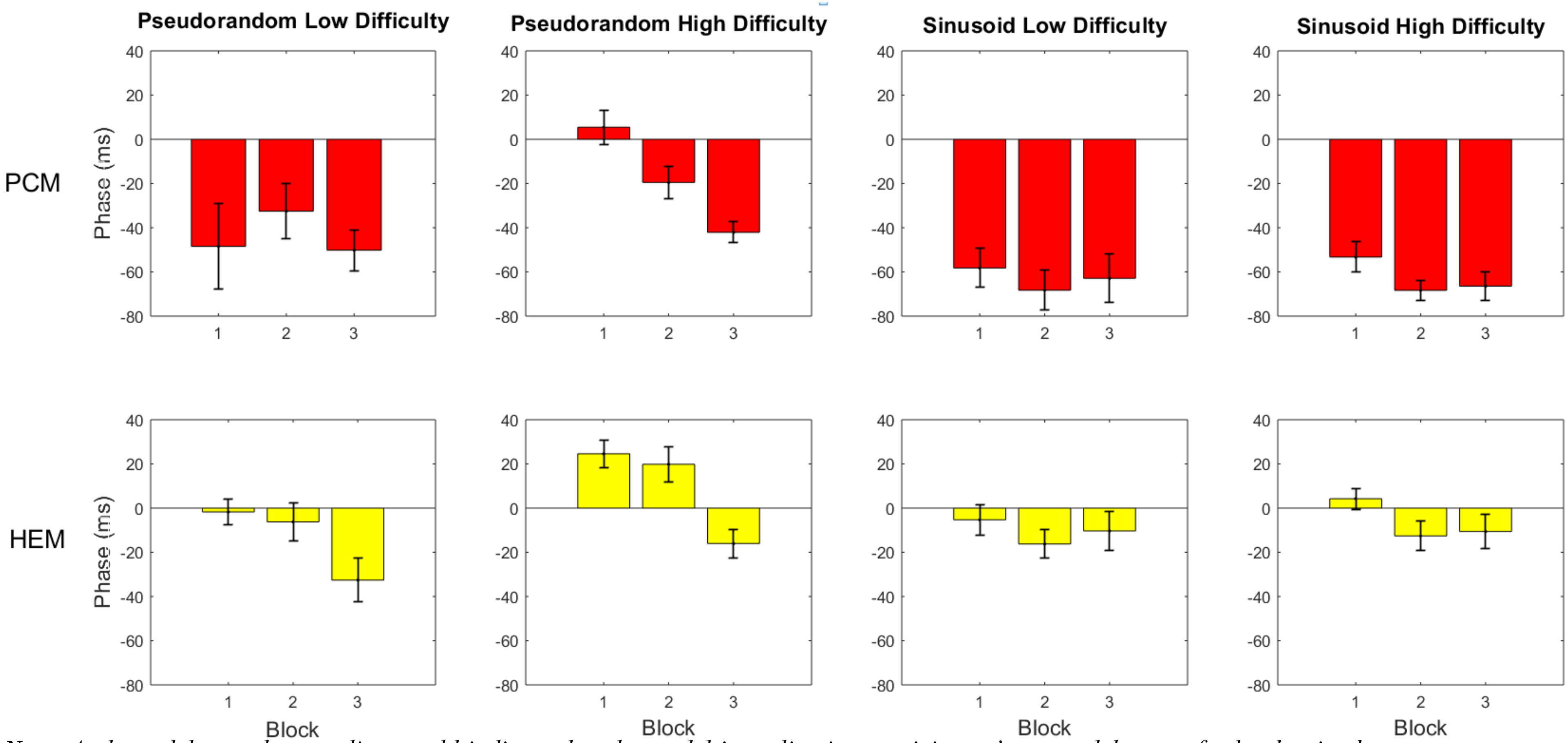
Table 7.7 ANOVAs of model simulation accuracy in Block 1

ANOVA	**Effect**	**DoF**	**F**	**p**	**partial η^2**
Three-way	Model	1, 23	24.93	<.001	0.52
	Target Type	1, 23	16.32	<.001	0.415
	Difficulty	1, 23	248.91	<.001	0.915
	Model x Target Type	1, 23	17.87	<.001	0.437
	Target x Difficulty	1, 23	5.09	0.034	0.181
	Model x Difficulty	1, 23	0.077	0.391	0.032
	Model x Target x Difficulty	1, 23	1.09	0.307	0.045
Two-way with Difficulty factored together	Model	1, 23	6.05	0.022	0.208
	Target Type	1, 23	7.99	0.01	0.258
	Model x Target	1, 23	1.782	0.195	0.072

The models differed significantly in how well they matched the phase delay that the participant produced (Figure 7.9). The HEM significantly more closely matched the phase delay for three of the target types; pseudorandom low difficulty targets, $t_{(22)} = 2.45$, $p = .023$, low difficulty sinusoids, $t_{(22)} = 9.31$, $p < .001$, and high difficulty sinusoids, $t_{(23)} = 2.59$, $p = .016$. The PCM more closely matched the target for high difficulty pseudorandom targets; $t_{(22)} = 5.18$, $p < .001$.

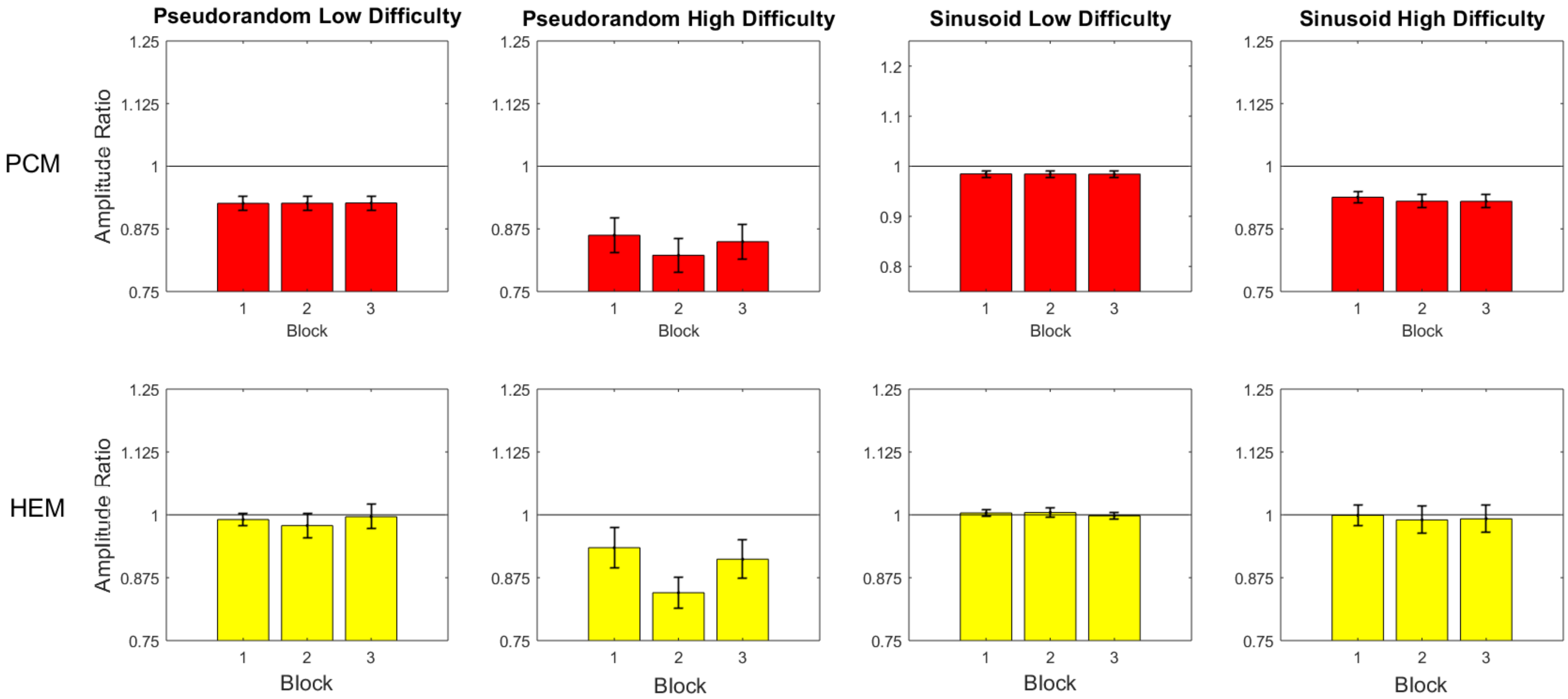
The HEM model more closely matched the amplitude that the participant produced for all target types and difficulty levels at optimisation (Figure 7.10): pseudorandom low difficulty targets; $t_{(22)} = 5.48$, $p < .001$; high difficulty pseudorandom targets, $t_{(22)} = 7.00$, $p < .001$; low difficulty sinusoid targets, $t_{(22)} = 3.44$, $p = .002$; and high difficulty sinusoid targets, $t_{(23)} = 3.68$, $p = .001$. The HEM more accurately emulated the phase and amplitude with which the participant tracked targets at optimisation.

Figure 7.9 Series of charts showing the phase delays of model cursors to participant cursors. Top row: PCM model, the bottom row: HEM.



Note. A phase delay at the zero line would indicate that the model is replicating participants' cursor delays perfectly, that is, the model-simulated cursor follows the target with the same phase delay as the participants did. Positive values indicate that the simulated cursor is advanced of the participants' cursors and negative values indicate a phase delay relative to participants' cursors. Error bars denote standard error.

Figure 7.10 Series of charts showing the amplitude ratios of model cursors to participant cursors. Top row: PCM model, the bottom row: HEM.



Note. *The line at 1 (solid line) indicates a perfect match between the model-simulated cursors and participants' cursors. A value above 1 indicates that models produced a larger cursor displacement than participants. A value below 1 indicates that models produced a smaller cursor displacement than participants. Error bars display standard error*

.

Validation: Blocks 2 and 3

Table 7.9 displays the four-way analyses of model simulation error across validations (blocks 2 and 3). All main effects were significant. Four interactions were significant: model and target type, block and difficulty, target type and difficulty, and block, model and target type (three-way). The other interactions were not significant.

Table 7.9 Four-way ANOVA of model simulation error across the two validation blocks

ANOVA	Effect	DoF	F	P	partial η^2
Four-way	Block	1, 23	20.26	<.001	.468
	Model	1, 23	23.88	<.001	.509
	Target Type	1, 23	5.88	.024	.203
	Difficulty	1, 23	103.11	<.001	.818
	Model x Target Type	1, 23	16.51	<.001	.418
	Block x Difficulty	1, 23	31.12	<.001	.418
	Target x Difficulty	1, 23	6.26	.020	.214
	Block x Model x Target Type	1, 23	4.82	.038	.173
	Block x Model	1, 23	0.71	.409	.030
	Block x Target Type	1, 23	0.65	.429	.027
	Model x Difficulty	1, 23	2.23	.149	.088
	Block x Model and Difficulty	1, 23	0.09	.773	.004
	Block x Target Type x Difficulty	1, 23	2.68	.115	.104
	Block x Model x Target Type x Difficulty	1, 23	1.49	.235	.061

Table 7.10 reports the three-way analyses of model simulation error in block 2, and the two-way analysis with difficulty levels factored together. In the three-way ANOVA, the main effects of model, target type, and difficulty were significant; as was the interaction between model and target type.

In the two-way ANOVA with difficulty levels factored together, there was a significant interaction. This indicated that for pseudorandom targets there was no improvement in tracking error for the HEM over the PCM. However, for sinusoid targets, the HEM resulted in significantly lower error than the PCM (Figure 7.11).

Table 7.10 Three-way and two-way analyses of model simulation accuracy in block 2

ANOVA	Effect	DoF	*F*	*p*	partial η^2
	Model	1, 23	16.08	< .001	.411
	Target Type	1, 23	5.58	.027	.195
	Difficulty	1, 23	140.83	< .001	.860
Three-way	Model x Target Type	1, 23	18.63	< .001	.447
	Model x Difficulty	1, 23	1.34	.260	.055
	Target x Difficulty	1, 23	1.21	.283	.050
	Model x Target Type x Difficulty	1, 23	1.10	.305	.046
Two-way,	Model	1, 23	16.08	.001	.411
Difficulty Levels	Target	1, 23	5.58	.027	.195
factored together	Target x Model	1, 23	18.63	< .001	.447

Figure 7.11 Model simulation errors for block 2 validation trials

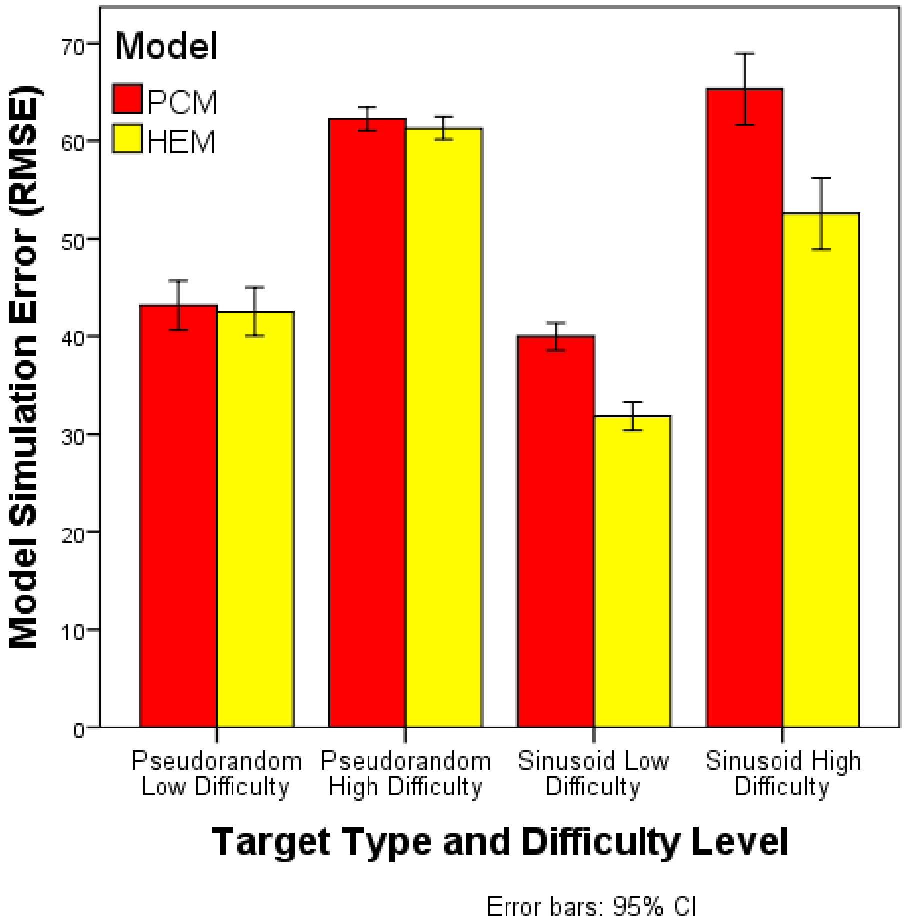
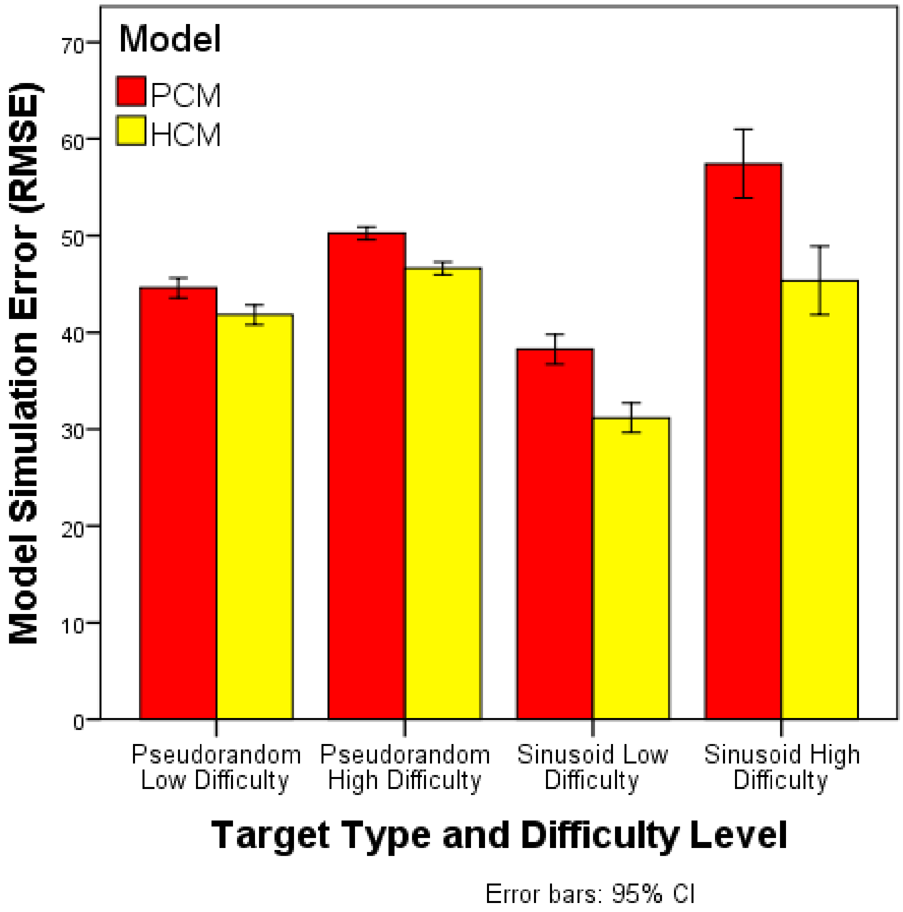


Table 7.11 displays the results of the three-way and two-way ANOVAs for block 3. In the three-way ANOVA, two main effects were significant; model and difficulty. The main effect of target was not significant. Two interactions were significant; model and target, and target and difficulty. In the two-way ANOVA that investigated the model and target interaction with difficulty level factored together, the interaction between model and target was significant. Within pseudorandom targets, there was no difference in simulation error between the PCM and HEM. However, for sinusoid targets the HEM simulated tracking with significantly reduced error relative to the PCM (Figure 7.12).

Table 7.11 Three-way and two-way analyses of model simulation accuracy in block 3

ANOVA	**Effect**	**DoF**	***F***	***p***	**partial η^2**
Three-way	Model	1, 23	27.84	< .001	.548
	Difficulty	1, 23	34.85	< .001	.602
	Target	1, 23	1.81	.191	.073
	Model x Target	1, 23	10.46	.004	.313
	Target x Difficulty	1, 23	8.33	.008	.266
	Model x Difficulty	1, 23	2.71	.113	.106
	Model x Target x Difficulty	1, 23	1.67	.209	.068
Two-way, Difficulty Levels factored together	Model	1, 23	27.84	< .001	.548
	Target	1, 23	1.81	.191	.073
	Model x Target	1, 23	10.46	.004	.313

Figure 7.12 Model simulation errors for block 3 validation trials



Figures 7.9 and 7.10, presented earlier, report the amplitude ratio and phase statistics for model-simulated cursors relative to participants' cursors in blocks 2 and 3. In block 2, the HEM model more accurately matched the phase of the cursor for three of the targets: low difficulty pseudorandom, $t_{(23)} = 2.59$, $p = .016$; low difficulty sinusoid targets, $t_{(23)} = 10.07$, $p < .001$; and high difficulty sinusoid targets, $t_{(23)} = 8.16$, $p < .001$. For high difficulty pseudorandom targets, there was a significant difference between the phase produced by the two targets, but the HEM was phase advanced whereas the PEM was delayed, thus no reasonable conclusion could be drawn regarding which matched the participant cursor more closely; $t_{(23)} = 7.92$, $p < .001$. In block 3, both models showed a phase delay for all targets, but the HEM model provided a significantly closer match to the cursor phase for three targets; high difficulty pseudorandom, $t_{(23)} = 7.00$, $p < .001$; low difficulty sinusoid, $t_{(23)} = 10.23$, $p < .001$; and high difficulty sinusoid $t_{(23)} = 8.23$, $p < .001$. The phase difference was not significant for pseudorandom low difficulty targets, $t_{(23)} = 1.61$, $p = .121$.

The amplitude ratios for the HEM simulated cursor were significantly closer to 1 than for the PCM in all targets in block 2: Low difficulty pseudorandom, $t_{(23)} = 2.54$, $p = .019$; high difficulty pseudorandom, $t_{(23)} = 3.23$, $p = .004$; low difficulty sinusoid; $t_{(23)} = 2.57$, $p = .017$; high difficulty sinusoid, $t_{(23)} = 2.89$, $p = .008$. This was also the case in block 3: pseudorandom low difficulty, $t_{(23)} = 3.23$, $p = .007$; pseudorandom high difficulty, $t_{(23)} = 7.01$, $p < .001$; sinusoid low difficulty, $t_{(23)} = 3.81$, $p = .001$; high difficulty sinusoid, $t_{(23)} = 2.87$, $p = .009$.

7.4.4 Test of individual specificity

Summary statistics are presented in Figure 7.13 (block 2) and Figure 7.14 (block 3). In line with predictions, in the four-way ANOVA, self-models simulated tracking data more accurately than aggregate models (main effect of model type); $F_{(1,23)} = 22.43$, $p < .001$, partial $\eta^2 = .494$. There were also significant main effects of target type; $F_{(1,23)} = 26.99$, $p < .001$, partial $\eta^2 = .540$; difficulty, $F_{(1,23)} = 81.21$, $p < .001$, partial $\eta^2 = .779$; and block, $F_{(1,23)} = 15.11$, $p = .001$, partial $\eta^2 = .396$.

Two interactions were significant; target and difficulty, $F_{(1,23)} = 34.78$, $p < .001$, partial $\eta^2 = .602$; and block, model type, target type and difficulty (four-way), $F_{(1,23)} = 5.59$, $p = .027$, partial $\eta^2 = .196$. No other interaction was significant; $p = .209$ - $.631$.

The four-way interaction was investigated to determine whether the predicted effect was qualified by the other independent variables. The four-way interaction could be qualified by a three-way interaction within sinusoid targets only. However, this could not be further qualified as no statistically significant two-way interactions ($p > .05$) were found when analysing levels of model or difficulty separately. However, the interaction when sinusoid targets were compared at high difficulty (block by model ANOVA) produced a trend towards significance in the two-way interaction, $F_{(1,23)} = 3.82$, $p = .063$, partial $\eta^2 = .142$. This difference can be observed in Figures 7.13 and 7.14 through comparison of the difference between self and aggregate model fits to high difficulty sinusoid targets. The main effect of model (self or aggregate) was significant in every ANOVA, indicating that it was not qualified by the interactions. Thus the prediction that self-models would show a superior fit to aggregate-models was confirmed.

Figure 7.13 Model simulation accuracy of self and aggregate models to participant tracking data in each of the four target type and difficulty level pairings: Block 2

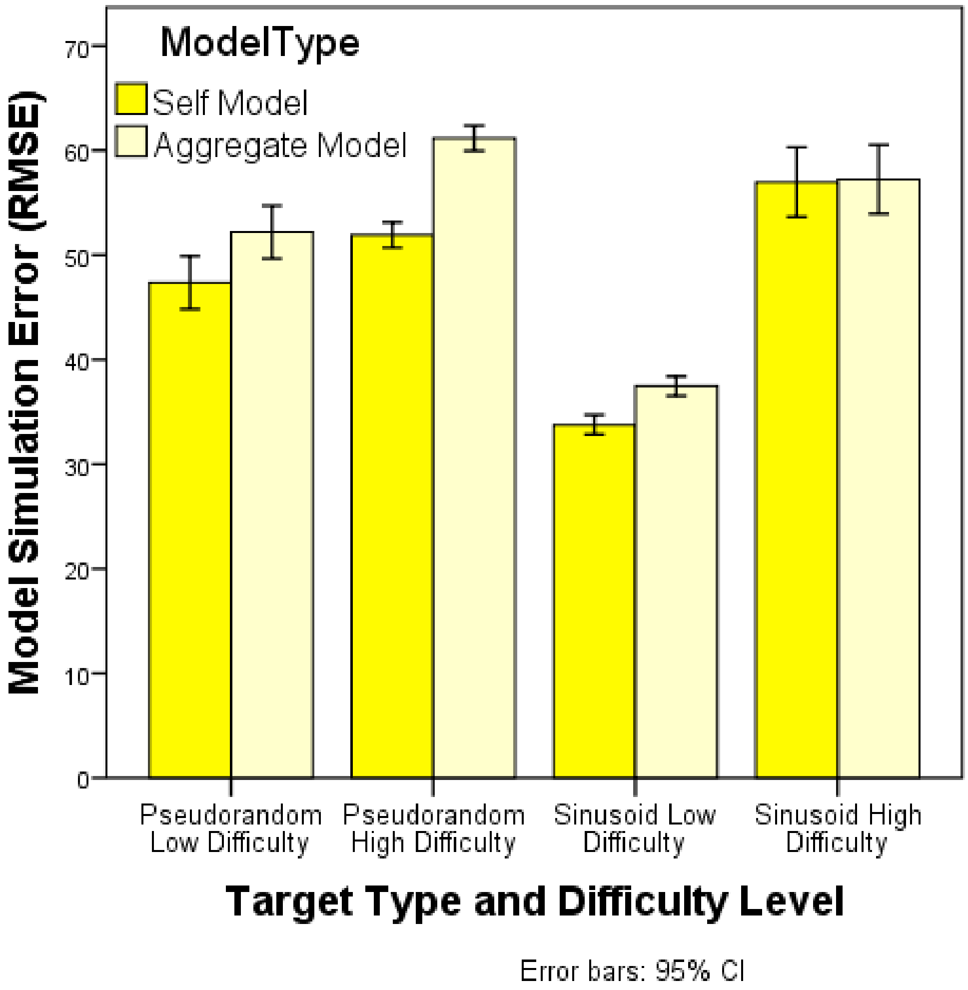
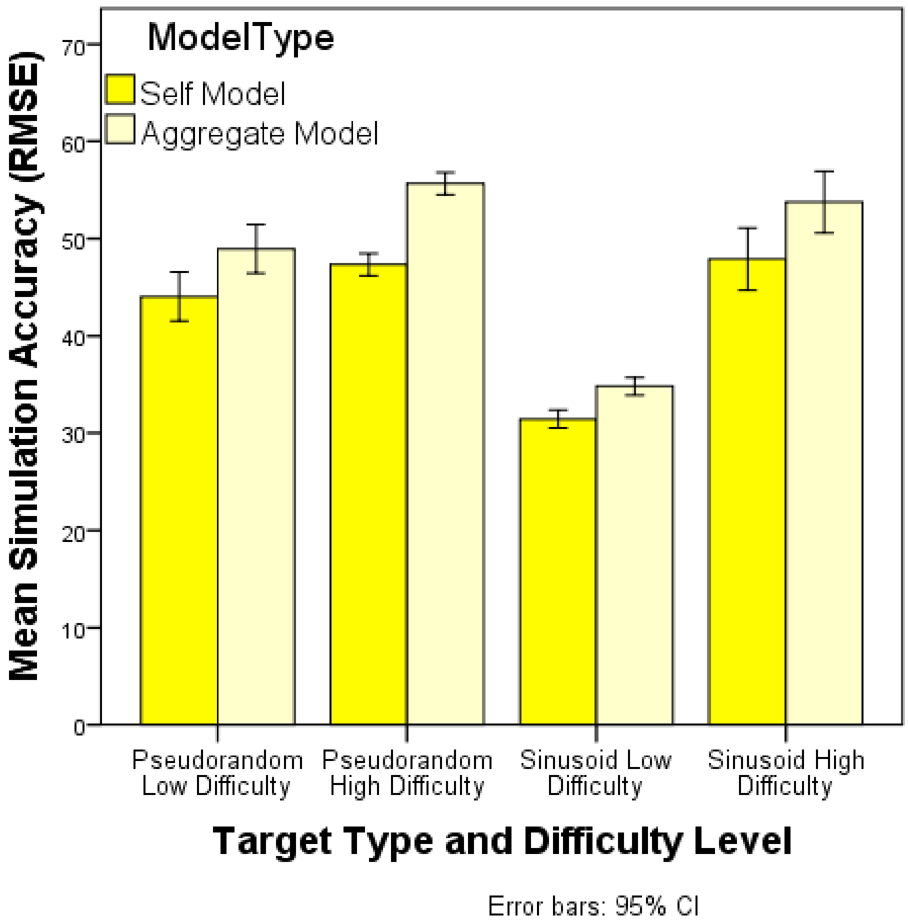


Figure 7.14 Model simulation accuracy of self and aggregate models to participant tracking data in each of the four target type and difficulty level pairings: Block 3



7.5 Discussion

7.5.1 Summary of findings

Tracking performance varied between target types and difficulty levels. Although accuracy was worse for higher difficulty targets within each target type, low difficulty pseudorandom targets were tracked with a similar accuracy to high difficulty sinusoid targets. There was an observed learning effect across blocks within each target and difficulty level combination. Participants tracked all targets but the low difficulty sinusoid with a phase delay. Cursor amplitudes were significantly below that of the targets for sinusoid targets, but not pseudorandom targets (though the average amplitude ratios were, on average higher for sinusoid targets than pseudorandom targets).

The prediction that the HEM would simulate sinusoid targets more accurately than PCM was supported across all three blocks. There was no difference in simulation accuracy between the models for pseudorandom targets at model validation, but the HEM simulated pseudorandom targets more accurately than PCM at optimisation (block 1). The HEM matched the phase delay and amplitude of the participants' cursors more accurately than the PCM for pseudorandom targets of low difficulty and sinusoids of both high and low difficulties. For the HEM, it was generally found that individual models simulated performance more accurately than models derived from other participants' tracking performance In other words, an individual's tracking movements for new target signals (of the same difficulty and type) could be predicted by their individual model with superior accuracy to a model of aggregated performance across individuals. This test was not conducted for the PCM as this was done in a previous paper (Parker et al., 2017).

7.5.2 Contribution of the reference value to model simulation accuracy

We hypothesised that the model reference values would contribute uniquely to the accuracy of the simulations of both pseudorandom and sinusoid tracking performance at both difficulty levels. The findings supported this prediction for simulations of low difficulty pseudorandom targets with the PCM. In addition, the quadratic regression model that included all parameters significantly predicted model fit. This was the same pattern of findings observed for low difficulty pseudorandom targets in the previous experiment (Parker et al., 2017). Taken together, the studies indicate that the individual-specific internally-specified reference signal is critical to individual PCMs of tracking performance for this target.

The current study extended this analysis to high difficulty pseudorandom targets, and also to another target type, sinusoid signals, at both high and low difficulty levels. The reference value of the PCM was not found to contribute uniquely to model fit to high difficulty pseudorandom targets. However, the reference value did contribute uniquely to model fit for sinusoid targets of both difficulty levels. This pattern of findings indicates that the position reference parameter is critical for model fits across target types. However, the absence of the finding within high difficulty pseudorandom targets may indicate that reference values were less consistent across trials for this target type and difficulty, and therefore not strong predictors of performance. This would indicate that participants were unable to keep the cursor in a tight and constant relationship with the target, perhaps due to difficulty of the task. Alternatively, it might indicate that participants learned to improve their performance over successive trials and this might have been associated with a change in the position reference over time.

In the HEM, the position reference significantly contributed to the model fit for pseudorandom targets but not for sinusoid targets. Given the different pattern of findings across target types for each model, we can deduce that a difference between the models, rather than the target patterns, led to the contradictory findings. The main difference between the models is that the PCM is a single-unit architecture and the HEM model is a two-unit hierarchy. Therefore, the HEM model comprises two reference values whilst the PCM has just one. In the HEM model, the reference value to the position control unit (superordinate unit) is a free parameter for optimisation. This reference therefore takes a constant value. In contrast, the reference value to the velocity control unit (subordinate unit) dynamically varies over the course of a trial. Only the constant position reference is included within the regression model for HEM targets. A proportion of the variance in fit may therefore be accounted for by the velocity reference value in the HEM.

7.5.3 Model simulation accuracy

During optimisation, both sinusoid and pseudorandom targets were simulated more accurately by the HEM than the PCM. However, at validation (blocks 2 and 3), pseudorandom targets were simulated equally accurately by the PCM and the HEM. In contrast, sinusoid targets were simulated significantly more accurately by the HEM. This corroborates previous work (Parker et al., in preparation), and additionally demonstrates temporal consistency of the fit. That is, models retain high accuracy when simulating new targets tracked by the same participant one week later. The accuracy of the models over time were similar to other studies of temporal consistency in the fit of PCM to tracking performance over one year (Bourbon et al., 1990b) and five years (Bourbon, 1996b). Regardless of the target type and difficulty level, HEMs seem to remain highly accurate in simulating the participant's performance.

The superior fit of the HEM compared to the PCM supports the general hypothesis that humans utilise both position and velocity inputs when tracking targets (Barnes & Asselman, 1991; Dessing, Peper, Bullock, & Beek, 2005; Fine et al., 2014; Hill, 2009; Hill & Raab, 2005; Krauzlis & Lisberger, 1994; Poulton, 1952b; Rosenbaum, 1975; Viviani et al., 1987; Viviani & Mounoud, 1990). Therefore it may be the case that participants utilise target velocity to compensate for sensorimotor delays when the target position when the motion of the target affords this (Khoramshahi et al., 2014; Yu et al., 2014). An example of a signal that would not afford this would be a step input signal. In a step signal, position change is instantaneous and therefore there is no change in velocity. In contrast, the target types used in this experiment could support both position extrapolation and velocity control because of the dependency between target velocity and position.

While velocity may be used during tracking of both targets, it appears that target extrapolation may be used to a greater degree during tracking of sinusoid targets than pseudorandom targets. This is evidenced within the model parameters of the HEM. For the HEM, loop delays were longer for sinusoid targets than pseudorandom targets (Table 7.4). Despite longer loop delays, the phase delay between simulated cursors and targets were shorter for sinusoid signals (these phase delays can be derived simply by addition of the tracking phase delays in Figure 7.7 and the model phase delays in Figure 7.9). Consequently the delay compensation is much larger for sinusoid signals than for pseudorandom signals, which would require a longer extrapolation. This is supported by the finding of larger extrapolation gain parameter estimates for sinusoid targets than for pseudorandom targets in the HEM model. Increases in this parameter value would increase the magnitude of the extrapolation, and consequently the magnitude of the delay compensation.

7.5.4 Individual specificity of the HEM

We hypothesised that the HEM would show individual specificity in predictions of tracking performance for each target type and difficulty level. This hypothesis was supported as we found that the HEM, optimised to an individual's training data, more accurately simulated that individual's validation data than did the general model. This was the case even for new targets that the participant tracked one week later. These findings replicated those of a previous study (Parker et al., 2017) which found that the PCM made individual-specific predictions of pseudorandom (low difficulty) tracking performance. Thus, like the PCM in that study (Parker et al., 2017), the HEM can make individual predictions of participant behaviour across target types and difficulty, which remain accurate over time. This supports previous evidence that control characteristics and parameters can be stable over time (Bourbon, 1996; Bourbon et al., 1990; Franks & Stanley, 1991; Miyake, Loslever, & Hancock, 2001).

Individual models may find application within the rehabilitation setting. Models may be used to identify or assess impairments within such populations (Allen et al., 2007; Oishi et al., 2010, 2011). Models may also be implemented to drive assistive robotic devices for physical therapy, many of which use tracking-type tasks within virtual environments (Maciejasz et al., 2014).

7.5.5 Model generalisability

In the current study the tracking apparatus was a steering wheel and the task required individuals to track on screen in the horizontal dimension. This was a departure from our previous experiments in which the experimental setup was a vertical tracking task with a joystick (Parker et al. 2017; 2018). Despite these differences, the key findings of the previous papers were replicated and extended. Thus, the models can robustly generalise to new physical environments in addition to target characteristics such as the complexity of the signal and its difficulty (speed). This is interesting because the movements required by the participant to control the cursor are very different between the steering wheel and joystick. Steering wheel rotation requires shoulder abduction and adduction in addition to pronation and supination of the forearm, whilst moving the joystick requires mostly elbow and wrist flexion and extension. Whilst the models in this paper do not attempt to account for the mechanism of muscle and joint action specifically, the model is equally able to account for the behaviour of the participant in both task designs. This indicates a perceptual and task-oriented basis to behaviour, whereby voluntary action is oriented toward reliably producing perceptual goals (target-cursor alignment in this case), where the physical means of achieving that end is only relevant insomuch as it achieves this goal (Marken, Mansell, & Khatib, 2013).

7.5.6 Limitations

An effect of practice was observed for all targets; that is, tracking performance improved for all targets between the first block and the third block one week later. However the pattern of improvement differed for different targets and difficulty levels. Whilst learning effects were not the focus of the paper, differing rates of improvement in tracking performance would have affected the fit of individual models. If participants are learning throughout the experiment, then their control characteristics (and parameters) may change between blocks. This would reduce the accuracy of the model fit in later blocks. This is most likely to be the case for high difficulty targets of both target types, as these showed the largest performance gains from blocks 1 to 3, and the largest changes in phase and amplitude ratio (though inter-block differences were not tested statistically). We controlled for learning in a previous experiment (Parker et al., 2017) by having a larger number of practice trials and changing the target difficulty (speed) for different individuals to produce a coherent error rate across individuals. This added a confound to detection of individual differences as task constraints were not the same for all individuals, and this may have affected parameter values and fits. This confound was avoided in the current experiment as target difficulty was manipulated experimentally, as one aim of the current experiment was to investigate model simulation differences for different target difficulties (speeds).

In the experiment we limited the models to a minimum loop delay value of 182 ms during optimisation. This was based on previous findings of loop delay optima in the region of 150 – 200 ms for PCM with pseudorandom targets, and approximately 250 ms for HEM (Parker et al. 2017, in preparation). The 182 ms value was a compromise between these estimates. However, this may have disadvantaged the PCM when simulating sinusoid targets as the optimised loop delays averaged to around this lower limit (Table 7.3). It is likely that the PCM would have produced better fits at shorter loop delays for sinusoid targets had this not been prevented. Although 180 ms is a plausible estimate of the sensorimotor delay in tracking, it is also plausible that visual feedback information may be used after about 100 – 150 ms (Brenner & Smeets, 2015; Day & Lyon, 2000; Foulkes & Miall, 2000; Franklin & Wolpert, 2008; Saunders & Knill, 2005). Future studies might use 100 ms as a threshold for loop delay during optimisations as a liberal estimate.

The HEM demonstrated an improved fit to sinusoid tracking relative to the PCM in all blocks. However, whilst sinusoid targets were modelled more accurately than pseudorandom targets with the HEM, the tracking accuracy for sinusoids was substantially higher than for pseudorandom targets to begin with. In fact, the improvement in HEM fit over tracking accuracy was substantially larger for pseudorandom targets than for sinusoids. This may indicate that there are aspects of the control strategy participants use when tracking sinusoids that are not accounted for even by the HEM. It is possible that participants use another strategy such as replicating the pattern of displacement over a cycle. This latter approach has been termed course anticipation (Poulton, 1952a). There are a number of studies that indicate that this method may be used to track objects once the participant realises the periodicity of the target signal (Bahill & McDonald, 1983; Leist et al., 1987). In addition, intermittent sampling models that generate ballistic movements (Gawthrop & Wang, 2011; Gollee et al., 2017; Inoue & Sakaguchi, 2014) have been proposed that may account for discontinuities in the trace , such as the inconsistency in phase delay during tracking of sinusoid targets (Inoue & Sakaguchi, 2014).

7.5.7 Conclusion

The current article we aimed to test the individual-specificity of a HEM of pursuit performance developed in a previous study (Parker et al., in preparation). The model can compensate for sensorimotor delays when tracking sinusoid targets. The model demonstrated temporal consistency in predictions of individual performance under different target conditions. Individual models fit data more accurately than did general models. Thus the HEM can both generalise across a range of task constraints and over time. The individual modelling approach facilitates robust testing of hypothesised mechanisms.

Chapter 8: General Discussion

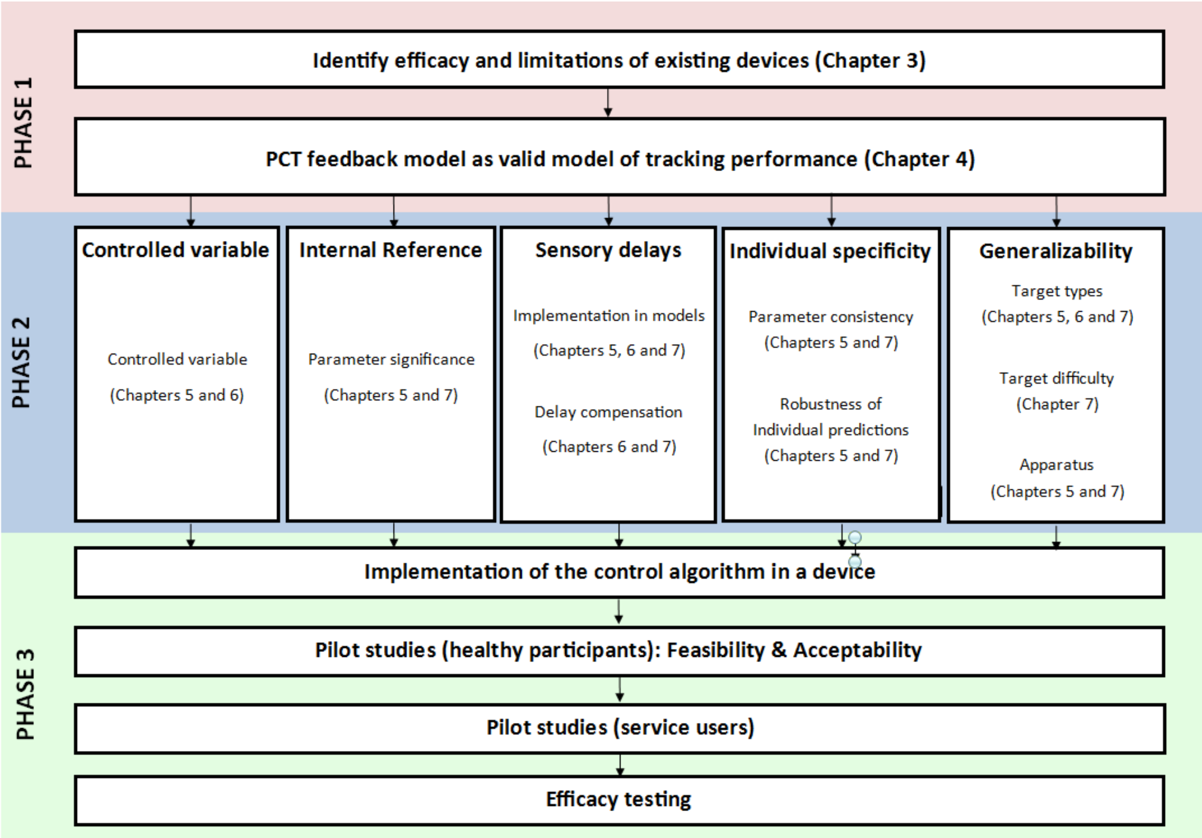
8.1 Chapter overview

This chapter will provide an overall, general discussion in relation to the body of work presented within this thesis. First, its overarching aim will be stated; followed by specific key objectives and specific hypotheses. In section 8.3, the findings of each thesis chapter are summarised in relation to these objectives and hypotheses; in section 8.4, overall strengths and limitations of the research presented in this thesis are discussed. In section 8.5 recommendations for future research priorities are made, framed within the present aims. The first subsection addresses further evaluations of the proof-of-principle of PCT. The second subsection addresses research priorities toward the development of an adaptive robotic device for motor rehabilitation. Finally, overarching conclusions for the thesis as a whole are presented in section 8.6.

8.2 Thesis aim

The aim of this thesis was to test the proof-of-concept for applying PCT to upper limb motor rehabilitation. The objectives followed directly from this aim, and the thesis is organised around these objectives. This research agenda, including both completed and projected future objectives, is outlined in Figure 8.1. Those objectives that are addressed within this thesis are highlighted in green.

Figure 8.1 Research agenda



Note. Phases one and two of the research agenda were completed within this thesis

8.3 Objectives, hypotheses and findings

8.3.1 Is RT with distal upper limb rehabilitation devices efficacious?

The primary focus of the scoping systematic review and meta-analysis presented in Chapter 3 was to address the efficacy of distal upper limb RT. Efficacy was defined as significant gains in clinical outcome measures categorised by domains of the World Health Organisation (WHO) International Classification of Functioning, Disability and Health (ICF; WHO, 2001). The categories were measures of impairment, and measures of activity and participation.

Hypothesis 1.a Training with a device will be efficacious for improving function following neurological conditions other than stroke.

The review identified only a single study that fit the inclusion criteria to evaluate the efficacy of distal UL training in a non-stroke population (Weightman et al., 2011).The sample was 18 children with CP. Whilst a number of kinematic variables improved, data were only collected on one clinical outcome measure; the COPM (Law et al., 1990). This was a self-report measure of activity and participation, on which the children showed significant gains. This suggests that device training may be feasible for this population. However, the lack of behavioural outcome measures or a control group of CP participants which did not undergo RT, in addition to the small overall sample, would make any judgement of efficacy would be premature. We could not find any other studies with samples of participants with neurological conditions other than stroke, who had received distal end-effector RT. Evidently we must conclude that it is currently unclear whether training would be suitable for populations other than stroke and CP.

Hypothesis 1.b Distal end-effector RT reduces impairment in the distal and proximal upper limb in stroke patients.

Two devices, the AMADEO and BiManuTrack, have undergone methodologically rigorous efficacy evaluations in randomised controlled trials (RCTs). In these studies, training with the AMADEO and BiManuTrack devices consistently resulted in reductions in impairment. The efficacy of training with the BiManuTrack relative to usual CT was evaluated in a meta-analysis. The clinical outcome measure was the FMA (Fugl-Meyer et al., 1975). The overall effect was non-significant, indicating that training with the BiManuTrack was equally efficacious in reducing impairment as CT. A number of other studies, mostly proof-of-concept, assessed impairment outcome measures in stroke populations receiving RT. These studies mostly found significant reductions in impairment measures. Those studies that did not find reductions in impairment did not have large enough samples to conduct statistical tests. In studies that reported reductions in impairment and had a follow up period, training gains were maintained at follow-up.

Hypothesis 1.c Distal end-effector RT leads to improved functional abilities in stroke patients as measured by activity/participation outcome measures.

The evidence for functional improvements with RT was assessed by activity and participation measures. There was some evidence of clinical improvement in these measures in RCTs. There was less consistent evidence of functional gains in proof-of-concept studies. It was concluded that the preliminary evidence suggests RT training can be efficacious in facilitating functional recovery in stroke patients. Functional imrovements were maintained in follow-up assessments.

Synthesis

With regard to the objective (8.3.1), findings indicated distal upper limb training can be reduce impairments and may facilitate functional recovery in stroke patients. In non-stroke populations, the number and quality of studies of distal upper limb training was insufficient to draw conclusions regarding efficacy. Most devices have not been evaluated in RCTs; trials are mainly early-stage pilot studies and comprise high risk of bias. Distal upper limb RT should be considered a potential technology for enhancing rehabilitation outcomes in stroke patients. As the range of training protocols differed widely between studies it is unclear which aspects of device or study design best promote functional recovery. However, it should be noted that reviews of proximal (elbow and shoulder) upper limb training report no improvements in functional outcome measures (Prange et al., 2006). This may be because distal training results in reduction in impairment throughout the whole upper limb (Hsieh et al., 2018; Mazzoleni, Tran, Dario, & Posteraro, 2018; Balasubramanian et al., 2010) while proximal training is specific to shoulder and elbow only. Conversely, proximal training does not generalise to reductions in distal upper limb impairment (Prange et al., 2006). This difference is likely due to the indirect use of the proximal upper limb in distal upper limb training. Therefore distal upper limb training may be more beneficial than proximal upper limb training. However, it should be noted that many more studies have trialled proximal upper limb RT than distal RT.

Further research should aim to establish which specific distal upper limb movements are most useful to patients. It may be the case that this depends on the individual’s specific impairments. Some movements may be identified as important by service users (Weightman et al., 2010). Devices could support movements that are critical to many Activities of Daily Living (ADL). For example, pronation and supination are used when turning knobs, opening doors and using cutlery (Lambercy et al., 2007). Although wrist adduction and abduction is used in few tasks and may be compensated for by other movements.

An additional question regards whether devices should use assistive or resistive strategies. Assistive devices apply force in the desired direction during a task. Resistive devices create force disturbances that must be compensated by the individual or amplify error to challenge the user to increase their effort. There is supporting evidence for both strategies (Marchal-Crespo & Reinkensmeyer, 2009). It may be the case that different strategies would more appropriate and useful at different points in the training program. Further device development considerations will be addressed in Section 8.5.

8.3.2 What is the state of the evidence for the PCT models in manual tracking studies?

PCT is a unifying theory of the behaviour of living systems (see Chapter 1 for summary). The theory proposes that individuals control their perceptions (Powers, 1973). Within this framework actions are varied via negative feedback to maintain perceptual variables at referent states (Powers et al., 1960). PCT has mostly been tested within manual tracking tasks. In these experiments the goal has been broadly to demonstrate specific theoretical principles by building a model and evaluating its fit to participant behaviour: the functional modelling approach (Mansell & Huddy, 2018; Runkel, 1990). The systematic review reported in Chapter 4 attempted to synthesise the findings of these experiments in relation to the core principles of the theory. In so doing, we identified those principles that required further evaluation. These became further thesis objectives and are addressed in experimental Chapters 5, 6 and 7. This section discusses the state of the evidence for PCT in manual tracking studies prior to those presented in this thesis. Note that the experiment reported in Chapter 5 was one of the studies reviewed in Chapter 4.

All of the included studies demonstrated that humans exhibit negative feedback control during manual tracking. Movements of the cursor in the task served to keep the cursor and target within a desired relationship with one another. The strongest evidence for this came from studies in which dynamic visual disturbances were applied to the cursor position (Marken, 2013; Marken & Horth, 2011; Powers, 1978, 1989). These unseen disturbances were compensated for by the individual's tracking movements. One limitation of the PCT literature is that PCT models did not include a parameter that estimated central delays. This limited the explanatory power of the PCT models. Moreover, it has been demonstrated in tracking studies outside of the PCT literature that humans exhibit anticipatory behaviour when tracking periodic targets (Poulton, 1952b, 1952a). Despite this, PCT models had primarily been tested with pseudorandom target and disturbance signals. There was no evidence that anticipatory behaviour could be modelled by perceptual feedback alone.

Several studies used the Test for the Controlled Variable (TCV; Marken, 2013; Runkel, 2007) to establish which perceptual variables participants were controlling. This was achieved by applying disturbances to different variables and measuring which disturbance was compensated for most effectively (indicating control). Most studies hypothesised that participants aimed to maintain a visual distance between a cursor and another cursor or target. One study found that individuals may control visual angle rather than position (Marken, 2013).

PCT states that an individual's intentions can be quantified within the reference value model parameter. Experiments showed that participants could alter this reference during the task (Bourbon, 1996; Bourbon et al., 1990; Powers, 1978, 1989). and models, endowed with this reference value, would accurately simulate that individual's behaviour (Powers, 1989).

Following from the previous point, individuals were able to maintain a perceptual variable in a desired 'referent' state. These referent states often specified alignment between the target and cursor. In the most persuasive evidence these reference states were a constant non-zero value or a dynamically changing value (Marken, 2014; Powers, 1989). However it had not been formally tested whether reference values were critical to model performance in cases where the target and cursor were aligned. This became a research objective for this thesis.

PCT expounds a functional modelling approach (Runkel, 1990; Runkel, 2007). Models are constructed of individual participants and aim to simulate that individual's behaviour with high accuracy. There was ample evidence that models fit individual performances for pseudorandom targets and disturbances (Bourbon, 1996; Bourbon et al., 1990; Marken & Horth, 2011; Powers, 1978, 1989). However, there was limited evidence that models captured individuals' control characteristics. Two studies measured model simulation accuracy over one and five years (Bourbon, 1996; Bourbon et al., 1990) and found parameters were still predictive of performance after this time. There had been no formal test of whether models demonstrated individual specificity, except for the study presented in Chapter 5.

There was some evidence that multiple degrees of freedom in the task or apparatus could be controlled simultaneously (Marken, 1986; Marken, 1991). This came from studies in which parallel control units operated in tandem, or in a hierarchical arrangement to control multiple perceptual variables simultaneously.

Additionally, no studies had explicitly modelled reorganisation, the learning algorithm proposed by PCT, although one study aimed to investigate increase in model gain over time as a proxy for reorganisation (Pavloski et al., 1990). Nor had PCT been used to emulate movements in a physical tracking environment.

The review also identified several methodological issues that were present in the majority of PCT tracking studies.

Synthesis

We found that many of the core principles of PCT were supported by research evidence. However, we also identified some key principles that had not been conclusively tested. These became research objectives, which we evaluated through experimental tracking and modelling studies within the thesis. These objectives were:

1) To determine which variables participant control during manual pursuit tracking.
2) To investigate whether the reference value, unique to PCT, was critical to model fit performance. This was evaluated in the experiments reported in Chapters 5 and 7.
3) To formally test the assumption that models were individual-specific. This assumption is central to the functional modelling approach which aims to construct models of individual performance (Mansell & Huddy, 2018). Two experiments formally evaluated this objective and are reported in Chapters 5 and 7.
4) To implement delays in PCT models and measure the effect of altering this delay parameter on model fit. Importantly, it was necessary to model tracking of periodic targets (such as sinusoids), as participants exhibit zero latency tracking for such targets (Poulton, 1952b; Stark et al., 1961; Stepp, 2009; Stepp & Turvey, 2017; P Viviani & Mounoud, 1990), We investigated how a model only using negative feedback could emulate zero-latency tracking whilst maintaining a biologically feasible duration of central delay. Chapter 6 reports an experiment investigating the role of delays in model fit. Chapters 6 and 7 report studies in which sinusoid tracking performances are fit by PCT models.
5) To investigate the generalisability of PCT models across tracking task conditions. The studies reported in Chapters 6 and 7 extended the conditions under which models had been tested.

The experiments designed to meet these objectives evaluated the proof-of-principle of PCT as a motor control theory. It would also have further implications for our overarching objective; to develop an adaptive robotic rehabilitation device. The results of these tests would determine whether it was possible to construct models of individual performance across different tracking contexts. The adaptive controller must identify the individual’s control characteristics, in order to adapt to their training requirements. Thus we needed to know whether models were individual specific (objective two). In addition, the steering wheel was chosen as the candidate device to implement the controller. It was therefore necessary to test whether the model was a good model of tracking performance for different types of signals (objective three) and for horizontally moving targets of different speeds with a steering wheel (objective four).

Critically, we did not include studies that used models that were not based on PCT. However, such a review would have been too broad as there is a very large literature using tracking paradigms. Different models tend to have been developed based on observation of a specific aspect of tracking behaviour. For example, models have been constructed that intermittently produce (ballistic) movements when the error in position or another variable exceeds a threshold (Gollee et al., 2017; Inoue & Sakaguchi, 2014; Miall et al., 1993). It would be useful to draw comparisons between models such as these and those based on PCT. However, comparisons should take the form of experimental studies in which models are compared on accuracy and tracking characteristics, rather than a qualitative narrative review.

8.3.3 What are the controlled variables in manual tracking?

In the manual tracking task there are many perceptual inputs that may be the basis of coordinated movement to maintain alignment between the target and cursor. Instantaneous target cursor distance might be considered the simplest explanation. Indeed, many models controlling cursor-target distance have been evaluated both within, and outside PCT. This section examines the range of perceptual inputs which may be controlled within the task.

Hypothesis 3.a The controlled variable is target-cursor distance

The very first manual tracking studies attempted to characterise human performance in the task, typically using frequency analyses to build transfer functions that approximated the dynamics of the 'human operator' (Noble et al., 1955; Poulton, 1952b, 1952a; Stark et al., 1961; Vince, 1948). This methodology lent heavily from control engineering and cybernetics, conceptualizing the human operator as a control system. Models were built to try and simulate human tracking performance. The input to this type of control architecture was the distance error between target and cursor (Bekey, 1962; Kreifeldt, 1965; Levison et al., 1969; McRuer & Jex, 1967; Navas & Stark, 1968). The PCT conceptualisation of the model, which included a reference value independent of the driving (input) signal that was thought to be internally-specified, and a leaky integrator to damp the response across trials, was published in 1978 (Powers, 1978). This basic model was expanded and evaluated in many subsequent studies. These studies were reviewed in

Chapter 4. Ten of the models reviewed used a single unit position control scheme (see Chapter 4), which used the immediate previous target and cursor inputs to coordinate cursor movements. Across these studies these models were shown to robustly simulate pursuit performance for pseudorandom targets and compensatory tasks with pseudorandom disturbances with a high degree of accuracy ($R^2 \approx .98$). This was argued to provide strong evidence that individuals controlled the perceptual variable of target cursor distance. Despite this evidence there are several reasons to think that the controlled variable is not simply the distance between the target and cursor on the previous time sample.

Firstly, one must consider that sensorimotor delays are intrinsic to the CNS (see Chapters 5 and 6). This necessitates that it is not immediate-previous sensory inputs which are basis of a current control action, but substantially delayed inputs. These delays are estimated to have a minimum duration of 100 ms. In Chapter 5, we report an experiment in which we used a PCM to simulate pseudorandom tracking data. However, we implemented a loop delay which was optimised alongside the other model parameters to account for the sensorimotor delay in manual movements to visual targets. Tracking performance could still be accurately simulated by this model when loop delays were in the region of 160 ms and above, supporting the interpretation that positional difference was a controlled variable in pseudorandom tracking.

A more damning criticism comes from the observation that individuals do not display long phase delays when tracking targets that move in a predictable pattern (Poulton, 1952b; Stark et al., 1961; Stepp, 2009; Stepp & Turvey, 2017; Viviani & Mounoud, 1990). In conjunction with the previous point this poses a series problem for the position control hypothesis because it might be assumed that with a long loop delay (sensorimotor delay), the model would not be able to emulate tracking without producing a phase delay in the response. However, it should be noted that PCT, and also within the free energy or AI formulation, the perceptual world is organised hierarchically (Adams et al., 2013; Friston et al., 2009; Marken, 1986; Powers et al., 1960). Within these theories, any task might involve a number of different perceptual variables controlled (or predicted in the case of AI) simultaneously. To propose that an individual controls a single perception within a task is likely a reduction. A number of models have been proposed that control, and combine, multiple perceptual variables during tracking and other visuomanual tasks.

Hypothesis 3.b Manual tracking involves simultaneous control of multiple controlled variables

The tracking review included three studies that modelled simultaneous perceptual control (Marken, 1986; Marken & Powers, 1989; Marken, 1991). Two of these studies used a hierarchical architecture in an attempt to account for changes in task design during manual tracking of pseudorandom targets. In one of these studies, Marken and Powers demonstrated that additional hierarchical units, tuned to likely disturbances could account for and mitigate the effects of these disturbances that a single position control unit would not (Marken & Powers, 1989). The disturbance in question was a switch of the directional feedback relation between output and cursor. This demonstrates that two units can operate simultaneously to produce an adaptive output.

As mentioned under the previous hypothesis, periodic targets pose a particular challenge for position control because of intrinsic sensorimotor delays which make it improbable that this method is used during 'anticipatory' tracking. In Chapter 6 we constructed three additional models, the PEM, HCM and HEM. Two of these models used simultaneous hierarchical control, and one did not. These models were compared with the PCM in their ability to simulate individual participants' cursor movements for sinusoid and pseudorandom targets. We found that hierarchical control of target-cursor position and velocity difference could not adequately account for the sensorimotor delay compensation observed in tracking of sinusoid targets. However, the PEM and HEM, which used an extrapolated target position (integrated perceptual signal) could track more accurately at feasible delay values and did not result in a significant phase delay relative to the participant's cursor. From these findings it might be concluded that whilst position information is vital, position may not be the *only* controlled variable in manual tracking. Individuals may use motion information during tracking in addition to position feedback information. The findings of Chapter 7 further supported this conclusion as the HEM, which controlled extrapolated position and velocity simultaneously, simulated the amplitude and phase delay of participant cursors more accurately than the PCM and resulted in reduced simulation error.

Synthesis

The question of which perceptual variables are controlled within a specific task has a complex answer. It is likely not the case that in any single task there is a particular controlled perceptual variable. Manual tracking is no different. In the current thesis we present and examine several possibilities: position control on immediate previous sensory information (Chapter 4), position control with modelled sensorimotor delays (Chapter 5, 6 and 7), hierarchical velocity and position control (Chapter 6), position extrapolation (Chapter 6), and hierarchical velocity and position extrapolation (Chapters 6 and 7). The HEM model consistently performed well across task constraints (Chapter 7) and was robust to many values of loop delay for both pseudorandom and sinusoid target types in Chapter 6. It may be considered that motion extrapolation is integral to visuomanual tracking. This conclusion is supported by neurological evidence of global motion processing (de la Malla, Smeets, & Brenner, 2018; Khoei et al., 2013; Newsome & Paré, 1988), in addition to evidence from smooth pursuit eye movements (Bennet & Barnes, 2003; Bennett et al., 2007; Mrotek & Soechting, 2007; Zago et al., 2010), manual tracking and object interception (Bosco, Delle Monache, & Lacquaniti, 2012; Brenner & Smeets, 2015; De La Malla, Smeets, & Brenner, 2017; Fine et al., 2014). However, a range of different models have been proposed that control different inputs and outputs. The fact that many models have been developed that can account for aspects of tracking performance suggests that there are multiple strategies that may be used track targets, participants may use any of these or even switch between them. A number of other tracking models are discussed in Chapters 6 and 7.

8.3.4 Is the PCT reference value critical to model performance?

The internally-specified reference signal is proposed to encode the state of the controlled perceptual variable within the control unit (Powers, 1973, 2008): the reference value. This has a functional role in PCT because control units are proposed to operate in hierarchies. Output signals of control units at one level become the reference values for the control units at the subordinate level. In complex systems with more than one control unit, the reference signal to the subordinate unit varies to satisfy or maintain control in the superordinate unit. This definition of the reference value is unique to PCT and distinguishes it from other negative feedback control models for which the reference originates outside of the system (Powers, 1973). It is therefore important to establish whether the reference value parameter can encode intentions and whether the parameter contributes to the fit of the PCT models to experimental data. If so, this would support a PCT interpretation of behaviour.

Hypothesis 4.a The reference value encodes intentions in the tracking task

As mentioned in the previous section, visual distance between the target and cursor is most commonly hypothesised to be the controlled variable (see section 8.3.4). The review in Chapter 4 established that in most studies the participants were instructed to keep the cursor aligned with the target as best they could (reference = zero). However, four studies demonstrated that the reference value could vary over the course of a trial, if the user was instructed to hold a different relationship (Marken & Powers, 1989; Marken, 2013; Powers, 1978, 1989). Models, endowed with the right reference values, would accurately simulate individual performance under these conditions. This demonstrates how crucial the reference value parameter is for models of performance.

Even in tasks in which the instruction to participants was to keep alignment between the target and cursor, individuals tended to exhibit a preference over a trial. This preference is expressed in the reference value for that trial (Bourbon et al., 1990b). In Chapter 5 we found just this. We observed consistent non-zero reference values when some participants were asked to keep the target and cursor aligned. This can be observed in Figure 5.3 of that Chapter. No single individual averaged more than four pixels below the target or two pixels above the target. However, for 11 of the 20 participants, a consistent offset one or other side of zero was observed. This supports the interpretation that reference values were structured. This could be interpreted as reflecting an intentional preference, or a perceptual bias. Non-zero reference values were also found in Chapters 6 and 7, though it was unclear whether there was a pattern either way.

Hypothesis 4.b PCT reference values will contribute significantly to model fit

In the same chapter (Chapter 5) we attempted to establish whether the reference parameter contributed to model performance. A significant proportion of the variance in PCM accuracy was uniquely accounted for by the reference signal parameter (Table 5.4). This indicated that the reference parameter quantified a tracking offset and that characterising this offset improves the model simulation. We repeated the regression analysis in Chapter 7 for the PCM and HEM models for the four targets. Reference values were broadly found to significantly predict model fit (Tables 7.5 and 7.6). In light of the findings in Chapters 5 and 7, across reference values were established to account for variance in model fit for both pseudorandom and sinusoid targets.

Synthesis

The chapters within this thesis provide compelling evidence that the internally-specified reference parameter captures an important aspect of tracking performance. In tasks in which the instruction is to keep the cursor on-target, it is unclear whether non-zero reference values reflect a perceptual bias. However, it should be interpreted that participants intended to keep a zero reference value, but were unable to exactly match this, and showed a small bias in one or other direction. Nonetheless, the regression models in Chapters 5 and 7 indicate that the reference parameter value is integral to model fit when simulating tracking data with computational models. This indicates that even small displacements relative to the target may contribute to tracking error in the controlling system. This analysis had not been conducted before in PCT tracking studies. The results support the proposal that individuals' control variables to referent states. It is useful to note that cursor data could be detrended for analysis, which would likely remove this perceptual bias from the data. This detrending is necessary for frequency analysis. In our experiments, we conducted detrending for frequency analysis after modelling the data in order that we captured these tracking characteristics within the model.

In Chapter 7, the analysis also provides evidence for hierarchical control because the position reference value to the HEM model was found to account for variance in the output, even when the output of the entire system was transformed through a second, dynamic, reference value. This provides evidence that cascade control exists in a hierarchy of control systems. That is, the model fit does not simply result from the operation of the unit on the lowest level. In this respect, Chapter 7 provides evidence for hierarchical control as a means to produce behaviour.

8.3.5 Do PCT models of tracking performance demonstrate individual specificity?

The PCT research method is the functional modelling approach (Mansell & Huddy, 2018; Runkel, 1990). The aim of this approach is to identify the variables which individual's control using the TCV, and construct a model and test the fit of this model to their performance. This is predicated on the assumption that individuals differ in the way they carry out the task. Specifically, PCT assumes that individual participants may control different perceptual variables (Marken, 1988; Marken, Mansell, & Khatib, 2013), or the same variables at different reference values (see previous Section 8.3.4).

Hypothesis 5.a Model parameters characterise individual control characteristics

In Chapter 5, we tested the hypothesis that the PCM could characterise individual performance for pseudorandom target signals. We found high intra-individual consistency in parameter estimates over a one-week period. We found that these parameter estimates differed significantly between individuals. All PCM parameters significantly contributed to the fit of the model to pseudorandom targets. Thus, individual control characteristics for pseudorandom tracking were captured within the PCM parameters. In Chapter 7, participants tracked sinusoid targets in addition to pseudorandom targets. The parameters of the PCM, and the HEM contributed to the overall fit of the models to tracking data. However, the pattern of individual parameter significance was unclear. The two models will be considered in turn, reference values will not be considered here because they have been addressed under the previous objective (Section 8.3.2).

For the PCM, there were two significant patterns in parameter significance. The output gain was a significant predictor of performance for all models. This was also the case in Chapter 5 and corroborates the finding of that study: that the output gain parameter was most idiosyncratic. However, in contrast to the findings of the regression in Chapter 5, damping constants and delays were not significant predictors of model fit in Chapter 7. This was true even for targets most similar in characteristics to those used in Chapter 5, the low difficulty pseudorandom target. Comparing across the studies, the proportion of variance explained by the regression model was substantially larger in Chapter 5 than in Chapter 7. These differences may have resulted from differences in the volume of data from which conclusions were drawn. In Chapter 5, 45 trials were used for the regression for each participant. In Chapter 7, just four trials were used from each participant on each target. Thus the regression model in Chapter 7 may be somewhat underpowered for assessing individual parameter contributions.

If this is the case, this issue may be amplified in the regression model for the HEM as the regression model included a larger number of predictors (model parameters). Indeed, the pattern of significant results was incoherent for many parameters. Unlike the PCM, the position output gain was not found to contribute significantly for any target. This may be additionally explained by the presence of three different gains in the model which interact and compete for variance. It may be the case that the parameter regression is unsuitable for assessing the contributions of parameters within a hierarchical structure.

Hypothesis 5.b Individual models predict individual participant performance

In Chapter 5, the PCM made accurate predictions performance, even after one week. To test whether these predictions were individual-specific, we conducted a novel analysis, comparing the fit of individual models to the fit of general (aggregate models). We found that models accurately predicted individual performance. Fits of individual 'self' models to that individuals' tracking data were significantly more accurate than those of aggregate models.

In Chapter 6, we developed three alternative models to the PCM. We evaluated the fit of the models to pseudorandom targets with a loop delay of 200 ms (a biologically plausible sensorimomtor delay value). There was no significant difference in the accuracy of fit between the three models. This established that humans, in general, do not seem to rely heavily on velocity information when tracking targets that move in pseudorandom patterns. A position control strategy may therefore be adequate for tracking pseudorandom targets. Considered alongside the observation that the estimated parameters of the PCM are individual specific (Chapter 5), this may indicate that the PCM parameters adequately predict individual performance. We will consider an alternate explanation in a later section.

In Chapter 6, we also modelled tracking performance for sinusoid targets. For these targets, velocity integration models simulated performance more accurately than the PCM. The additional parameters of these models (the extrapolation gain and velocity control gain) may enable them to characterise elements of the tracking strategy that the PCM did not. The values of these parameters were optimised for each individual. We could not evaluate the accuracy of individual models over time, as the validation data were collected within the same session as the optimisation data.

In the follow-up study reported in Chapter 7, we tested the accuracy of the models to validation data collected one week after the training data. The findings of this study replicated those presented in Chapter 6. The PCM simulated pseudorandom tracking with similar accuracy to the HEM model. It also supported the conclusion that the HEM model was a more accurate model of sinusoid tracking performance; even after one week had elapsed. The 'self-aggregate' analysis of Chapter 7 demonstrated that individual models could account for variance in individual performance one week later with a greater degree of accuracy to an 'aggregate' model. Thus the HEM model was established to make individual-specific predictions of performance.

Both the PCM and HEM model were shown to demonstrate individual specificity for pseudorandom targets when compared to the PCM and HEM. For sinusoid targets the

HEM model and PEM were superior in modelling the general strategy used by participants. The HEM model predicted individual performance for sinusoid targets.

Synthesis

It is clear that individual differences do exist and can be parameterised (Chapter 5). Individual models yield an improvement in fit over general models, even when simulating validation data collected one week later (Chapters 5 and 7). This novel finding provides evidence for the utility of the functional modelling approach used in PCT research (Mansell & Huddy, 2018; Runkel, 1990). This methodology may be utilised across the behavioural sciences to remediate issues concerning replicability (Mansell & Huddy, 2018), as internal consistency measures are inherent to the functional modelling approach. Evaluations of individual specificity may be a useful criterion for model evaluation.

An additional benefit of individual modelling is in its potential application. Indeed it is the objective of this research agenda to apply individual models within the rehabilitation device. Computerised tracking tasks and games have already been implemented in passive and active devices to collect kinematic data, with a view to using these quantitative measures to detect impairments and inform individual rehabilitation programmes (Maciejasz et al., 2014). Further studies have attempted to detect impairments in Parkinson's Disease (PD) with computational models of tracking performance (Abdel-Malek et al., 1988; Allen et al., 2007; Au et al., 2010; Oishi et al., 2010, 2011; Paolo Viviani et al., 2009).

One potential challenge to applying PCT in this manner regards whether impairments can be characterised within the existing model parameters. We have demonstrated that PCT models can characterise healthy human performance in tracking. However, it is unclear whether PCT model parameters would be able to capture specific control characteristics and impairments from tracking performances by neuro-atypical participants. Whilst we have not conducted experiments with such participants, others have simulated tracking data of people with PD and shown that the model parameters can effectively capture characteristic impairments in these populations. For example the models of PD participants tend to be overdamped relative to those of healthy participants (Au et al., 2010; Oishi et al., 2011). Another study modelled eye tracking behaviour of people with a diagnosis of schizophrenia over short occlusions (Adams et al., 2012). These authors showed that relative to neuro-typical participants, individuals with schizophrenia exhibited difficulties in anticipating the target displacement over the occluded period. This was interpreted as representing a lack of integration of prior expectation and was modelled in an AI model. While uncommon, such studies of tracking in neuro-atypical population demonstrate that models may be able to capture impairments within existing parameter estimates. The extrapolation models proposed in this thesis may be able to simulate the pattern of results in these previous studies. For example, the variance in accuracy of participants' tracking over short occlusions could be simulated by manipulating the extrapolation gain parameter. This parameter represents the extent to which participants extrapolate target position, which may be interpreted as the extent to which they can anticipate future target positions.

The next steps in the application of individual models to rehabilitation should involve using models during tasks rather than modelling the data after the task is completed. In this project we aimed to make the first steps toward developing a model that could be implemented in a device. Indeed, the next steps in the current research project aim to test the ability for the models we have developed to drive an end-effector device. This future work is documented further in Section 8.5.2.

8.3.6 Can PCT models incorporating delays account for tracking behaviour for predictable and unpredictable targets?

Biological plausibility should be considered when designing theoretical models of human behaviour. This is particularly relevant for computational models as the fit to experimental data will always improve with additional parameters (Busemeyer & Wang, 2000; Forster, 2000). Human neurophysiology necessitates delays in afferent and efferent signal transmission, in addition to processing delays in hierarchically organised cortical and subcortical brain areas (Carlton, 1981; Carlton, 1992; Scott, 2016). These sensorimotor delays are fundamental to the operation of the CNS and should be represented in the parameters of models of human motor performance. Delay compensation can be observed when humans engage in anticipatory movement (Kowler, Martins, & Pavel, 1979; Noble et al., 1955; Poulton, 1952a; Stepp & Turvey, 2015, 2017). The mechanism of compensation is a focus for scientific debate and research (Scott, 2016). We aimed to model the role of sensorimotor delays in manual tracking and the mechanism by which humans compensate for delays during anticipatory tracking of periodic targets.

Hypothesis 6.a A PCT model with a delay can simulate pseudorandom tracking performance

In the systematic review of the tracking literature (Chapter 4), we found that PCT modelling studies did not include a parameter that characterised sensorimotor delays. Two studies phase-shifted the target pattern post-hoc to account for these delays (Marken, 2013; Pavloski et al., 1990). This left a substantial explanatory gap, as it was unclear whether PCT models would accurately simulate tracking behaviour when delays were included. All three experimental papers in this thesis (Chapters 5, 6 and 7) included a delay parameter. In Chapters 5 and 7, delays were optimised as a free parameter. In Chapter 5 this could take a value between 0 ms and 1 second in 17 ms intervals. In Chapter 7, the parameter could take a minimum value of approximately 182 ms and a maximum of 500 ms. In Chapter 6 models were optimised at 11 delay values that ranged from 17 ms to 500 ms.

When humans track pseudorandom or sum-of-sines targets they exhibit a phase delay in their response (Abdel-Malek & Marmarelis, 1988). This phase delay results from internal sensorimotor delays involved in action execution, with an estimated duration of between 100 ms and 250 ms (see Chapter 6 for summary). Sensorimotor delays have been found to vary between individuals (Viviani et al., 1987). In Chapter 5, we optimised PCMs with an internal sensorimotor delay parameter to pseudorandom tracking performance. Optimal delay estimates differed between individuals, ranging from 140 ms to 240 ms and averaged 180 ms across participants. Thus, our findings support the estimates in the literature. This range resulted in the best fits to tracking data; therefore the PCM demonstrated biological plausibility with regard to sensorimotor delays.

In Chapter 6, the phase delay for pseudorandom targets was approximately 150 ms. The PCM was compared with three alternative models for the fit to these target data. These models utilised velocity information in addition to position information. All models simulated pseudorandom tracking performance equally well up to the previously identified biologically plausible delay estimate of 200 ms, though HEM models produced a phase advance for these targets relative to the participant cursor whereas the PCM did not. For longer delays, the PEM and HEM models showed improved performance relative to the PCM. This suggests that the models are biologically plausible with respect to delays.

Chapter 7 showed a similar pattern of results as Chapter 6. Low and high difficulty pseudorandom targets were both as accurately simulated by the PCM as the HEM. However, the optimal delay durations of the HEM model (which extrapolated position) were longer than those for the PCM (Tables 7.3 and 7.4). The HEM model more accurately simulated the phase delay for pseudorandom targets than the PCM. This is likely because in this study the models were compared at their parameter optima (with a lower limit of 182 ms), the optimum HEM loop delay was over 400 ms; twice the value on which it was compared in Chapter 6, which may explain the phase advance observed for the extrapolation models in that experiment when fit to tracking cursors for pseudorandom targets.

Hypothesis 6.b A PCT model with a delay parameter can simulate sinusoid tracking performance by utilising velocity information

Periodic patterns such as single sinusoids are typically tracked without a phase delay in steady state (Poulton, 1952b, 1952a; Stepp & Turvey, 2017; Viviani & Mounoud, 1990). Average phase delays in our experiments for sinusoid targets were in the range of 14 to 55 ms. Humans must utilise additional information (either immediately from the display, or stored in memory) to compensate for the CNS delay (see Chapter 6). A single unit PCM cannot achieve zero latency tracking with a delay because, in the steady state, increasing the delay value increases the number of samples of phase delay in the response. This was evidenced in Chapter 6 when the PCM simulated sinusoid tracking most accurately when delays were at a minimum value. Simulation error increased as a function of increasing delay. For the HCM (without extrapolation) this same principle extended to the velocity control loop. That is, increasing the delay will have increased the phase delay of the response, increasing error in fit.

This was not the case with the extrapolation models. Linear extrapolation of the target position based on its velocity, and a gain factor, enabled the model to compensate for the sensorimotor delays and track with zero phase delay. This led to improved performance at the critical delay value of 200 ms and longer durations. The PCM and HCM models showed a significant phase delay relative to the participant cursor whereas the PEM and HEM did not. This shows that the PEM and HEM captured a qualitative aspect of tracking behaviour that the other models do not. That is, they typical overshoot and phase delay during target deceleration, and cursor catch-up and overtake it during target acceleration.

Thus in Chapter 6, the PCM and HCM were not sufficient to account for sinusoid tracking when sensorimotor delays were present. In contrast, models that extrapolated target position were able to emulate zero-latency tracking with a biologically plausible delay estimate. These findings were replicated in Chapter 7. The HEM consistently fit sinusoid tracking more accurately than the PCM. However, the loop delay parameters were constrained to a minimum of 182 ms. This was done for several reasons. Firstly, this was the approximated the average loop delay in optimised models in Chapter 5. Secondly, the sample rate (26 ms) would not allow a 200 ms loop delay, therefore we decided to take a more liberal estimate (182 ms) rather than a more conservative one (208 ms). This limit likely negatively affected the PCM accuracy and phase compensation. In future it may be a fairer test of the models to use the lowest sensorimotor delay estimate of 100 ms. However, the fact that the HEM more accurately simulated the phase delay and amplitude ratio of the participant cursor, and did so with an optimised loop delay value of over 400 ms provides evidence that that delay compensation can be achieved in a biologically plausible manner by perceptual extrapolation over long sensorimotor delays.

Synthesis

Position extrapolation is a biologically feasible process that can generalise across the smoothly varying continuous targets that individuals would track in the physical world. The model provides face validity in emulating zero phase delay tracking movements for periodic sinusoid targets whilst maintaining central delay values. For pseudorandom targets a position control strategy may be used with delays of approximately 200 ms. Extrapolation may preserve performance at longer delay values. It may be the case that position extrapolation is used when tracking pseudorandom signals, for a number of reasons.

Firstly, it is unlikely that participants use different strategies for different target types (see section 8.3.3), particularly when the same information is available. Extrapolation is a general strategy that can be used when tracking any smoothly varying target. Secondly, the phase delay can be shorter in duration than the estimated sensorimotor delay even for pseudorandom, as evidenced in both Chapters 6 and 7 for both models. Thirdly, phase delay increases linearly with increasing bandwidth of a sum-of-sines (pseudorandom) target signal (Neilson et al., 1993), this effect is observed in Chapter 7 where high difficulty targets of each target type produced longer tracking phase delays. This indicates that delay compensation reduces as a function of target frequency. As frequency increases, the coherence between the delayed velocity measurement and the current target velocity should decrease. This would reduce the accuracy and usability of position extrapolation. Consequently, increases in target frequency may result in overuse of a position control strategies, increasing the phase delay.

Alternative methods may be plausible, some of which are discussed in Chapter 7, such as matching the frequency and amplitude of a sinusoid or elliptical target. However, no clear neurophysiological analogue or substrate for determining relative frequency was found; nor an identified threshold for how long extraction of frequency information might take. Another possibility is that humans may be able to utilise a phase detector and oscillator in a phase locked loop (Voss, 2000). Phase difference could be estimated from positional difference.

8.3.7 Do PCT models generalise across task designs and apparatus?

The PCT model should generalise across task designs and across different apparatus. This is evaluated as a bi-product of testing the theory. However it is particularly relevant given our intended application to a robotic device with computerised tracking task.

Chapter 4 documents a number of studies that test the generalisability of the PCM across task designs and apparatus; though largely for pseudorandom target and disturbance patterns. The PCT model was demonstrated to emulate participant behaviour in pursuit and compensatory tasks, in both horizontal and vertical dimensions (and simultaneously), with handles, computerised mice and other apparatus. In Chapter 4 we argue that there is limited evidence that PCT models can generalise to robotic control. Whilst some devices have been produced (see Chapter 4 for summary), there are few published studies demonstrating their performance.

In the experimental Chapters, the generalisability of the model was tested as we altered the task and apparatus. In Chapter 5, the PCM accurately simulated pseudorandom target tracking with a computerised joystick.

In Chapter 6, we extended the model to enable it to emulate human tracking of sinusoids when accounting for sensorimotor delays. In Chapter 7 we demonstrated that one extended model could simulate performance for sinusoids and pseudorandom targets when participants tracked targets with a new apparatus (steering wheel) and across the different target difficulty levels (speeds). Thus it seems reasonable to expect that the model could generalise performance on a range of tracking task set ups, albeit with different parameters. The next steps in the research agenda intend to test the models' predictive capabilities with irregular step input signals and occluded sinusoid signals (this will be discussed in a later section).

Synthesis

PCT models have been shown to simulate performance across many tracking environments and apparatus. PCT models have also been applied in domains outside of tracking. One key challenge will be to test whether PCT generalises to device control in physical environments, either in tracking or in other tasks (see Chapter 4).

In the current thesis we did not apply disturbances during target tracking. Disturbances can take the form of visual disturbances to cursor position; as are often implemented in other PCT tracking studies (see Chapter 4), or force disturbances applied to the apparatus during tracking. Findings from many studies have demonstrated that the PCM can compensate for visual disturbances (; Marken, 1986; Marken, 1991; Powers, 1978). Indeed, this is a primary justification for feedback control (Powers, 1978). There is no discernible reason why this would not be the case with models that extrapolate target position, although for completeness this should be evaluated.

Visual disturbances in the literature have been mostly pseudorandom (Marken, 1986; Powers, 1978, 1989). However there may be a specific benefit to applying step changes to hypothetical controlled variables (either in the input target signal or disturbance signal). This stems from the proposal that control units at different hierarchical levels operate at different time constants (Marken, 1990; Powers, 1999). So, if a step change is applied to the velocity of a signal for example, this should be compensated by the velocity control system with a specific time constant. If this time constant is longer than that for the elimination of error in visual position, then this would indicate that velocity is integrated at a superordinate level in the hierarchy relative to position. No difference in delay would indicate that the two systems operate on the same hierarchical level (in parallel). This would help to elucidate the organisation or architecture of control in tracking.

8.4 Summary of findings and key contributions

Together the thesis comprises five chapters of original research which make several key contributions to the fields of psychology and rehabilitation.

At the time of writing Chapter 3, previous research had highlighted distal upper limb end-effector devices as a research priority for two reasons. First, end-effector devices are more practical than alternative devices for rehabilitation due to their simplicity, size and cost (Balasubramanian et al., 2010; Brackenridge, Bradnam, Lennon, Costi, & Hobbs, 2016). Second, results had indicated that reductions in impairment due to distal upper limb training may generalise to improved functional ability (Sivan et al., 2011). Despite this priority, there had been no published review of these devices. Thus the review filled an important gap in the rehabilitation research literature. However, at the time of submission, another group published a very similar article (Veerbeek et al., 2016). This highlights that at that time such a review was needed, and may have been a critical and relevant contribution to the literature had we been able to publish the work.

Chapter 4 represented the first systematic critique of the PCT modelling literature. This was needed as many studies had been conducted, over a long period of time. The studies varied in model design, methodology, and methodological quality. The review highlighted critical limitations of the current evidence base for PCT, summarised in Section 8.3.2. Several of these became research objectives for the current thesis. Others, such as the observation that the PCT architecture does not comprise a mechanism for attenuating the effect of neural noise remain research priorities for further research (discussed further in Section 8.5.2). This review should assist researchers in comparing PCT with other theoretical models of motor control, and may motivate further research to address the current limitations of the PCT model.

Chapter 5 develops a methodological tool for evaluating whether optimised computational models can make idiosyncratic predictions about human performance. This is particularly useful as computational models of behaviour as modern computational methods have enabled psychological research to move from frequentist statistical tests of normative behaviour to predictions of performance that take account of individual differences. Many recent examples of such models exist in cognitive science (for example: Bartlema, Lee, Wetzels, & Vanpaemel, 2014; Lee & Webb, 2005) and in motor control (for example: Foulkes & Miall, 2000; Miall & Jackson, 2006). The methodology offered in Chapter 5 enables researchers to quantify the difference in the predictive power of individually-parameterised models and general models. Individual models such as these may, in future, be used for practical benefit to assess motor or perceptual impairments or biases, which would not be evident simply from a metric of performance accuracy (Allen et al., 2007; Oishi et al., 2010). This is evident as models attempt to separate and independently parameterise the component processes that result in a performance variable. Thus, measuring the reliability and robustness of predictions from these individual parameters, as we have done here, is a valuable procedure. Whilst the method was applied only to PCT models within this experiment, this methodology can be applied to evaluate models across all fields within the behavioural sciences. In Chapter 5, individually-optimised PCT models were shown to simulate performance more accurately than general models, providing evidence that PCT models can capture individual control characteristics within a relatively small number of parameters.

Chapter 6 uses another novel methodology; evaluating model performance over a range of fixed delay values rather than optimising delay as a fixed parameter. This methodology is useful because it enables hypothesised sensorimotor delay compensation mechanisms to be evaluated. This method may be used in a similar manner to test other computational models that make continuous or time-sensitive predictions of human performance, such as models of oculomotor behaviour or reaction time. This is particularly evident for models of anticipatory performance as movements initiated prior the feedback delay time. For example, in visuomotor tasks in which participants utilise the regularity of stimulus onset delays, patterns in spatial location, or other cues to orient movement prior to stimulus onset. Indeed, this was the case in the tracking study addressed in this Chapter. The specific limitation of the previously proposed PCT architecture is that position feedback cannot account for anticipatory tracking movements. It was necessary to introduce feedback control on a novel perceptual signal: extrapolated position. This is a departure from other motor theories that rely on a forward, probabilistic model to produce anticipatory behaviour (Adams et al., 2012; Perrinet et al., 2014). This architecture is relatively simpler, and conforms to known characteristics of the visual cortex: dual encoding of object position and velocity (Krauzlis & Lisberger, 1994; Lisberger et al., 1987), representation of global motion vectors (Aina, Elliveau, Oziers, & Effiro, 1998). Using extrapolation, the model is capable of preserving simulation accuracy to human anticipatory tracking data at increasingly long delay values. This shows that the model, like humans, can engage in anticipatory tracking performance. The model provides evidence against the hypothesis that forward predictions are necessary to compensate for sensorimotor delays or produce anticipatory motor behaviour, an often-cited justification for forward models (Michel Desmurget & Grafton, 2000). The developed model could be adapted for simulation of performance in other motor tasks, including ocular smooth pursuit.

Chapter 7 replicated and extended the findings of the previous two chapters. We found that the best-fitting model from Chapter 6 could compensate for delays and produce anticipatory tracking performance at different target frequencies, and that the model could make idiosyncratic predictions of performance with greater accuracy than general models for all target types. These generalisability tests are a significant validation step for the model, and for the individual-specificity test methodology developed in Chapter 5.

Taken together this thesis addresses several limitations of the PCT literature, but also develops useful methodological tools to be applied across the behavioural sciences. Set within the research agenda, the thesis aims to highlight the potential for motor control theory to inform rehabilitation via the application of computational models and takes the first steps toward this aim.

8.5 Limitations

8.5.1 Tracking and modelling methodology

The first limitation regards the sampling rate for the model simulations. As the sampling rates of the tracking programs were 17 ms and 26ms, data were modelled with this sampling delay. However, this is unrealistically low for the sampling rate of the CNS; it would have been possible to interpolate the target and cursor signals. This could be achieved by zero padding in the frequency domain and applying the Inverse Fast Fourier Transform (IFFT) to generate an interpolated signal in the time domain (similar to how I up-sampled via zero padding in the time domain to get a high frequency resolution in the spectral analysis). This would have allowed us to run the simulations with a sample rate of 1 ms. Had this been performed, it would be possible to find the true optimum delay value by optimising models at 1ms intervals between 1 ms and 500 ms. However, the author's mathematical and programming skills were not sufficiently advanced at this time to have done this. In addition, as access to sufficient computing power was not available, running such simulations would have been a very lengthy process with the resources available. However, given it would have improved the fidelity of the results, it is certainly something to consider in the future

The bandwidth of the input signals was very low across all studies, even for the high difficulty target patterns in Chapter 7. We could have used signals that excited more frequencies. For sinusoids, this could be a sinusoid of single amplitude that changes frequency over the course of the trial. For pseudorandom targets this could be a Fourier series comprising sinusoids of a broader range of frequencies than in our current study. From this tracking data, we could have made more general proposals about performance. However, the analysis would have been more difficult. We would have had to conduct frequency analysis and perform calculations on subsets of the data that fall into component frequencies of the input signal. As parameters are dependent on task constraints, models would have to be fit at excited frequencies on the power spectrum.

In Chapter 5, participants' tracking performance was worse for pseudorandom targets in the second block (post-training) than the first (training). This runs counter to the expectation that, if anything, participant performance should improve as a result of practice. This decrement to performance may be the result of reduced attention or effort in the second block. Participants had only a short break between blocks (if they chose to take it at all), and the experiment was very repetitive as the target type and basic frequency was constant across all the trials. This comparison could not be made in Chapter 6 as participants tracked different target types in each block. In Chapter 7 a relative reduction in performance was not found for any target type between blocks and 2. Conversely, performance tended to improve between experimental blocks. Participants may have remained attentive because the target type and difficulty level changed frequently within blocks and a questionnaire broke up blocks 1 and 2.

One potential limitation is that the models simulated performance for a whole trial, using only the initial cursor positions of the participant. Whilst this shows that models are very capable of tracking the targets in a similar manner to participants, it would also be possible to compare how well the model fit specific sections of target trace given certain initial conditions based on the movements of the participant cursor. For example, given a series of cursor data points immediately before a target switch, how accurately would the model fit the behaviour at the switch point. This might show at which specific points the model was most accurate and give insights toward improving models. A similar exercise may be considered for calculation of phase and amplitude ratios. It is clear that phase differs over the course of a trial, and this may be structured rather than Gaussian, particularly for sinusoid targets. Characterising how phase changes during different points in tracking trials may allow for better models to be constructed.

8.5.2 Computational models

In this thesis, only models based on PCT were designed and tested. It was not our objective to compare PCT models with other motor theoretical models within the tracking task. However it should be considered whether the findings of this thesis are consistent with the predictions of other approaches. Therefore, a number of other theoretical models are compared with PCT below, based on their predictions.

With regard to reference values, referent states are not unique to PCT. However, the references within each theory refer to different constructs. In the Equilibrium Point hypothesis (EP; Shadmehr, 1998) these refer to frames of reference, a shift in the equilibrium point throughout a trajectory that would alter the parameters of the system (Feldman, 2015). This, in turn, alters the properties of the law-constrained variables such as muscle torques (Feldman et al., 2007; Feldman & Levin, 1995). This accounts for the lack of resistive postural forces in response to voluntary action control (Feldman, 2015). In PCT, the reference signals directly quantify intentional states of controlled perceptual variables (Powers, 1973; Powers, 1999). As PCT claims to apply universally, these controlled variables may extend far beyond perceptual variables closely associated with action; such as higher order variables (Powers, 1973). Whilst authors in PCT have described how torque may be produced at the limb to control perceptual distance (Powers, 1999), the PCT models implemented in this thesis are not inconsistent with an EP explanation of referent action. The models used in this thesis output positional coordinate reference. There is a linear relation between the output coordinates and the resultant model cursor position. There is no specification of how this output is translated to actual movements. Therefore it is possible that the reference position shifts an equilibrium point. This could result in changes in the parameters of the physical system and therefore the manner in which it operates under physical laws, resulting in the appropriate torques.

With regard to sensorimotor delays, contemporary theories invoke internal models which produce state estimates for future inputs (Wolpert, 1997). In AI, a hierarchy of control units is proposed that is not dissimilar to PCT (Brown et al., 2011; Friston et al., 2009). However, rather than reference signals, downward projections are predictions of future inputs (Adams et al., 2013). Predictions are validated against prediction errors which are projected back up the hierarchy such that predictions can be optimised. Minimising prediction error equates to free energy minimisation (Brown et al., 2011). Applied to the extrapolation scenario, this mechanism could extrapolate target and cursor position, and then assess the accuracy of the extrapolation. The resulting prediction error would be used to improve the accuracy of future extrapolations. This would equate to a dynamically varying the extrapolation gain during a trial. Models based on AI should enable compensation of the sensorimotor delay during tracking. It is not clear whether participants' extrapolations are optimised in this way. One might assume that if predictions were optimal then the participants would exhibit a constant zero-phase delay during sinusoid tracking. Alternatively, if extrapolations are not optimised dynamically, participants may exhibit alternate phase lead (during target deceleration) and phase lag (during target acceleration). The latter is observed in the data, which might suggest that extrapolations are not optimised in this way. However, no analysis has been conducted to confirm this.

OFCT proposes that the CNS approximates the optimal feedback control law based on the task at hand (Todorov & Jordan, 2002). This involves minimising a cost function by online calculation of possible action effects and selection of an appropriate trajectory (Todorov, 2004; Todorov & Jordan, 2002). The theory adequately simulates a range of movement trajectories that humans take in real tasks, and could no doubt produce accurate simulations of the data presented in this thesis. The main issue is whether it is plausible that the CNS is able to compute the optimal solution to a task from the practically infinite number of possible trajectories (given motor redundancy).

One significant limitation of the experimental work in this thesis is we did not did attempt to explain how sensorimotor and neural noise are attenuated during tracking. Sensors and actuators in living systems are noisy (Barlow & Kaushal, 1987). This noise must be filtered out in order to produce accurate and smooth movements (Scott, 2008). In the experimental work reported in this thesis, models operated in a noise-free environment (no uncertainty regarding the location of the target or cursor). It is likely that if noise were introduced via the addition of Guassian error in the perceptual signal, this would pose a significant challenge to the PCT models. No PCT implementations have been tested with noisy input data, nor has any mechanism for attenuating this noise been suggested within PCT. The development of a mechanistic explanation within PCT must be a priority.

One suitable mechanism for noise attenuation in action control is Bayesian inference (Friston et al., 2010). Bayesian inference recursively predicts the next state, given a probability distribution of previous states (prior). When a new observation is made the probability of attaining this observation, given the prior, is calculated (likelihood). This is used to update the posterior distribution which becomes the prior used to estimate the state in the next recursive step. This is applied in AI (Adams et al., 2012; Brown et al., 2011; Perrinet et al., 2014) to optimise predictions of proprioceptive input (see Section 1.5.2). In addition, Bayesian filters, such as the Kalman filter (Kalman & Bucy, 1961) have been applied in computational models of movement to improve the accuracy of control outputs by reducing the discrepancy between predicted states and measurements, taking account of the reliability of the measurements. Kalman filtering is used in optimal control solutions to motor problems (Todorov, 2004a; Todorov & Jordan, 2002b), including manual tracking in which it has proven a robust method for attenuating the effect of noise on performance (Hoff & Arbib, 1993; Miall & Wolpert, 1996; Saunders & Knill, 2004). However, although humans produce near optimal trajectories, it is unclear whether the CNS can compute optimal control solutions like this (Markkula, Boer, Romano, & Merat, 2018).

It may be possible that simpler, less powerful weighted average methods might be applicable, that do not require as many assumptions. For example, increasing the interval over which velocity is calculated within proposed PCT model would give a measurement more robust to sensor noise (provided a Guassian distribution of noise). However, target acceleration would make calculations over longer intervals inaccurate. Thus the optimal balance of noise reduction and relevant measurement must be found. This is the advantage of the Bayesian inference method in which the prior distribution is centred on the immediate previous measurement, but also sets a gain that optimally controls the relative contribution of the prediction based on the distribution of the measurement error.

Another alternative explanation sees human sensorimotor control as intermittent rather than continuous. In this view, a ballistic movement is initiated once the error (or time since the last movement) has exceeded a threshold (Gawthrop & Wang, 2011; Gollee et al., 2017; van de Kamp, Gawthrop, Gollee, & Loram, 2013). This hypothesis has recently been extended by a model which combines classical control theoretic foundations and incorporates prediction error-based evidence accumulation thresholds, and motor primitives (Markkula et al., 2018). Motor primitives are defined as a repertoire of stereotyped movement patterns that are scaled and combined, and are thus independent of mass (Giszter, 2015). The model performs well in tracking in the presence of sensor and motor noise (Markkula et al., 2018), and may be an appropriate alternative mechanism to compensate noise that does not rely on optimal control principles. Indeed, the mechanisms outlined above may prove useful when considering how PCT models might simulate neural noise attenuation. This would improve the biological plausibility of the theory.

Critically, the models implemented in this thesis aim to simulate the perceptual process. They do not offer an explanation for how motor execution is achieved. They attempt to determine which perceptual variables are controlled in the task but not how this control is achieved biomechanically. Thus we cannot make assertions regarding the mechanism based on our findings. However, the position extrapolation strategy proposed in this thesis appears to simulate the most fundamental aspects of the participant's tracking movements, with a very simple and biologically feasible scheme. Indeed, a key criticism of negative feedback control approach has been that the presence of sensory delays invalidates the control command. As we have shown, this is not necessarily the case. If the right perceptual variable is controlled to a reference value, sensory delays can be compensated without an internal model.

In the hierarchical models implemented in this thesis, the delay values at each level were equivalent. This is an intentional simplification. Ascending levels of the PCT hierarchy are proposed to operate at longer delays than subordinate units (Marken, 1990; Powers, 1999). In this way, the reference values for subordinate control units vary faster than those in the level above, and therefore have time to meet their respective reference values. It is uncertain how this simplification may have affected the operation of the hierarchical models in these experiments.

It would also be possible to extrapolate cursor position using the same linear method (Pavel et al., 1992); this could then be compared with extrapolated target position in the position controller. This is justified by the same evidence that supports target extrapolation (Fine et al., 2014; Khoei et al., 2013; Makin, Poliakoff, Chen, & Stewart, 2008; Pavel et al., 1992; Rosenbaum, 1975; Zago et al., 2010). However, this was not implemented as we wished to differentiate motor prediction from emergent predictive behaviour through sensory integration. PCT proposes that perceptions, not actions, are controlled. As described in the introduction (Chapter 1), this differentiates PCT from other contemporary motor theories which state that forward or inverse internal models are used to predict either the effect of action from the motor command (Adams et al., 2013; Brown et al., 2011), or derive the appropriate motor command from the action effect (Wolpert, Ghahramani, & Jordan, 1995; Wolpert & Kawato, 1998). Cursor extrapolation could be the result of a perceptual process (summation of visual representations of velocity and position), but could also be explained by motor prediction approaches. That is, that the extrapolated cursor position is a prediction of the future position of the cursor based on an efference copy of the motor command to the arm (Desmurget & Grafton, 2000; Grush, 2004). Thus, we did not implement cursor extrapolation in models, as we aimed to demonstrate that delay compensation was in the tracking task was a result of a perceptual process rather than via internal feedback (motor prediction).

8.6 Future research suggestions

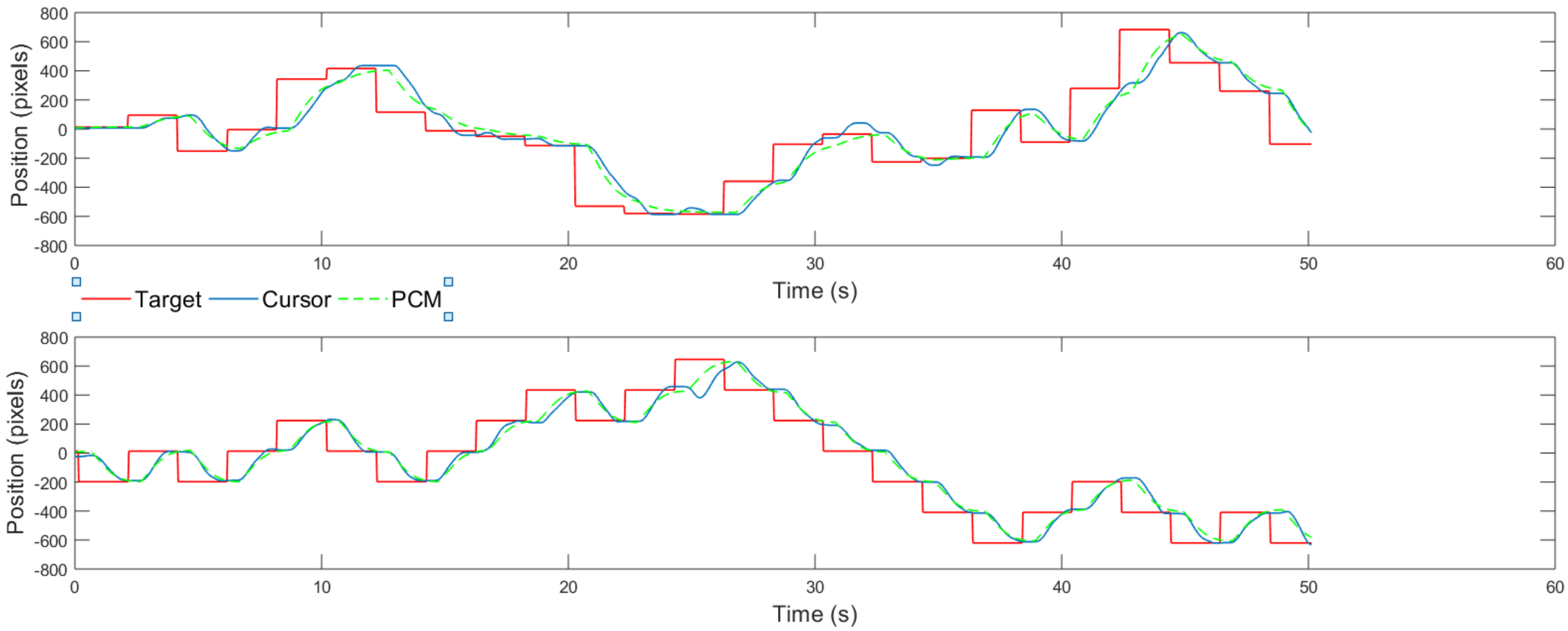
8.6.1 Concerning objectives of the thesis: Proof-of-principle for Perceptual Control Theory

The immediate research priority is to systematically evaluate whether the HEM model can simulate the data that we have collected that has not been analysed within this thesis which were collected on two target signal types: irregular steps and sinusoids with a visual occlusion for the last 20% of the trace. These were chosen to elucidate the distinction between anticipation or prediction and position feedback. For irregular step signals, there is no change in target velocity or acceleration. Instead, there is an instantaneous position change in an unknown direction (though the timing of each step is constant). We expect that models can therefore use only a position control strategy (the extrapolation gain would become zero in the HEM model).

A pilot analysis shows that the PCM model has face validity in characterising performance as it appears to replicate the characteristics of the movement (Figure 8.2). Moreover, the simulation accuracy in this example data is comparable to model fits to sinusoid and pseudorandom targets. In the depicted trials, model simulation error rates (RMSE) were 53.34 (top) and 36.46 (bottom), comparatively, participant tracking errors 195.65 (top) and 163.32. Thus whilst participants may produce larger errors in tracking, model fit values may be in a similar range to those for smoother target signals. I have conducted no statistical analyses on step signal data; these results are purely for demonstrative purposes.

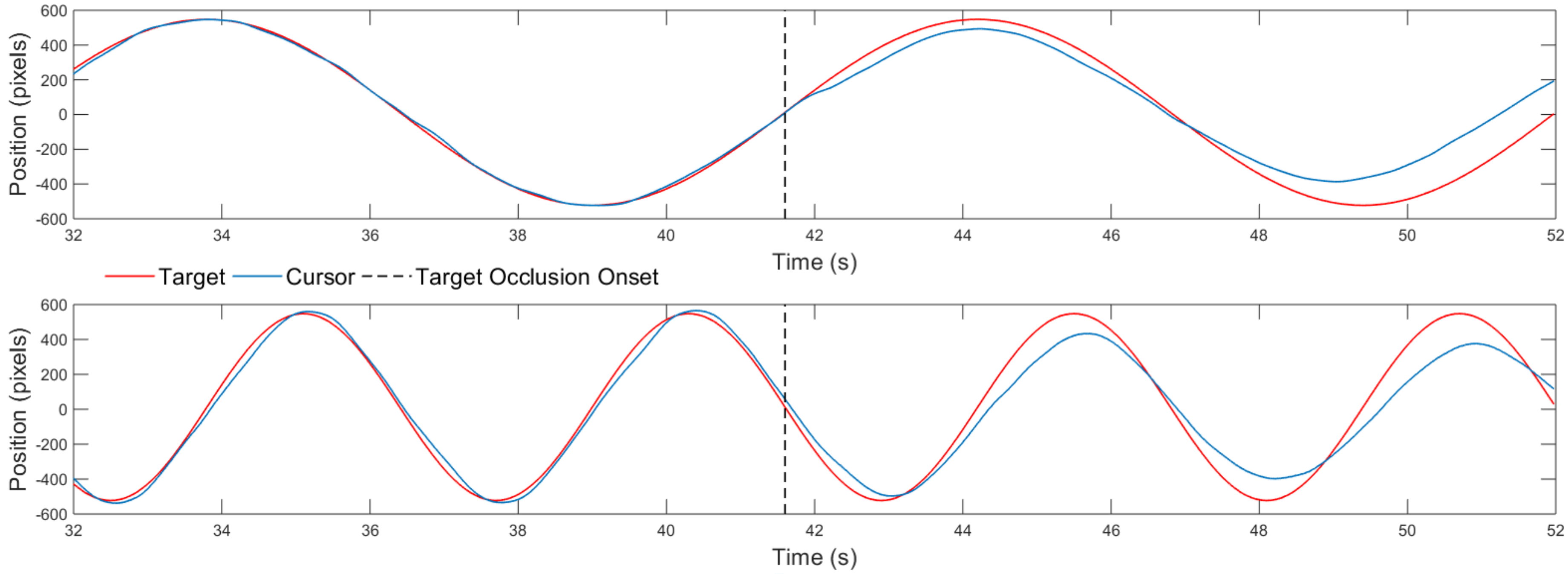
In the case of step signals, participants would not be able to use extrapolation because the velocity is constant until an instantaneous step appears. Individuals must only use a position control strategy (the extrapolation gain is reduced to zero). In this task we would predict no benefit in accuracy for models that utilise velocity over the standard PCM. A second reason to test the model on these targets arises because others have hypothesised that for discrete movements to unexpected targets, the feedback gain increases to the midpoint of the trajectory and decreases toward the end of the trajectory (Dimitriou, Wolpert, & Franklin, 2013), producing a bell-shaped velocity profile (Hogan & Flash, 1987). This is not represented in PCT models in this thesis. In these models, the output gain is static as a result of the optimisation procedure. However, the value of gain parameters (and other parameters) is proposed to vary during motor learning. This is very different to the prediction that the parameters change rapidly during movement based on the current task state (Crevecoeur & Scott, 2014; Scott, 2013). This should be built into future models.

Figure 8.2 Graphs of two 52 s segments of step input tracking trials and PCM model-simulated



Visual occlusions during sinusoid tracking pose a different challenge. Over the target occlusion, the participant receives no visual input for the target position over the occluded period. Despite this, participants can continue to track the target using their memory of the previous target trajectory, although with some decrement to performance over the occluded period (as shown in Figure 8.3). For short occlusions of a few hundred milliseconds, the extrapolation strategy might reasonably accurately emulate the participant's behaviour. When the target disappears then the model would continue to track for the duration of the delay parameter following occlusion (as the model is using previous input). For longer occlusions in which whole cycles of the sinusoid are occluded (Figure 8.3), the extrapolation model would not adequately capture this behaviour. A computational model of occluded tracking performance would require longer term storage of the frequency and amplitude of the target signal which must be used as inputs to the system; albeit with some error of recall or memory 'noise'. It would be interesting to establish whether participants consistently over- or under- represent the target trajectory at different sinusoid speeds.

Figure 8.3 Graphs of of a high and a low difficulty sinusoid target occlusion trial. Depicted segments are 20 s in duration with an occlusion beginning at 10 s (42 s on graph axes)



As mentioned in an earlier section (8.4.2), it would be useful to compare different theoretical models with PCT models within the tracking environment. The tracking task could use a range of target patterns, perhaps in two dimensions. This would enable functional evaluations of the merits of different theoretical models.

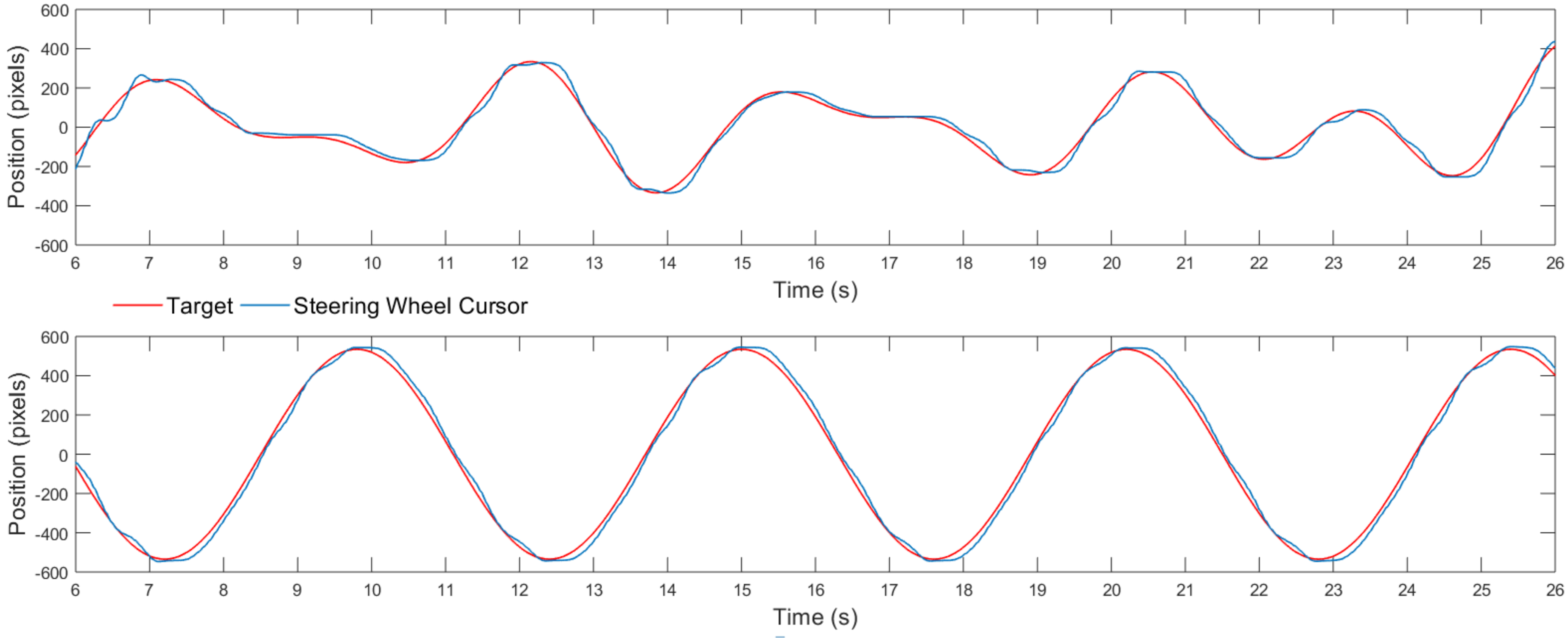
8.6.2 Toward development of a device for rehabilitation

The current project intended to test the proof of principle for PCT to be applied to a robotic rehabilitation device (Figure 8.1). We have extensively demonstrated that a model can characterise and simulate healthy human performance in a one-dimensional task with a one DoF device (joystick *y* dimension or steering wheel rotation). However, a number of key considerations must be addressed in further research studies if the model is to be applied in this setting.

The first question is whether a PCT model can drive a device to track a target accurately. We have developed a model that will drive a force feedback steering wheel to track a target in one dimension, with the type and difficulty level of tracking signals presented in this thesis. Pilot data appear to show that it can track with comparable accuracy to a healthy human participant (Figure 8.4). In the depicted trials the tracking error produced by the model were 46.35 (pseudorandom high difficulty) and 35.25 (sinusoid high difficulty). These are substantially more accurate than human RMSE errors for these targets, which averaged around 80 (pseudorandom high difficulty) and 50 (sinusoid high difficulty) respectively (Figure 7.6). However, we have not trained the model with a systematic optimisation method, or algorithm, and therefore cannot currently establish the maximum accuracy of the model when tracking targets. Nor have we collected enough data to make statistical comparisons. Even if the model is as accurate (or more accurate) than participants, it is unclear whether it tracks in the same way. Phase and amplitude ratio comparisons would elucidate this.

We chose the steering wheel used in this study because it could produce enough torque to turn the force feedback steering wheel whilst a human participant was using it (see device specifications, Chapter 2). However we have not, to date, attempted to evaluate whether the model can drive the steering wheel to track accurately when a human is exerting force on the steering wheel. The steering wheel must be able to do this in order to assist or resist individuals in tracking the target accurately.

Figure 8.4 A demonstrative sample of the HEM driven steering wheel (manually optimised) tracking pseudorandom (top) and sinusoid (bottom) targets (20 s segments)



One intended aim of the research agenda is to establish whether we can emulate individual performance, with the model-driven steering wheel, in the same manner as we have demonstrated with the software models. This would require extensive optimisation of the model to find parameters that characterise the individual's control characteristics, rather than finding an optimal parameter combination for tracking accuracy (see earlier point regarding characterising impaired performance, Section 8.3.2). This would require real-time optimisation. That is, the steering wheel would have to track the target many times and alter its parameters until it most accurately simulates that individual's tracking performance for the target. We have not yet produced an optimisation algorithm that will do this. However, models of optimisation based on the PCT reorganisation algorithm have been demonstrated within software and hardware environments. For example, a reorganisation algorithm was developed for real-time reorganisation of a virtual robotic arm (Powers, 2008).

Critical to rehabilitation device development is whether the device training is efficacious, in terms of reducing impairment, but also improving functional abilities and increasing use of affected limbs (see Chapter 3). In the review of tracking devices for hand and wrist training (Chapter 3), we established that devices that train distal upper limb movements may be more effective than those training proximal upper limb movements. We used two devices in the experiments presented within this thesis: a joystick and a steering wheel. Whilst both devices support shoulder movements in a number of dimensions, the steering wheel primarily supports forearm pronation and supination. On the other hand, the joystick supports some wrist and elbow flexion and extension if used in the forward/backward (y) axis; and forearm pronation and supination in the left/right (x) axis. Whilst the latter can clearly train more different movement DoF, this is not the only relevant consideration.

Firstly, the range of movement may be important and is much more restricted with the joystick than with the steering wheel. (See device specifications; section 2.4). Secondly, authors have suggested that devices may be more effective at improving functional and activity related outcomes if they train ADL-relevant movements (Balasubramanian, Colombo, Sterpi, Sanguineti, & Burdet, 2012). The steering wheel has the obvious application to driving, whereas the possible applications for the joystick are less clear However, the current tracking task is not task-relevant and thus the tracking environment may be adapted: for example with pick and place reaching tasks with the joystick or with driving simulations with the steering wheel. The latter may be particularly beneficial to enhancing road safety. Training may benefit individuals before they embark on relearning driving in real vehicles. In addition, the steering wheel supports both uni-manual and synchronous bimanual training, whilst the joystick supports only uni-manual training. It is important to consider whether bimanual training confers additional benefits relative to uni-manual training; a systematic review and meta-analysis of bimanual devices concluded that there is insufficient evidence to suggest that bimanual training conferred additional benefit over uni-manual training. However there were only a small number of studies of methodological quality and sufficient sample size from which to draw such conclusions (van Delden et al., 2012). Judging which device would be more appropriate for rehabilitation is a difficult task and there may be no clear answer. Most likely, it would be dependent on the needs of the individual using the device. That said, the joystick supports a larger range of movements, particularly if used in both dimensions at once (with a two-dimensional tracking task).

8.7 Conclusions

This thesis completed the first two phases of a research agenda oriented towards testing the proof-of-principle of applying PCT to robotic rehabilitation. Integrating theory with application required a multidisciplinary research agenda. This was predicated on the development and testing of a handheld robotic rehabilitation device, used in a tracking environment and driven by an adaptive PCT-based controller. As this was a completely novel application of the theory, the preliminary steps were to assess both the efficacy of robotic devices for hand rehabilitation, and to evaluate the state of the evidence for PCT models within tracking experiments. In the first phase we completed two systematic reviews. In a first systematic review we found that RT reduced impairment in the upper limb and increased functional abilities for stroke patients. Thus we concluded that distal upper limb RT is a promising approach for neurorehabilitation. The second review indicated that most PCT tracking studies fit a canonical PCM to performance. This model performed well in replicating tracking behaviour for pseudorandom targets and disturbances. However, it did not include any delay, nor was there evidence of fit to anticipatory behaviour. Whilst the theory promoted a functional (individual) modelling approach, it had not been assessed whether models' predictions were individual-specific.

In three experimental chapters we addressed these objectives by constructing models of individual tracking performance, and completed phase two of the research agenda. Addressing the objectives, we distilled a model, based on PCT that would be biologically plausible, functionally generalisable and individual-specific. This model could then be implemented to drive the robotic device. The outcome was a model that extrapolated position by using velocity information within a hierarchical control structure. This model generalised across target types and speeds, replicating individual participant behaviour in the tracking task whilst maintaining biologically feasible sensorimotor delay duration. This demonstrated the utility of the perceptual control approach to tracking. Future work will intend to implement this model within a robotic device. The device would assist or resist an individual's movements in a tracking environment, adapting to their needs based on their individual control characteristics. We intend to evaluate the potential for neurorehabilitation with this device as per the outlined research agenda.

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Appendices

Appendix A Edinburgh Handedness Inventory Short Form (Veale et al. 2014)

Edinburgh Handedness Inventory - Short Form

Please indicate your preferences in the use of hands in the following activities or objects:

	Always right	Usually right	Both equally	Usually left	Always left
Writing					
Throwing					
Toothbrush					
Spoon					

<u>Scoring:</u>

For each item: Always right = 100; Usually right = 50; Both equally = 0; Usually left = -50; Always
left = -100

To calculate the Laterality Quotient add the scores for the four items in the scale and divide this by four:

Writing score	
Throwing score	
Toothbrush score	
Spoon score	
Total	
Total ÷ 4 (Laterality Quotient)	

Classification:	Laterality Quotient score:
Left handers	-100 to -61
Mixed handers	-60 to 60
Right handers	61 to 100

Veale, J. F. (2014). Edinburgh Handedness Inventory - Short Form: a revised version based on confirmatory factor analysis. *Laterality*, *19*(2), 164–77. doi:10.1080/1357650X.2013.783045

Appendix B Model AIC values and optimal parameters at each loop delay value, and their uncertainties (Chapter 6): Pseudorandom targets

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Position Control Model (PCM)														
17 ms	33940.42	2246.01	6.33	2.12	-0.42	3.55	0.05	0.07						
50 ms	33851.29	2265.04	6.18	2.03	-0.42	3.55	0.05	0.07						
100 ms	33716.12	2296.70	5.92	1.87	-0.43	3.56	0.06	0.07						
150 ms	33582.54	2333.51	5.60	1.52	-0.44	3.57	0.06	0.06						
200 ms	33507.16	2352.08	5.18	1.14	-0.45	3.59	0.06	0.06						
250 ms	33706.51	2270.50	4.62	0.80	-0.47	3.63	0.07	0.06						
300 ms	34370.73	2059.38	4.04	0.57	-0.51	3.77	0.08	0.06						
350 ms	35441.54	1881.13	3.52	0.42	-0.57	4.01	0.09	0.06						
400 ms	36678.90	1715.39	3.10	0.35	-0.74	4.45	0.11	0.08						
450 ms	37911.79	1640.77	2.76	0.30	-0.89	5.06	0.13	0.09						
500 ms	39084.59	1618.95	2.47	0.28	-1.07	5.98	0.16	0.11						

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Position Extrapolation Model (PEM)														
17 ms	33940.79	2246.35	6.18	2.01	-0.41	3.58	0.05	0.07	0.45	3.88				
50 ms	33851.58	2265.07	5.96	1.87	-0.41	3.58	0.05	0.07	0.58	4.06				
100 ms	33691.37	2304.31	4.70	1.87	-0.40	3.62	0.04	0.05	7.21	17.24				
150 ms	33452.22	2375.38	3.04	1.67	-0.40	3.68	0.03	0.03	19.10	21.86				
200 ms	33204.26	2456.46	2.32	1.23	-0.44	3.72	0.03	0.03	22.86	16.80				
250 ms	33050.44	2483.49	2.13	0.91	-0.48	3.77	0.04	0.03	23.36	13.12				
300 ms	33180.51	2409.27	2.05	0.64	-0.51	3.90	0.04	0.03	23.03	10.95				
350 ms	33710.42	2254.41	1.93	0.60	-0.60	4.11	0.05	0.04	24.50	10.16				
400 ms	34571.39	2091.37	1.75	0.45	-0.70	4.47	0.06	0.04	26.80	8.99				
450 ms	35595.72	1975.10	1.55	0.43	-0.84	5.01	0.07	0.05	31.02	9.55				
500 ms	36753.67	1852.19	1.39	0.39	-0.86	5.94	0.08	0.06	34.76	9.66				

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Hierarchical Control Model (HCM)														
17 ms	33939.65	2243.00	965.71	158.57	-0.41	3.56					2.21	18.61	0.05	0.07
50 ms	33850.52	2261.84	963.23	168.49	-0.41	3.55					0.70	5.74	0.05	0.07
100 ms	33715.15	2292.83	946.58	199.68	-0.42	3.56					0.37	3.22	0.06	0.07
150 ms	33581.07	2327.54	880.03	302.89	-0.43	3.57					0.63	2.81	0.06	0.06
200 ms	33500.25	2346.27	487.59	471.53	-0.45	3.58					2.54	4.07	0.06	0.06
250 ms	33555.78	2323.23	59.63	223.99	-0.46	3.59					10.32	6.95	0.06	0.06
300 ms	33785.88	2247.65	1.39	13.20	-0.46	3.61					18.03	6.96	0.06	0.05
350 ms	34246.89	2119.10	0.19	0.11	-0.46	3.66					22.88	6.63	0.06	0.05
400 ms	34918.27	1954.29	0.15	0.15	-0.48	3.73					26.64	6.13	0.06	0.05
450 ms	35726.33	1806.82	0.11	0.06	-0.50	3.85					29.17	5.84	0.07	0.05
500 ms	36726.74	1736.58	0.09	0.05	-0.50	4.17					30.57	5.75	0.07	0.05

Delay	*AIC* Mean	SD	Pgain M	SD	Pref M	SD	Pdamp M	SD	Xgain M	SD	Vgain M	SD	Vdamp M	SD
Hierarchical Extrapolation Model (HEM)														
17 ms	33940.00	2243.32	964.36	157.16	-0.40	3.57			0.41	3.44	0.16	1.84	0.05	0.07
50 ms	33851.41	2261.80	951.83	185.41	-0.40	3.58			0.92	5.64	0.05	0.47	0.05	0.07
100 ms	33690.95	2300.68	797.29	307.50	-0.40	3.60			11.02	19.81	0.43	4.82	0.04	0.05
150 ms	33451.58	2370.90	651.27	321.19	-0.40	3.67			18.35	20.75	0.13	0.67	0.03	0.04
200 ms	33202.92	2452.43	476.52	280.52	-0.42	3.72			21.97	16.33	0.23	1.10	0.03	0.03
250 ms	33030.45	2486.30	225.62	228.01	-0.46	3.76			23.76	13.09	2.48	4.50	0.03	0.03
300 ms	32987.12	2475.58	59.40	124.61	-0.51	3.83			24.43	11.57	9.87	8.90	0.04	0.03
350 ms	33071.62	2431.85	6.90	39.76	-0.53	3.91			27.30	11.52	18.28	10.60	0.04	0.03
400 ms	33335.83	2332.01	3.68	24.33	-0.56	4.01			30.62	11.13	25.05	9.96	0.04	0.03
450 ms	33809.28	2194.73	3.13	19.93	-0.61	4.19			35.29	10.49	29.29	9.61	0.04	0.03
500 ms	34529.16	2018.75	3.61	27.31	-0.53	4.56			39.49	9.55	31.96	8.35	0.04	0.03

Appendix C Model AIC values and optimal parameters at each loop delay value, and their uncertainties (Chapter 6): Sinusoid targets

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Position Control Model (PCM)														
17 ms	34545.81	2028.73	27.70	26.57	1.12	4.19	0.15	0.29						
50 ms	34559.44	2028.62	19.91	10.62	1.12	4.19	0.12	0.20						
100 ms	34640.68	2028.60	13.73	3.70	1.11	4.18	0.08	0.11						
150 ms	34862.99	1993.23	10.22	1.36	1.04	4.14	0.06	0.08						
200 ms	35227.99	1936.27	8.04	0.58	1.08	4.08	0.06	0.06						
250 ms	35756.61	1833.48	6.46	0.37	0.95	4.09	0.06	0.05						
300 ms	36378.70	1721.65	5.39	0.27	0.87	4.08	0.06	0.05						
350 ms	37032.15	1598.72	4.65	0.19	1.12	4.13	0.06	0.04						
400 ms	37712.57	1468.24	4.08	0.14	1.18	4.18	0.07	0.04						
450 ms	38371.21	1342.88	3.64	0.10	1.60	4.28	0.07	0.04						
500 ms	39099.21	1363.24	3.27	0.17	1.06	4.41	0.08	0.04						

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Position Extrapolation Model (PEM)														
17 ms	34526.92	2023.12	8.26	7.21	1.15	4.24	0.03	0.08	16.59	22.61				
50 ms	34521.74	2022.59	4.97	4.49	1.15	4.22	0.02	0.05	25.91	25.19				
100 ms	34514.00	2022.73	5.15	4.80	1.16	4.23	0.03	0.04	24.82	23.95				
150 ms	34509.19	2025.52	4.66	3.56	1.15	4.25	0.03	0.03	22.42	21.27				
200 ms	34503.43	2027.41	5.12	2.92	1.12	4.26	0.04	0.04	18.06	20.30				
250 ms	34505.55	2024.89	4.05	2.27	1.11	4.27	0.05	0.04	21.60	21.02				
300 ms	34506.28	2027.72	3.48	1.80	1.13	4.29	0.05	0.04	22.99	19.98				
350 ms	34504.09	2024.01	3.08	1.52	1.12	4.31	0.06	0.03	25.16	20.46				
400 ms	34500.35	2025.23	2.68	1.20	1.16	4.36	0.06	0.03	26.68	18.90				
450 ms	34464.66	2033.91	2.71	1.03	1.28	4.29	0.06	0.03	24.96	17.61				
500 ms	35005.15	2160.84	2.20	0.87	1.60	4.51	0.08	0.03	29.68	15.74				

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Hierarchical Control Model (HCM)														
17 ms	34548.39	2028.86	268.82	347.91	1.12	4.20					34.53	56.70	0.14	0.27
50 ms	34567.64	2028.86	383.45	405.30	1.12	4.19					8.66	17.23	0.11	0.19
100 ms	34653.90	2027.84	126.20	236.46	1.13	4.19					4.81	8.86	0.07	0.11
150 ms	34873.33	1994.26	76.53	208.68	1.08	4.15					4.54	6.06	0.06	0.08
200 ms	35213.83	1937.01	10.60	69.90	0.93	4.15					6.04	3.94	0.06	0.07
250 ms	35685.26	1850.65	1.10	0.41	0.95	4.13					7.22	3.77	0.05	0.06
300 ms	36234.05	1746.47	0.85	0.35	1.02	4.11					8.16	4.49	0.05	0.05
350 ms	36835.54	1630.09	0.81	0.47	1.16	4.14					7.22	3.56	0.05	0.04
400 ms	37427.87	1518.65	0.56	0.21	1.16	4.27					8.79	3.59	0.05	0.04
450 ms	38048.73	1417.06	0.49	0.21	1.38	4.34					9.31	4.17	0.06	0.04
500 ms	39131.16	1681.44	0.39	0.21	1.07	4.49					11.51	6.78	0.07	0.03

	AIC		Pgain		Pref		Pdamp		Xgain		Vgain		Vdamp	
Delay	**Mean**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Hierarchical Extrapolation Model (HEM)														
17 ms	34527.37	2023.65	216.38	321.06	1.14	4.24			12.11	17.94	12.89	36.53	0.03	0.09
50 ms	34521.92	2022.95	197.91	322.02	1.15	4.22			20.65	21.50	9.32	20.50	0.03	0.06
100 ms	34514.66	2024.44	143.83	276.12	1.16	4.22			20.03	20.95	8.89	18.85	0.04	0.07
150 ms	34505.58	2025.53	100.75	217.67	1.15	4.22			17.85	18.93	6.32	13.28	0.04	0.06
200 ms	34495.72	2029.05	93.20	172.39	1.17	4.24			16.30	17.83	5.37	11.76	0.04	0.05
250 ms	34492.13	2026.91	77.87	131.25	1.17	4.24			18.63	17.96	6.39	12.20	0.04	0.04
300 ms	34490.70	2028.71	74.81	113.13	1.14	4.28			18.85	16.86	6.10	12.37	0.05	0.04
350 ms	34467.85	2039.51	69.01	123.40	1.22	4.29			19.87	16.98	4.93	8.81	0.05	0.04
400 ms	34474.49	2033.07	48.65	72.63	1.17	4.33			20.65	15.52	6.93	11.40	0.06	0.04
450 ms	34464.49	2030.16	63.56	96.77	1.23	4.33			21.95	14.83	5.60	10.07	0.07	0.03
500 ms	34554.32	2005.92	17.71	47.31	1.64	4.46			22.94	12.74	10.98	11.07	0.07	0.03

Appendix D Results of parameter mixed model regression for all models (Chapter 6): Pseudorandom targets

Control Model	**Regression Model**	**Parameter**	**Coefficient**	***p***	**95% Confidence Interval**		***AIC***	**Participant Variance**
					Lower	**Upper**		
PCM	Linear	Input Delay	0.05	< .001	0.04	0.05	-12453.40	.073
		Intercept	16.29		14.38	18.20		
	Quadratic	Input Delay	-0.06	< .001	-0.07	-0.05	-12220.00	.086
		Input Delay^2	0.00	< .001	0.00	0.00		
		Intercept	24.70		22.55	26.85		
HCM	Linear	Input Delay	0.02	< .001	0.02	0.02	-11795	.097
			19.29		17.45	21.13		
	Quadratic	Input Delay	-0.03	< .001	-0.04	-0.02	-11709.2	.103
		Input Delay^2	0.00	< .001	0.00	0.00		
		Intercept	23.48		21.45	25.52		
PEM	Linear	Input Delay	0.02	< .001	0.02	0.02	-11690.1	.086
		Intercept	18.87		17.11	20.63		
	Quadratic	Input Delay	-0.05	< .001	-0.06	-0.03	-11543.3	.095
		Input Delay^2	0.00	< .001	0.00	0.00		
		Intercept	24.20		22.27	26.14		

Control	Regression				95% Confidence Interval			
Model	Model	Parameter	Coefficient	*p*	Lower	Upper	*AIC*	Participant Variance
HEM	Linear	Input Delay	0.00	< .001	0.00	0.01	-11531.5	.057
		Intercept	20.57		18.89	22.25		
	Quadratic	Input Delay	-0.02	< .001	-0.04	-0.01	-11501.8	.058
		Input Delay^2	0.00	< .001	0.00	0.00		
		Intercept	22.89		21.02	24.76		

Appendix E Results of parameter mixed model regression for all models (Chapter 6): Sinusoid targets

Control Model	Regression Model	Parameter	Coefficient	p	95% Confidence Interval Lower	95% Confidence Interval Upper	AIC	RE proportion of variance
PCM	Linear	Input Delay	0.06	< .001	0.05	0.07	-14554.50	.103
		Intercept	21.27		17.74	24.79		
	Quadratic	Input Delay	0.01	< .001	-0.02	0.03	-14537.60	.104
		Input Delay^2	0.00	< .001	0.00	0.00		
		Intercept	25.54		21.41	29.68		
HCM	Linear	Input Delay	0.05	< .001	0.04	0.05	-13483.76	.147
		Intercept	21.97		19.08	24.85		
	Quadratic	Input Delay	-0.01	.583	-0.03	0.01	-13454.31	.150
		Input Delay^2	0.00	< .001	0.00	0.00		
		Intercept	26.24		22.98	29.50		
PEM	Linear	Input Delay	0.00	.921	0.00	0.00	-11749.67	.254
		Intercept	26.27		24.10	28.45		
	Quadratic	Input Delay	0.00	.924	-0.01	0.01	-11747.67	.254
		Input Delay^2	0.00	.942	0.00	0.00		
		Intercept	26.24		23.89	28.59		

					95% Confidence Interval			
Control Model	**Regression Model**	**Parameter**	**Coefficient**	***p***	**Lower**	**Upper**	**AIC**	**RE proportion of variance**
HEM	Linear	Input Delay	0.00	.358	0.00	0.00	-11854.45	.233
		Intercept	25.99		23.85	28.14		
	Quadratic	Input Delay	0.00	.876	-0.01	0.01	-11854.29	.233
		Input Delay^2	0.00	.687	0.00	0.00		
		Intercept	26.18		23.85	28.52		