

GENERALISATION IN HUMAN MOTOR LEARNING: EXPERIMENTAL AND MODELLING STUDIES

by

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ABSTRACT

Humans can interact with their environment by tuning the properties of the musculoskeletal system to control force and impedance at the contact points with the environment. Many activities that require the use of tools, such as handling a screwdriver or a chisel, involve an unstable interaction with the environment. This instability will amplify any disturbance or noise and cause unpredictable motion. For example, when chiselling a piece of rough wood, motor noise or involuntary movements can make the hand slip out of the desired track. When a single reaching movement is repeated in unstable dynamics, the central nervous system (CNS) learns to compensate for the instability by coordinating muscles in an appropriate way. However, it is still unclear how humans can learn to perform unstable tasks in various directions. Do they co-contract in an isotropic way to ensure good performance in all directions, or do they learn direction specific impedance? And what are the underlying processes of this adaptation?

This thesis addresses those questions through psychophysical experiments in which arm movements were investigated as subjects interacted with computer controlled dynamics produced by a robotic interface, as well as by developing computational models of human motor learning. Observations of learning unstable dynamics simultaneously in two different directions show that the CNS is able to compensate for the instability specifically for each direction, by adapting impedance optimally to the environment.

A computational model was developed to simulate human reaching movements in stable and unstable dynamics in various directions of the workspace. The model learns feedforward muscle tension by minimising movement error in muscle space and energy. The computer model is a useful tool to predict and investigate (generalisation in) motor learning. It can predict the results of our experiment as well as many motor learning observations in past experiments.

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Chapter 1

INTRODUCTION

1.1 Motivation

Humans have the distinctive ability to handle different tasks while compensating for external disturbances. For example, when we use tools such as chisels, drills and screwdrivers, we need to compensate for the forces to produce the intended movement while adapting with the interaction forces and the intrinsic instability of these tasks. Due to the rigidity of the material and the intrinsic motor noise, any misdirected force can cause loss of contact between the chisel and the surface.

How are humans able to learn using such tools skilfully? Recent work investigating the adaptation to lateral instability in one repeated reaching movement (Burdet et al. 2001) has shown that the central nervous system (CNS) can learn to compensate for the instability independently of endpoint force. Control of mechanical impedance (i.e. the resistance to perturbations) of the arm was predicted by (Hogan et al. 1985), but experimental evidence was provided only recently (Burdet et al. 2001). Extending the results of (Burdet et al. 2001), Franklin and colleagues (2007) demonstrated that the CNS could selectively activate suitable antagonist muscle pairs to match instability in various directions, and suggested that reflexes may be involved in this impedance control.

However, these previous studies have only examined movements in one direction of the workspace, while for example a carpenter sculpting a piece of wood would use the chisel in multiple directions and in a continuous manner (Figure 1.1.1). This is the central question this thesis will investigate. That is, how can the CNS adapt in this unstable environment with varying position and velocity? Can the CNS tune force and stiffness selectively for each direction, or would it merely use an overall strategy such as uniform increase of stiffness valid for all movements?



Figure 1.1.1: Multiple directions learning in unstable dynamics interaction. Using a chisel, the carpenter makes skilled movements while sculpting a piece of wood. This task is unstable and requires skilful control of both force and impedance in various directions, thus some generalisation. Photo from www.fotofsearch.com

One possible explanation for the ability to adapt in simultaneous movements is that the CNS could generalise learning across directions. In other words, learning from one direction influences performance in other (neighbouring) directions, because the CNS could interpolate or extrapolate necessary arm impedance by using information from previously visited states (e.g. position and velocity). Previous studies investigating transfer of learning in stable dynamics found that error from past experience in a single movement would affect subsequent movements in other directions (Sainburg et al. 1999), or in other arm configurations (Shadmehr and Moussavi, 2000), and would even affect the other arm during bimanual studies (Criscimagna-Hemminger et al. 2003).

Another possibility as to why the carpenter is capable of skilfully adapting in concurrent movements is that he or she compensates for the dynamics in each direction separately, and is able to blend movements learned in several directions by memory consolidation. That is, the CNS could develop separate mappings between visited states

and corresponding impedance for each direction, which is then recalled whenever needed in either one direction or during a combined movement.

All previous work related to generalisation of learning and consolidation of memory in humans was achieved using a modified visual or dynamic environment that resulted in a stable interaction. However, stable tasks require only suitable force, while unstable tasks additionally require adapting impedance, which suggests that different mechanisms may be employed in the unstable case (Osu et al. 2003). By examining impedance adaptation necessary to perform unstable tasks in multiple directions, it will be possible to unveil properties of impedance motor adaptation, because it is actually not trivial whether muscle force (which depends on moment arms, arm geometry and force length relationship) could change simultaneously when compensating for instability in multiple directions of movement.

1.2 Aims of thesis

Learning to compensate for a novel force field producing a stable interaction when performing movements in several directions has been studied in several experiments in the past (e.g. Conditt et al. 1997, Gandolfo et al. 1996, Conditt and Mussa-Ivaldi 1999, Shadmehr and Mussa-Ivaldi 1994, Donchin et al. 2003, Thoroughman and Taylor 2005, Ghahramani et al. 1996). The results demonstrated that the CNS gradually forms an internal model of the novel dynamics, which is used to perform the learned movements and to generalise learning to the neighbouring states. However, because no work has examined adaptation of impedance control for movements in several directions, the first question that is addressed in this work is whether the CNS is essentially able to compensate for instability in multiple directions. If so, then by using which computational mechanisms, and how do trajectories and muscle transients change to accommodate instability in several directions?

The first objective of this thesis is to address these fundamental questions through psychophysical experiments, in which subjects make arm movements while interacting with unstable computer controlled dynamics produced by a robotic interface. Trajectory, success performance, force, stiffness and electromyography (EMG) data are collected in two learning paradigms: single direction learning, and simultaneous multiple directions adaptation. Particularly, data will be analysed to

examine whether the CNS is capable of optimising endpoint stiffness, in the second learning phase, specifically to each direction or whether a simple isotropic arm-stiffness strategy is used, which would be valid for all directions. Also, subjects are tested whether they produce similar stiffness when learning in one direction only as compared to when learning in multiple directions concurrently and whether there is any interference in adaptation in the two cases.

In order to explain the differences between strategies used during force and impedance control tasks, previous work by (Tee et al. 2004, Burdet et al. 2005, Burdet et al. 2008) proposed a set of control models allowing adaptation in stable and unstable tasks. The concurrent learning algorithms were implemented in joint space (Tee et al. 2004, Burdet et al. 2006) and muscle space (Burdet et al. 2008) models, and then tested for tasks of multiple point-to-point movements. However, none of the models was conceived to investigate generalisation of learning during simultaneous multiple targets movements.

Therefore, the second goal of this thesis is to develop a unified computational framework based on previous models and physiological findings, able to simulate motor learning in both stable and unstable dynamics when several distinct movements are performed. The model learns feedforward muscle activation by minimising movement error and activation in muscle space and energy, and should be able to transfer training error of movements to untrained directions while encoding different parameters of movements. The computer model, using measurable variables, should be usable as a tool to simulate and predict generalisation in motor learning in different environments.

The computer model will be tested by simulating past experiments showing transfer of learning across movements, such as results reported in Conditt et al (1997), Thoroughman and Taylor (2005) as well as the experiment performed in this work, which investigates generalisation in unstable dynamics. The model is also used to predict human motor learning for future experiments or other tasks that are otherwise cumbersome to accomplish in the laboratory. This includes, for instance, experiments that require measurements of stiffness in, say, five directions simultaneously that would require hours of measurements using the current methods, which may be too challenging for subjects.

1.3 Organisation of the thesis

This thesis is divided into the following chapters:

The first Chapter is a general introduction to thesis and description of the specific aims. Chapter 2 encompasses definitions of various concepts that are related to the thesis goals and gives a literature review of past experimental and computational studies. This review covers the following topics: motor learning, stable and unstable tasks learning, generalisation of learning, consolidation of motor memory and interference, impedance control assessment, and computational modelling.

Chapter 3 of the thesis describes the computational model used to investigate motor learning in both stable and unstable dynamics in various directions of movements. Chapter 3 develops a simple algorithm that is implemented at the joints level in a two-link arm, and is able to adapt during reaching movements tasks and to generalise learning across movements. The algorithm is then implemented and simulated for movements in various directions while compensating for both stable and unstable dynamics. The model was initially used as a forecasting tool for the experiments that follow.

Chapter 4 describes the main experimental work and related results obtained. This chapter presents the overall aim as well as the methods of the experiment used and analysis performed. Then, the main results for investigating impedance control in two directions in an unstable environment are illustrated. The discussion elaborates on the reasons for choosing the task for subjects and explanations on why the experiments were conducted in that preferred paradigm.

In Chapter 5, a unified mathematical frame for motor adaptation at the muscle level is presented, which is valid for a general musculoskeletal system, and suitable to assess motor learning and generalisation patterns. Chapter 6 describes how the unified model can be implemented on a two-joints and six-muscles arm, using a neural network feedforward controller where the motor command for the current trial is updated using feedback from the previous trial. Simulations are performed to test the model and validate it against results from past psychophysical experiments. Finally, predictions of future experiments are presented, including simulations of how the CNS might tune endpoint stiffness in more than two directions, as well as a comparison of

generalisation performance between fitting position and/or velocity data to the neural network.

Finally, Chapter 7 summarises the contributions of this thesis and gives recommendations for future work to be performed.

The work in this thesis has led to the following scientific contributions:

Conference contributions:

- A. Kadiallah, G. Liaw, E. Burdet, M. Kawato, D.W. Franklin, *Impedance control is tuned to multiple directions of movement*, EMBC Annual Meeting, Vancouver, Canada, 2008
- A. Kadiallah, E. Burdet, D.W. Franklin, *A computational model of unstable tasks learning*, Society for Neuroscience Annual Meeting, San Diego, USA, 2007
- A. Kadiallah, E. Burdet, D.W. Franklin, *A 2 DoF Arm Simulator with an ANN to Model Human Motor Learning*, first international conference on control, instrumentation and mechatronics, Johor Bahru, Malaysia, 2007
- A. Kadiallah, D.W. Franklin and E. Burdet, *A learning Controller as a Tool to Investigate Muscles Coordination in the Control of Force and Impedance*, Society for Neuroscience Annual Meeting, Atlanta, USA, 2006

Peer-reviewed journal contributions:

- A. Kadiallah, G. Liaw, D. W. Franklin, M. Kawato, E. Burdet, *Impedance Control is Tuned to Multiple Directions of Movement* (submitted).
- A. Kadiallah, E. Burdet, D. W. Franklin, *Generalisation in Concurrent Adaptation of Force and Impedance* (submitted).

Chapter 2

LITERATURE REVIEW

Humans have the ability to learn numerous skills through the use of their limbs. The central nervous system (CNS) is required to produce complex and integrated movements to perform daily tasks such as opening a door or typing on a computer keyboard. Such coordination of actions requires selecting the correct set of muscles for each action, as for example adjusting to produce the appropriate force to opening doors with various dynamics at various locations.

While motor learning has been investigated extensively in the last 30 years, it is still not clear how the central nervous system (CNS) is able to coordinate muscles in order to learn motor programmes generalising over different movements and tasks. Understanding how motor learning enables generalisation is the main topic, which will be addressed in this thesis. This chapter reviews the published literature on various aspects of motor learning and generalisation, related to the experimental and modelling investigations, which will be presented in the following chapters.

2.1 Evidence of generalisation in motor learning

2.1.1 Motor learning of stable and unstable tasks

When humans first perform a movement in a novel environment there is generally a large error associated with the movement, because the CNS executes the task corresponding to the dynamics previously experienced, and needs to correct for the unexpected dynamics. However, after repeating the same action over a number of times, the task becomes easier to perform and requires less feedback control.

This learning was studied systematically in many works such as (Lackner and Dizio 1994, Shadmehr and Mussa-Ivaldi 1994). In these experiments, subjects performed point-to-point reaching movements in altered dynamics, where initial trials were distorted relative to the undisturbed straight-line movements. However, after repeating a number of trials, the hand trajectories became closer to the straight-line path and error was reduced. When the force field was removed unexpectedly during adaptation, then trajectories became distorted in the opposite direction. These results indicate the acquisition of an internal representation of the task. This is also referred to as an *internal model* enabling adequate mapping from motor commands to motion,

while sensory feedback is used to compensate for motion error and stabilise motion (Milner and Cloutier 1993, Thoroughman and Shadmehr 1999).

Mainly two kinds of internal models have been proposed in the literature (Kawato and Wolpert 1998). An *inverse model* would be used to compute the motor commands to realise a desired motion or action. A *forward model*, on the other hand, can predict the sensory consequences of motor commands. In skilled motor behaviour such as object manipulation, it is likely that both inverse and forward models are implemented, where the CNS employs both feedback and feedforward control mechanisms (Kawato and Wolpert 1998).

Different types of control are required for tasks producing *stable* versus *unstable* interactions (Figure 2.1.1). Stable interactions include simple tasks such as pushing or pulling a door, where the interaction force will be similar in consecutive trials. The force needed to perform these tasks can in principle be learned from the experience in one trial and used for further trials. However, many tasks, in particular those involving tools such as the use of a screwdriver, chisel or drill, are inherently unstable (Rancourt and Hogan 2001). In unstable interactions, the force to produce a successful movement cannot be predicted from experience in one trial, because of the unavoidable intrinsic motor noise and relatively large deviation in consecutive trials are amplified by the instability and may steer the hand in an unpredictable direction (Hamilton et al. 2004, Harris and Wolpert 1998, Osu et al. 2004). For instance, keeping a screwdriver in a perpendicular position to the slot of the screw is an unstable task, because any misdirected force can cause loss of contact and the destabilising force increases with error.

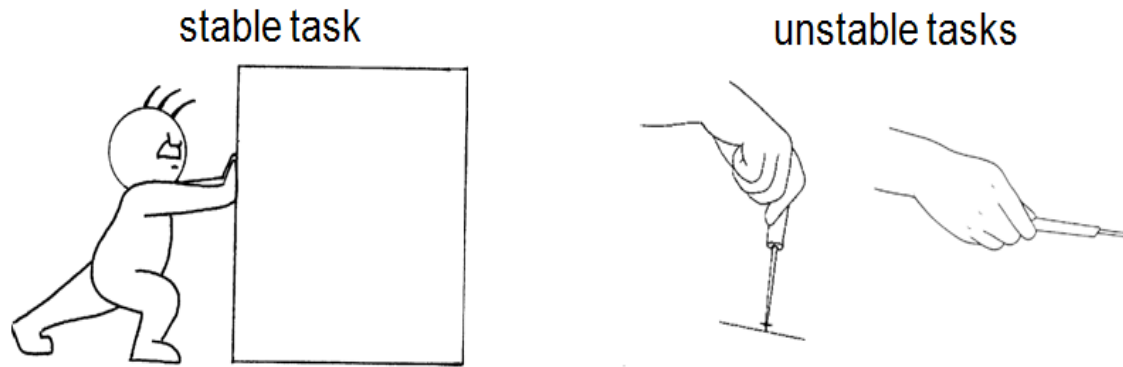


Figure 2.1.1: Examples of stable and unstable tasks. During stable interaction with the environment the same force leads to the same action. However, during unstable interactions the outcome is unpredictable.

2.1.2 Impedance control

In order to succeed in tasks producing an unstable interaction, the CNS has to employ the *mechanical impedance* of the arm to counter the instability. Mechanical impedance, defined as the resistance to perturbation of the state, can be seen as composed of stiffness, damping and inertia. Stiffness is the spring-like properties of the muscles that are activated to produce the restoring force. Stiffness increases in size while adapting to the disturbance (Hogan 1984). Stiffness and damping of the hand are generally referred to as viscoelasticity (Huxley and Simmons 1971). The mechanical viscoelasticity of the muscles is nonlinear and depends on the activation of muscle, velocity, length (Rack and Westbury 1969) and prior history (Kearney and Hunter 1990). Increase in torque about a joint would trigger a linear increase in viscoelasticity (Weiss et al. 1988) while inertia moment remains constant (Hunter and Kearney 1982).

When antagonist muscles acting on opposite sides of a joint are co-activated, the torques produced by the muscles subtract, but the overall impedance is the sum of the impedances in each of the muscles (Barnett and Harding 1955). The net torque about a joint is then determined as the vector sum of the antagonist muscles and the net stiffness, and viscoelasticity about the joint is the sum of the stiffness and viscosity in all muscles multiplied by the respective moment arms. It was shown in (Akazawa et al. 1983, DeSerres and Milner 1991, Milner and Cloutier 1993) that stiffness can be modified to compensate for instability using increased muscle co-contraction and reflex gain in single joints. The theory explaining how joint torque and stiffness could be

controlled independently in the case of one joint was formulated by (Hogan 1984) and demonstrated by (Milner et al. 1995).

In multi-joints systems, static stiffness was first found to depend on position (Mussa-Ivaldi et al. 1985), and joint stiffness was then shown to depend only on torque (Gomi and Osu 1998). Single joint stiffness in multi-joints system increases linearly with joint torque for elbow and shoulder, while the double joint stiffness increases linearly with elbow torque (Franklin and Milner 2003, Perreault et al. 2004). Damping was found to have a limited effect and that it increases nonlinearly with the rising torque (Perreault et al. 2004).

In the more complex case of multi-joints, the CNS needs to solve coordination, timing and interaction between the different joints. However, Mussa-Ivaldi et al. (1985) found that subjects could co-contract muscles to attenuate disturbances and increase endpoint stiffness without altering joint torque. It was further shown that increase of impedance is achieved through muscle co-contraction and reflex gain in arm posture (Darainy et al. 2004, Perreault et al. 2002, Milner 2002), finger posture (Akazawa et al. 1983) and point-to-point reaching movements (Gribble et al. 1998, Takahashi et al. 2001). Furthermore, co-contraction of antagonistic muscles may counteract the effect of signal-dependent noise (Osu et al. 2004, Selen et al. 2005).

In 1985, Hogan proposed that the CNS is able to control impedance to perform skilful movements whilst interacting with the environment. This could be realised in two ways. One way is that subjects could produce specific impedance for a task by adopting a suitable posture. The results of Milner (2002) using an unstable task suggest that humans are able to use this impedance control strategy. Alternatively, humans may be able to modify impedance by coordinating muscles in a suitable way. Burdet et al. (2001) used a position-dependent divergent force field (DF) producing an unstable interaction with the arm to demonstrate that the CNS is capable of controlling magnitude and shape of endpoint stiffness without varying endpoint force. More recently, Franklin et al. (2007) showed that subjects tuned their arm stiffness in the direction of instability and selectively co-activated different pairs of muscles to produce suitable impedance in a required direction.

Franklin et al. (2003A) proposed that the impedance controller employs a fast activation process in response to error signals and a slower deactivation process while learning in either stable or unstable interactions. For example, during initial learning of movements there is a natural increase in limb impedance, but as the subject becomes

more successful in counteracting the instability, the electromyography (EMG) of muscles gradually reduce, resulting in optimal stiffness geometry (Franklin et al. 2003A). This reduction in superfluous co-contraction would reduce metabolic energy requirement (Franklin et al. 2004) and possibly would also reduce variability in motor output, as noise tends to increase with muscle activity (Clancy and Hogan 1995, Harris and Wolpert 1998, van Galen and van Huygevoort 2000).

A few studies have produced evidence that the CNS may be able to control both force and impedance simultaneously (Takahashi et al. 2001, Osu et al. 2003). In Takahashi et al. (2001), when learning to move in a random force field, subjects increased impedance to resist the perturbation as demonstrated by the decrease in the size of the after-effects. Simultaneously, subjects also formed an internal model of the dynamics, as was demonstrated by the decrease in trajectory error. Impedance is necessary to stabilise the arm against environmental instabilities while any change of force is used to compensate for a force bias.

How can impedance be estimated?

Endpoint stiffness has been rigorously investigated during postural control in single-joint (Houk and Rymer 1981, Rack and Westbury 1969, Rack and Westbury 1974) and multi-joints (Gomi and Osu 1998, Mussa-Ivaldi 1985, Tsuji et al. 1995, Milner and Franklin 1998) arm configurations. In multi-joints movements, Gomi and Kawato (1997) used force impulses along the trajectory in order to estimate stiffness and damping. This method was limited in the way that the resulting position amplitude of the disturbance could not be controlled accurately, which may bias the estimation (Shadmehr et al. 1993). In addition, negative damping was found, which contradicts a physical analysis. Bennett and colleagues used random force disturbances and measured the resulting change in hand position (Bennett et al. 1992, Lacquaniti et al. 1993). However, this method would result in stiffening of the joints due to muscles co-contraction (Milner and Cloutier 1993). Another proposed method consists of displacing the hand by a constant amount relative to the undisturbed trajectory to estimate joint stiffness during elbow movements (Bennett et al. 1993). The method was generalised to multi-joints movements in (Burdet et al. 2000) using a model-based prediction of the actual trajectory. This method used one third as many trials as required

by the method from (Gomi and Kawato 1997) and has been implemented in many recent studies measuring endpoint stiffness in a single direction (e.g. Burdet et al. 2001, Franklin et al. 2003A, Franklin et al. 2007). Another approach to measure full impedance in the multi-joints arm using random perturbations was developed in (Acosta et al. 2000, Perreault et al. 1999), though it has only been tested at static positions so far.

2.1.3 Generalisation of learning

Complex learning is distinguished from simple memorisation by the ability to generalise from one context to another. For instance, as a football player practices on taking a better direct free kick, he/she needs to combine the right amount of force, speed of the ball, curvature of trajectory, dynamics of the ball, and so on. This learning affects other broader areas of play, because players who take direct free kicks are better suited to take corner and penalty kicks for example. Similar principles apply to other sports such as tennis. It is understood that no two kicks are the same, because the neural-system needs to adapt to the particular circumstances each time. Generalisation was defined as the ability to correctly interpolate between data points that have been previously fitted to a multivariate function (Poggio and Bizzi 2004). So, what are the mechanisms that allow for the generalisation of motor learning?

A study carried by Gandolfo et al. (1996) investigated generalisation of motor learning in unpractised movements after extensive training in some directions. Subjects started the task by making straight-line reaching movements in a rotating velocity-dependent force field in two directions of the workspace separated by a 45-degrees angle. Then, the force field was switched off (i.e. after-effects were tested) in both trained directions and other directions where subjects had not previously trained. Results showed that subjects produced after-effect trajectories, which were curved in the opposite direction of the force field, in all directions including those not initially trained before. Furthermore, the amount of curvature in the after-effects trials was disproportionate in the test movements. The magnitude of curvature decreased progressively in directions further away from the training directions. These results prove that the CNS could generalise learning beyond the area of training, but generalisation was found to be relatively local to the visited positions. Additionally, generalisation seems to arise in joint or intrinsic coordinates rather than in Cartesian

hand space coordinates as demonstrated by (Shadmehr and Mussa-Ivaldi 1994, Sainburg et al. 1999).

Spatial generalisation was also investigated in visuomotor adaptation and similar results were observed during finger tapping movements as generalisation decreased away from training areas (Ghahramani et al. 1996). Conditt et al. (1997) further demonstrated that the CNS can acquire an internal model of a viscous force field and generalise learning over different tasks. During the experiment, subjects initially performed multi-directions reaching movements to eight targets. After learning the task, they were presented with circular movements, which they could trace as if they had learnt the task. Transfer of learning was shown to happen during adaptation in the velocity-dependent field as well as during the after-effects trials. Results show that the CNS can generalise learning across other forms of movement that visit similar regions of the field. These results suggest the formation of state dependent internal models. Further evidence for this hypothesis was provided by the results of (Goodbody and Wolpert 1998). They examined transfer of learning in movements of half the duration and twice the amplitude, after subjects had initially learnt in a viscous force field to make movements towards different targets. Results suggest that subjects could linearly extrapolate learnt velocity into test directions in order to perform successful movements.

Prior exposure to the dynamics in limited space was found to affect unvisited states. Error experienced in a single movement has been found to affect subsequent movements to other directions (Sainburg et al. 1999), other arm configurations (Shadmehr and Moussavi 2000), movements of the other arm during bimanual studies (Criscimagna-Hemminger et al. 2003), and movements in the same direction but of different amplitudes (Goodbody and Wolpert 1998, Scheidt et al. 2001).

Other studies showed that learning in one direction affected adaptation towards several other directions in the workspace (Thoroughman and Shadmehr 2000, Thoroughman and Taylor 2005). In these studies, subjects were required to make movements in a velocity-dependent force field towards up to 16 targets. Results demonstrated that the measured kinematic error from one movement affected the following movement as a function of its direction, with the effect decreasing as the movement direction moved away from original direction (Thoroughman and Shadmehr 2000). A negative influence was particularly evident in movements that were more than 90 degrees away from the original movement direction. The dynamics of the force field

across the workspace were represented by broadly tuned Gaussian-like basis functions. A work by (Donchin et al. 2003) confirmed previous results by (Thoroughman and Shadmehr 2000). In addition, the quantified trial-to-trial generalisation showed improvement in movements 180 degrees from the original movement direction (Donchin et al. 2003). A more recent work by Thoroughman and Taylor (2005) used the same principles during adaptation to three increasingly complex force fields while making movements in 16 directions. In addition to previous findings, the subjects seemed to be able to adapt to the task complexity and tune their trial-to-trial basis functions accordingly. Results suggested that the CNS changes the neural tuning of space, which determines generalisation, in response to environmental complexity and is not fixed as was previously thought.

All previous work that investigated generalisation of learning concentrated on tasks requiring force adaptation (using either dynamic or visual disturbances), while no such study has yet investigated the generalisation of impedance learning. Osu et al. (2003) examined directional generalisation in both stable and unstable tasks similar to previous work by (Gandolfo et al. 1996, Goodbody and Wolpert 1998). A short experiment consisted of testing subjects in two adjacent movements after compensating for dynamics in a forward movement in respective force fields. In a viscous field subjects could accurately reach the test targets suggesting local generalisation using the inverse model acquired. However, in the position-dependent field subjects missed the targets suggesting little generalisation.

2.1.4 Consolidation of motor memory

Humans are able to acquire motor tasks and retain them in the long-term memory, such that there is no need to relearn every time how to perform the same task. Tasks such as swimming, bike riding or car driving are examples of skills that once learnt remain in memory. *Consolidation* is a term usually associated with a set of processes that allow long-term memory to become more stable with the passage of time (Dudai 2004). However, it is not yet clear under what circumstances consolidation or interference between motor tasks would occur.

Previous studies suggested that new motor learning could be consolidated in memory and would become resistant to interference from learning other tasks after a period of at least six hours (Brashers-Krug and Shadmehr 1996, Shadmehr and

Brashers-Krug 1997). These studies suggested that learning could be retained between adaptations to two opposite velocity-dependent fields if they were presented at least four to six hours apart (Brashers-Krug and Shadmehr 1996). Similar evidence of consolidation was shown in a study where subjects were asked to perform a finger-tapping task in a four-digit sequence (Walker et al. 2003b). Here, subjects could retain learning of task A after being exposed to two tasks A and then B, which were of different sequences. It seems from these studies that motor memory consolidates when there is a limited time-window during which original learning can be disrupted.

However, other studies rejected the consolidation theory by claiming that motor learning could not be retained in memory even after a long time-window in neither opposing visuomotor rotations nor in velocity- and position- dependent dynamic fields. They reported that interference occurred in task A even after a period of 24 hours elapsed between initial learning in A and B (Bock et al. 2001, Caithness et al. 2004, Krakauer et al. 1999, Tong et al. 2002, Wigmore et al. 2002). Miall et al. (2004) argued that visuomotor interference on retesting A in the ABA paradigm is not achieved by retrograde (i.e. transfer from task A to B) but rather anterograde (i.e. interference from B back to A) mechanisms. However, Caithness et al. (2004) used washout trials after B in an attempt to see retention of learning in A, but they still found that no retention of A was observed.

Mattar and Ostry (2007) found that consolidated skills could be modified by practice, but are not wholly replaced by new learning in dynamic fields. They argued that the CNS represents motor learning as a weighted combination of previous learning. In their experiment, subjects made movements towards five targets while their hands were displaced by viscous force fields that rotated in five directions either clockwise or anticlockwise. Training was achieved in two sessions either 24 hours or 1 month in between. When training was achieved in similar fields then the two sessions facilitated learning, but when learning was in opposite fields then interference occurred. Between these two extremes, subjects showed progressive change from interference to facilitation of adaptation. Furthermore, recent work by Overduin et al. (2006) found that when catch trials (i.e. when the force field is suddenly switched off during adaptation) were applied during learning of a task, then memory is consolidated after 6 and 24 hours, but not if another task is presented right away. These results show that the two tasks of adaptation are competing for memory, as similarly proposed in

previous work (Criscimagna-Hemminger and Shadmehr 2008, Krakauer and Shadmehr 2005, Krakauer et al. 2003).

Over the past decade, an increasing number of studies have concentrated on the role of sleep on memory consolidation, which provided evidence that offline processing occurs in the brain (Huber et al. 2004, Karni et al. 1994, Stickgold et al. 2000, Walker, 2008, Walker et al. 2003ab, Walker and Stickgold 2004). In motor learning, it was shown that overnight sleep could increase the performance of finger tapping sequence tasks (Walker et al. 2002, Walker et al. 2003a). In this experiment, subjects were trained in a finger-tapping task where performance was assessed based on the number of five-key press sequences during a 30-seconds interval. Results showed that subjects who benefited from a night-sleep performed 20% better in term of motor speed on the same task as compared to subjects who did not have a night-sleep. Indeed, overnight sleep enhancement, and not simply the passage of time, has been observed in visual tasks (Gais et al. 2000, Karni and Sagi 1993, Stickgold et al. 2000) and motor skill learning (Brashers-Krug and Shadmehr 1996, Karni et al. 1998, Walker et al. 2002), which has then been established as a central claim that sleep is required for memory consolidation and improvement.

2.1.5 Multiple models learning

Generalisation may occur by using multiple internal models. The MOSAIC model proposes that the central nervous system may acquire several internal models and switch between them using contextual information (Haruno et al. 2001). Evidence for this hypothesis was provided by work from Wada et al. (2003) where colour cues were used to help subjects learn two dynamic force fields that depended on the same state variable that is velocity. Subjects learnt two internal models and could switch between them simultaneously using the colour cue only (Wada et al. 2003, Osu et al. 2004). This suggests that in order to acquire two internal models, the CNS would require dominant contextual information and not any other factors such as consolidation time (Brashers-Krug and Shadmerh 1996), kinematic versus dynamic (Krakauer et al. 1999), extrinsic room light (Gandolfo et al. 1996), state variable (Tong et al. 2002) or sequential cues (Karniel and Mussa-Ivaldi 2002).

2.2 Computational modelling

2.2.1 *Forward and inverse models*

The concept of internal models has been developed in computational modelling to reflect the contribution of both forward and inverse models. Forward models are used to predict the next position or velocity, using the current position or velocity and the change in motor action (Ito 1970, Jordan 1996, Miall and Wolpert 1996). Forward models are usually straightforward to implement using for instance supervised learning techniques to predict the output of an action as the actual input is provided. On the other hand, inverse models provide necessary motor commands to achieve a desired state and are implemented using supervised learning in the form of direct inverse modelling (Albus 1975, Kuperstein 1988, Miller 1987, Jordan and Rumelhart 1992) or feedback-error-learning (FEL) (Kawato 1990). However, using either approach could represent a drawback, because inverse models are affected by noisy signals while large errors are observed for fast movements. Forward models can compensate for the delays encountered during the inverse model evaluation by estimating the next state from the current state, but the estimate can drift over time if the forward model is not very precise. Thus, Kawato and Wolpert (1998) proposed the MOSAIC system based on multiple paired forward-inverse models where an appropriate module is selected depending on information from sensory signals and forward commands.

2.2.2 *Nonlinear adaptive control*

Several models have been developed for the learning of inverse dynamics in stable interactions using neural networks (Kawato et al. 1987) or adaptive control (Burdet, 1996, Sanner and Kosha 1999). For example, the feedback-error-learning algorithm learns the feedforward force to perform stable actions by minimising feedback during repeated trials (Kawato et al. 1987). In multi-joints arm movements, FEL was found to be consistent with patterns of force adaptation in stable interactions with the environment, and similar algorithms are used as an efficient way to learn the inverse dynamics of robots (Slotine and Weiping 1991, Niemeyer and Slotine 1991, Burdet and Milner 1998).

Recent studies suggested that different mechanisms might be employed during motor learning in stable and unstable tasks. The results of Osu et al. (2003) suggested that the CNS could use an inverse dynamics model to compensate for the dynamics in a viscous field producing a stable interaction with the hand and impedance control to overcome the unstable interaction induced by a position dependent divergent force field. The evolution of trajectories suggested that during stable interactions an inverse dynamics model is realised through feedback-error-learning. During initial impedance learning, signed-error deviated inconsistently suggesting that the CNS tried to use feedback-error-learning, but without success. However, subjects were able to overcome instability by co-activating appropriate agonist and antagonist muscles pairs.

In general, conventional feedback-error-learning does not address mechanical impedance tuning to counter instability. In addition, FEL cannot predict the correct transients of muscle activations in stable dynamics as observed in (Franklin et al. 2003B), and it cannot stabilise unstable dynamics as seen in (Osu et al. 2003). This is because in the presence of a deviation, it seems unclear to decide whether this deviation should be attributed to insufficient impedance or force (Burdet et al. 2006).

2.2.3 Modelling impedance learning

Optimisation models such as that by Stroeve (1999) or Todorov and Jordan (2002) enable to compute the force and impedance after learning, but they do not predict the transients of learning. Similarly, the model of (Tee et al. 2004) can predict force and impedance after learning in a stable or unstable environment. This model permitted to predict stiffness during arbitrary movements adapted to a known stable or unstable environment using measurements of stiffness in static interactions with different levels of force applied in various directions. A learning algorithm predicting the evolution of force and impedance trial-after-trial was later implemented (Burdet et al. 2006). However, both models (Tee et al. 2004, Burdet et al. 2006) used a joint based approach, while muscle geometry was overseen, which resulted in an incorrect prediction of the muscle activity transients.

Franklin et al. (2008) and Burdet et al. (2008) developed a new algorithm to include muscle space features during learning of interactions with both stable and unstable dynamics. The principle of this muscle space model of motor adaptation is that kinematic error in muscle space contributes to both the formation of an inverse

dynamics model and to an increase of muscle co-activation, simulating a kind of a feedback-error-learning algorithm at the muscle level. Simulations using a two joint and six muscles biomechanical system demonstrated that this model was capable of stabilising unstable dynamics by learning optimal impedance and force.

The principle of the model was to assume that sensory feedback is used to modulate the feedforward command. Feedforward was then produced by concurrent minimisation of neural feedback and the total muscles activations. This modification of feedforward minimises motion error experienced in a movement. Both muscle stretch and shortening lead to augmentation of muscle activity in the next movement, and muscle activation is minimised with learning. This model could predict transients of muscle activation, endpoint force and stiffness similar to experiments observations in (Burdet et al. 2001, Franklin et al. 2003AB, Osu et al. 2003, Osu et al. 2002, Franklin et al. 2004). The controller could selectively tune stiffness of the arm to the environmental instability using co-contraction of agonist-antagonist muscles. However, the model was developed for simulating force and impedance learning in a single direction only and hence was not suitable to simulate multiple-directions learning and generalisation.

2.2.4 Models for generalisation of learning

Poggio and Bizzi (2004) proposed a neural network architecture, which consists of multiple tuned units (i.e. Gaussian functions) to generalise learning in both visual and motor systems. This model was developed to imitate the functioning of multiple neurons (and connecting synaptic circuitry) activating together. Here, a number of neurons would contribute towards activating a muscle subset and then several subsets help in generating the movement. Further, the criterion for successful generalisation was that the Gaussian functions should not be flattened and learning is accomplished through continuous updating of the weights of the network.

Donchin et al. (2003) used a state space function to fit physiological data from the trial-to-trial variations and generated a generalisation function. They fitted force and trajectory error based on the assumption that the brain seeks to minimise error between the desired and actual trajectories by adjusting the actual force. Force, encoded in velocity of the hand, would depend on updating the weight matrix based on experienced error between desired and required force. The weight matrix was associated with basis elements (Thoroughman and Shadmehr 2000) from which the

generalisation function was derived. Weight change is smallest for elements less active during error. This way, it was possible to estimate how error in one movement affected the subsequent movement. Physiological data was gathered during out-and-back reaching movements towards eight targets in curly velocity-dependent force fields. The derived generalisation function was at its maximum when movements were towards adjacent targets, but dropped to a minimum between targets that were 90° apart.

On the other hand, no previous work has yet investigated how muscle activity is modified movement after movement in a mechanism that would enable learning both stable and unstable dynamics while performing movements in various directions and generalising to unvisited areas of the workspace.

Therefore, the main aim of the work in this thesis will be to investigate generalisation of impedance during human motor learning. From one side, the objective is to examine learning by conducting experiments using healthy human subjects, and from another is to further advance theoretical ideas of motor learning through the development of accurate computer models.

Chapter 3

IMPLEMENTATION OF A TWO-LINK MODEL IN JOINT SPACE

Abstract

In order to succeed in tasks such as chiselling or drilling, the CNS builds an internal representation of both force and mechanical impedance. However, no previous computational study has examined the transfer of learnt dynamics and impedance during the execution of unstable tasks. In this chapter, a novel model using a radial basis function neural network was developed to simulate reaching movements in different directions by performing analysis at the joint level. The results demonstrate the locality of learned impedance, and suggest that humans may be able to learn optimal impedance for movements in several directions. The neural network model is used as a tool to predict hypotheses about the neuro-mechanical control of the human arm, which would facilitate the design of the experiments in Chapter 4.

3.1 Motivation and aim

Previous motor learning studies involving stable interactions with the environment have shown that the CNS forms an internal representation of the environment, which enables generalisation of force over movements (Conditt et al 1997). They observed transfer of learning from straight line reaching movements in various directions to circular movements demonstrating that the CNS forms a state dependent internal model. Others have investigated how the adaptation along one trajectory influences other movements with increasingly wider angles in the workspace (Gandolfo et al. 1996, Thoroughman and Taylor 2005).

In the best knowledge of the author, no previous computational study has examined the generalisation of impedance learning necessary to control movements in unstable tasks. Hence, the goal of this study is to investigate motor adaptation to an unstable force field along different trajectories, in order to draw the learning relationship between visited and non-visited states. This chapter will present a simple implementation of an algorithm based on previous results in joint space, which will be enhanced with a radial-basis-function (RBF) artificial network in order to simulate multiple directions learning (Kadiallah et al. 2007). The model is implemented to simulate how the CNS is capable of adapting to instability when making movements towards more than one direction and then testing along some untrained trajectories. Endpoint stiffness will be examined as well as trajectories of movements in order to assess adaptability. Results from this study would enable predicting the outcome of adaptation experiments involving human subjects assuming that the central nervous system is trying to compensate for the environmental force and instability.

Understanding how humans are able to interact and adapt to different dynamics of the environment can provide an insight into the neural mechanisms of motor learning. Additionally, a good understanding of motor behaviour could lead to the development of computer models with applications, for instance, in physical rehabilitation using robots to assist patients who suffer from motor control disorder. Meanwhile, investigating motor learning properties requires the development of computational models that reflect the biological phenomena. Biologically inspired models may lead to efficient control beyond current robots' capabilities, which are still far below human performers in terms of flexibility. Therefore, psychophysical studies

are required to understand human learning, and modelling is needed to validate and predict experiments.

3.2 Model of motor adaptation in joint coordinates

The human arm is a redundant and complex multi-joints musculoskeletal system where it is almost impossible to interpret all variables during learning. Therefore, previous studies have mostly focused on examining planar two degrees-of-freedom (DoF) and six muscles arm movements. This way, the properties of the arm while interacting with the environment would be preserved and the study becomes easier to analyse while results are still interpretable. Both experimental and computational modelling studies usually consist of making goal-directed movements between two points in the presence of a disturbing force that subjects need to overcome over a number of trials. The force field applied is intended to create the different kind of environments that are met in daily life.

The joint space models of Tee et al. (2004) and Burdet et al. (2006) were conceived to adapt one movement at a time and were tested for forward movements only. However, to account for any transfer in learning between different movements, complete force and impedance adaptation in several learning directions must be achieved before testing in non-visited states, and this is developed in this section.

The model presented in this section illustrates how the arm force and impedance, which are needed to simulate arm interactions in an external environment, could be calculated from the dynamic properties of such environment. In the following description, scalars will be in italic s , bold represents vectors $\mathbf{v}$ and matrices will be shown in capital bold $\mathbf{M}$.

3.2.1 Arm dynamics

The joint torque, $\boldsymbol{\tau}$, produced by the muscles to perform the task consists of a torque necessary to move the limb, $\boldsymbol{\tau}_{IN}$, as well as the external force $\mathbf{F}_{EX}$ applied on the hand (Figure 3.2.1):

$$\begin{aligned}
\boldsymbol{\tau} &= \boldsymbol{\tau}_{IN} + \boldsymbol{\tau}_{EX} \\
\boldsymbol{\tau}_{IN} &= \boldsymbol{\tau}_{FF} + \boldsymbol{\tau}_{FB} + \boldsymbol{\tau}_N \\
\boldsymbol{\tau}_{EX} &= \mathbf{J}(\mathbf{q})^T \mathbf{F}_{EX}
\end{aligned} \tag{3.1}$$

where $\mathbf{J}(\mathbf{q})=(\partial x_i/\partial q_j)$ is the position-dependent Jacobian matrix transforming between Cartesian and joint coordinates, and $\mathbf{q}$ is the vector of joint angles (refer to Table 3.2.1 for equations used to transform between hand and joint coordinates). Torque $\boldsymbol{\tau}_{IN}$ consists of the driving force generated by the descending motor command (i.e. $\boldsymbol{\tau}_{FF}$), the feedback torque (i.e. $\boldsymbol{\tau}_{FB}$) that is generated due to the reflexes and elastic muscle properties, and the environmental variability due to motor noise, which is represented by $\boldsymbol{\tau}_N$.

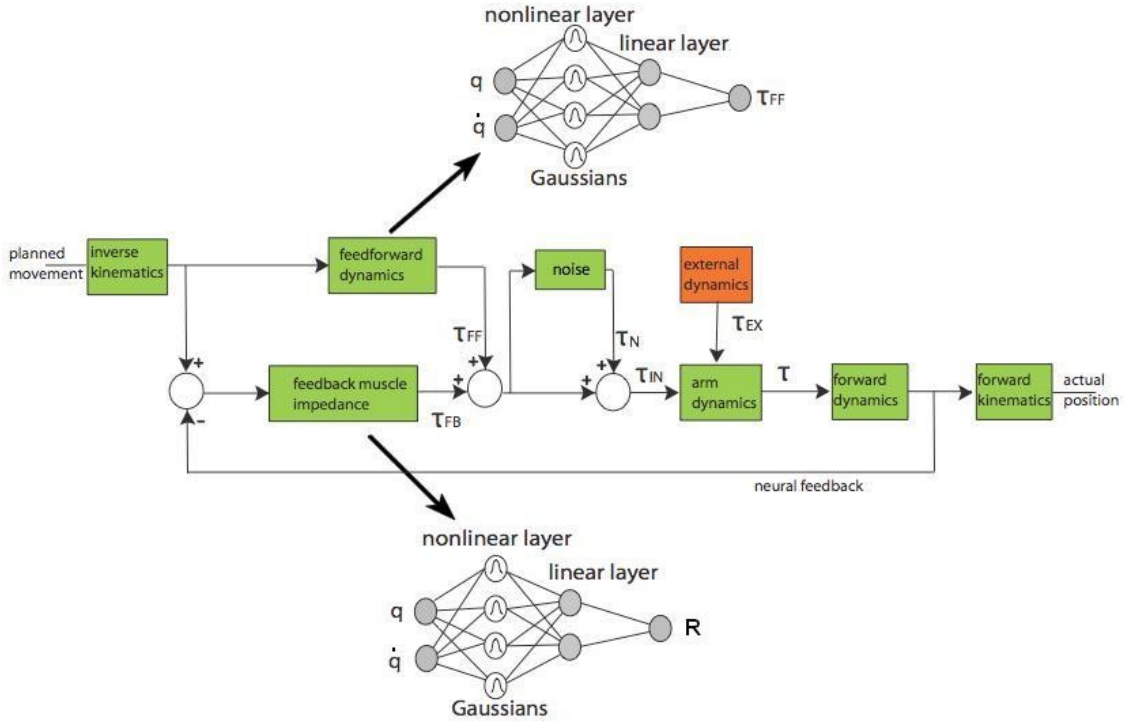


Figure 3.2.1: Scheme of neural control and feedback error learning in novel dynamics. The diagram shows that it is possible to include a radial-basis-function (RBF) neural network to predict either torque or joint stiffness using joint position ($\mathbf{q}$) and velocity ($\dot{\mathbf{q}}$) data from the state space. Choosing between torque ($\boldsymbol{\tau}_{FF}$) and joint stiffness ($\mathbf{R}$) depends on whether the task requires compensating for stable or unstable dynamics.

When the environment does not produce any disturbances on the hand, the CNS is said to adapt and produce movements with similar trajectories over repetitive trials.

Therefore, the driving force, τ_{FF} , would correspond to the rigid-body dynamics (Craig 1989) described by:

$$\tau_{FF} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) \quad (3.2)$$

where $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ are the joint position, velocity and acceleration vectors, respectively, $\mathbf{M}(\mathbf{q})$ is the position-dependent mass matrix, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}}$ represents the Coriolis and centrifugal velocity-dependent forces, and $\mathbf{G}(\mathbf{q})$ is the gravity force. The force due to gravity is neglected during planar horizontal movements.

The restoring feedback force, τ_{FB} , is composed of both muscle elasticity and reflexes, and is assumed to be linear transformations of the trajectory error, $\mathbf{e}$, and its derivative, $\dot{\mathbf{e}}$:

$$\begin{aligned} \tau_{FB} &= \mathbf{R}\mathbf{e} + \mathbf{D}\dot{\mathbf{e}} \\ \mathbf{e} &= (\mathbf{q}_d - \mathbf{q}), \quad \dot{\mathbf{e}} = (\dot{\mathbf{q}}_d - \dot{\mathbf{q}}) \end{aligned} \quad (3.3)$$

where $\mathbf{q}_d$ and $\dot{\mathbf{q}}_d$ are the desired joint positions and velocities, respectively. $\mathbf{q}$ and $\dot{\mathbf{q}}$ are the actual joint positions and velocities, respectively. $\mathbf{R}$ is the intrinsic joint stiffness matrix that increases with muscle activation, and $\mathbf{D}$ is damping that is assumed to be dependent on joint stiffness through (Tsuji et al. 1995, Tee et al. 2004):

$$\mathbf{D} = \frac{0.42}{\sqrt{\dot{\mathbf{q}}^T \dot{\mathbf{q}} + 1}} \mathbf{R} \quad (3.4)$$

The previous Equations (3.1-4) could be used to simulate reaching movements of the redundant limbs over various dynamic environments. The inverse dynamics model depends on the planned rather than on the executed trajectory, which is compatible with the feedforward nature of the motor command.

But, how is stiffness calculated? Joint stiffness, $\mathbf{R}$, was shown to linearly depend on torque magnitude, $|\tau_{FF}|$, during both static (Gomi and Osu 1998, Pearrealut et al. 2001) and motion (Burdet and Milner 1998, Franklin et al. 2003B) interactions with the environment. In this model, $\mathbf{R}$ was used as the mean stiffness of five subjects

measured in Gomi and Osu (1998), which depends on joint torque of elbow and the shoulder:

$$\mathbf{R} = (|\boldsymbol{\tau}_{FF}|)$$

$$\mathbf{R} = \begin{bmatrix} 10.8 + 3.18|\boldsymbol{\tau}_s| & 2.83 + 2.15|\boldsymbol{\tau}_e| \\ 2.51 + 2.34|\boldsymbol{\tau}_e| & 8.67 + 6.18|\boldsymbol{\tau}_e| \end{bmatrix} Nm / rad \quad (3.5)$$

where $\boldsymbol{\tau}_s$ and $\boldsymbol{\tau}_e$ denote shoulder and elbow torques, respectively.

Table 3.2.1: Kinematics and dynamics transformations between Cartesian and joint space coordinates

hand		joint	
$\mathbf{x}$	$\xleftarrow{\text{forward kin.}}$	$\mathbf{q}$	position
$\dot{\mathbf{x}}$	$\xleftarrow{\mathbf{J} \dot{\mathbf{q}}}$	$\dot{\mathbf{q}}$	velocity
$\mathbf{F}$	$\xrightarrow{\mathbf{J}^T \mathbf{F}}$	$\boldsymbol{\tau}$	force
$\mathbf{K}_x$	$\xrightarrow{\mathbf{J}^T \mathbf{K}_x \mathbf{J} + (d\mathbf{J}^T/d\mathbf{q})\mathbf{F}}$	$\mathbf{R}$	stiffness

3.2.2 *Learning and stabilisation*

Learning in the model consists of updating the inverse dynamics torque using:

$$\boldsymbol{\tau}_{FF}^{i+1} = \boldsymbol{\tau}_{FF}^i + \lambda \boldsymbol{\tau}_{FB}, \quad \lambda > 0 \quad (3.6)$$

where i is the trial number and λ is a chosen learning factor.

The previous learning law in Equation (3.6) is used to update the torque necessary to learn force control in a stable environment. However, in order to stabilise unstable dynamics, it is essential to compensate for the external perturbations by updating the arm stiffness. Previous results from Burdet et al. (2001) and Franklin et al. (2003A) showed that stability is achieved through the co-activation of both agonist and antagonist muscles. This implies that the torque dependent stiffness term ($\mathbf{R}|\boldsymbol{\tau}_{FF}|$) corresponds to the reciprocal activation process, and hence additional increase in the stiffness term, say $\mathbf{K}_s$, is required to represent the co-activation of muscles (Burdet et al.

2005). $\mathbf{K}_s$ is stiffness in Cartesian space, which is independent of torque and opposes the environment instability. Therefore, the joint stiffness is updated trial after trial according to:

$$\begin{aligned}\mathbf{R}^i &\equiv \mathbf{R}^i + \mathbf{J}^T \mathbf{K}_s^i \mathbf{J} \\ \mathbf{K}_s^{i+1} &= (1 - \alpha) \mathbf{K}_s^i + \alpha \Delta \mathbf{K}^i, \quad 0 < \alpha < 1\end{aligned}\tag{3.7}$$

where i denotes the trial number, α is a learning factor to realise smooth update of $\mathbf{K}_s$, and $\Delta \mathbf{K}$ is the change in stiffness to counteract the environmental force, and is estimated from:

$$\mathbf{F}^i - \bar{\mathbf{F}} = \Delta \mathbf{K}^i \mathbf{e}^i \tag{3.8}$$

where $\mathbf{e}^i$ is the tracking error at the i -th trial, $\mathbf{F}^i$ is the force produced during the current trial, and $\bar{\mathbf{F}}$ is the mean endpoint force over previous trials.

In order to predict the necessary force and stiffness to compensate for the disturbing environment in a different direction from that of adaptation, a radial-basis-function (RBF) neural network is employed. The network is introduced to calculate the feedforward torque τ_{FF} and impedance $\mathbf{R}$ using information from previous trials. In other words, the RBF network is created to map joint position and velocity together to either the feedforward torque or the arm impedance.

3.2.3 Force and impedance neural network learning

The neural network used in this model was obtained from the Matlab (R2007a) neural network toolbox and set according to the simulation requirements. The function *newrbf* creates a radial-basis-function (RBF) network where it is possible to set the desired input and output data as well as the width of the basis functions. The RBF network has one input layer, a hidden nonlinear weight layer, and a linear output layer (Figure 3.3.1). The network dynamics are given by:

$$z = \omega_0 + \sum_{i=1}^n \omega_i f(\|\mathbf{v} - \mathbf{c}_i\|) \quad (3.9)$$

$$f(\mathbf{v}) = e^{-\frac{(\mathbf{v}-\mathbf{c})^2}{2\sigma^2}}$$

where z is the output of the network, ω_i represents the weights of the neurons, ω_0 is the output offset, $\mathbf{v}$ are the inputs to the network, $\mathbf{c}_i$ are the centres associated with the basis functions (also called centroids or centres of neurons), n is the number of basis functions in the network, and $\|\cdot\|$ denotes the Euclidean norm. Gaussian basis function, f , was chosen as the transfer function in the hidden layer where σ represents the width (or activation field) of the transfer function. This activation field could be adjusted to become narrow or wide.

The input data is chosen to be either joint position or both joint position and velocity, while the output is either force if the network is used to predict the feedforward torque in stable tasks, or stiffness if the network is used to stabilise unstable dynamics. Training is achieved by updating the weights of the network using the input and desired output data (Equation 3.9), as the sum-squared error between the desired and actual output falls to near desired error value of zero.

3.3 Implementation of the model

The task considered was to make horizontal arm movements at shoulder height towards different selected targets, similar to previous experiments (e.g. Gomi and Kawato 1998, Thoroughman and Shadmehr 2000, Franklin et al. 2007). The model was implemented to realise reaching arm movements from a starting point at $(0.0, 0.31)m$ to a selected target that is $25cm$ distant, in approximately $650ms$. Figure (3.3.1) shows a movement towards one selected target as an example. The desired movements were assumed to follow a minimal-jerk planned trajectory in Cartesian space (Flash and Hogan 1985) according to:

$$\begin{bmatrix} \mathbf{x}_d(t) \end{bmatrix} = \begin{bmatrix} x_i + (x_f - x_i) \left(10 \left(\frac{t}{T} \right)^3 - 15 \left(\frac{t}{T} \right)^4 + 6 \left(\frac{t}{T} \right)^5 \right) \\ y_i + (y_f - y_i) \left(10 \left(\frac{t}{T} \right)^3 - 15 \left(\frac{t}{T} \right)^4 + 6 \left(\frac{t}{T} \right)^5 \right) \end{bmatrix} \quad (3.10)$$

where $\mathbf{x}_d(t)$ represents the desired hand position coordinates, (x_i, y_i) is the start position of the movement, (x_f, y_f) is the finish point, t is the time at each position during the movement, and T is the duration of the whole movement. Joint angles $\mathbf{q}=(q_s, q_e)^T$ for shoulder and elbow, respectively, were obtained from Cartesian position $\mathbf{x}=(x, y)^T$ using inverse kinematics transformation (Craig 1989):

$$\begin{aligned} q_e &= \cos^{-1} \left(\frac{x^2 + y^2 - l_1^2 - l_2^2}{2l_1l_2} \right), \quad \text{for } 0 < q_e < \pi \\ \omega &= \cos^{-1} \left(\frac{x^2 + y^2 - l_1^2 - l_2^2}{2l_1\sqrt{x^2 + y^2}} \right), \quad \text{for } 0 < \omega < \pi/2 \\ q_s &= \tan^{-1} \left(\frac{y}{x} \right) - \omega \end{aligned} \quad (3.11)$$

The horizontal movements at shoulder height use a two-link mechanical structure, whose anthropometric parameters were obtained from Diffrient et al. (1978) and are summarised in Table (3.3.1). The task dynamics of the arm were modelled using Equation (3.2), where for a two-link rigid arm:

$$\begin{aligned} \boldsymbol{\tau}_{FF} &= \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} \\ \mathbf{M}(\mathbf{q}) &= \begin{bmatrix} J_1 + J_2 + M_1 l_{m1}^2 + M_2 (l_1^2 + l_{m2}^2 + 2l_1 l_{m2} \cos q_e) & J_2 + M_2 (l_{m2}^2 + l_1 l_{m2} \cos q_e) \\ J_2 + M_2 (l_{m2}^2 + l_1 l_{m2} \cos q_e) & J_2 + M_2 l_{m2}^2 \end{bmatrix} \quad (3.12) \\ \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} &= \begin{bmatrix} M_2 l_1 l_{m2} \dot{q}_e (2\dot{q}_s + \dot{q}_e) \sin q_e \\ M_2 l_1 l_{m2} \dot{q}_e^2 \sin q_e \end{bmatrix} \end{aligned}$$

where M denotes the segment mass, J denotes the segment inertia, l its length, l_m the distance between the center of mass of the segment and the proximal joint, with

subscripts ₁ and ₂ denoting the upper arm and forearm respectively, and subscripts _s and _e denote the shoulder and elbow joints respectively (refer to Table 3.3.1).

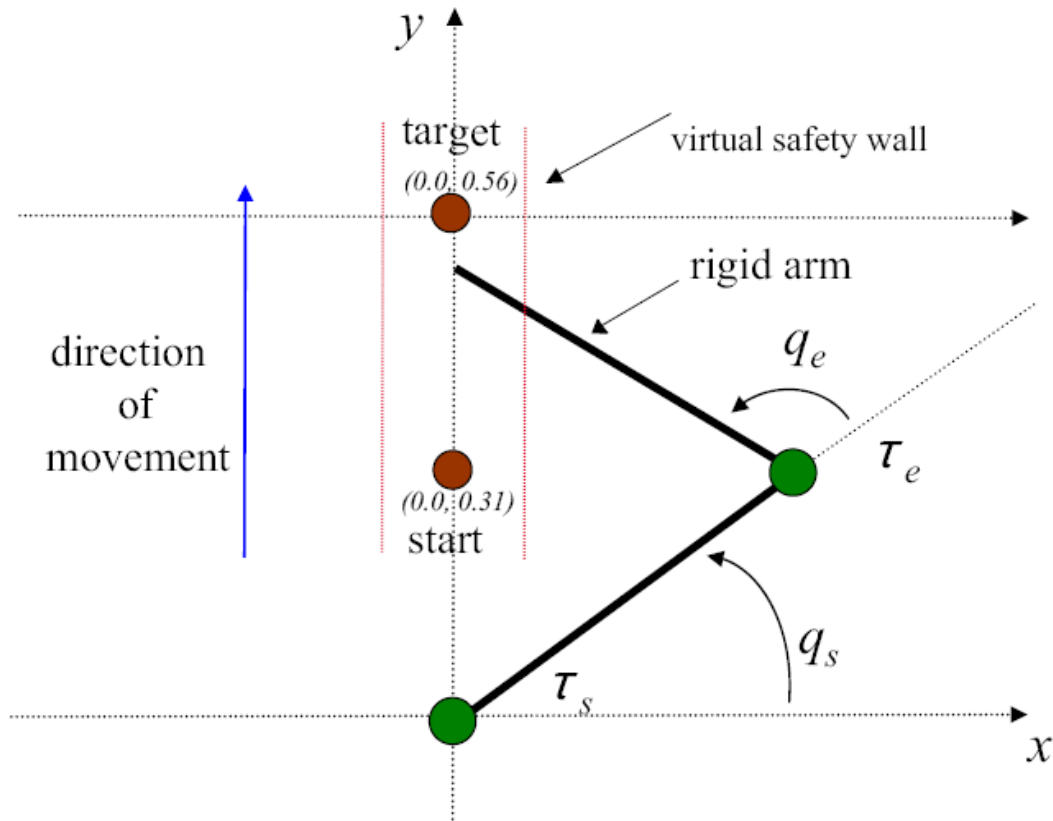


Figure 3.3.1: A two degrees-of-freedom rigid body arm shown when making a single movement between start and finish points (red circles) for a chosen movement in the task space. Shoulder and elbow joints are shown with the green circle with the respective torques acting on them. A virtual wall (red dashed line) is placed at both sides of the straight-line desired trajectory for safety reasons to prevent “breaking the arm”. The movement is realised between two points that are *25cm* distant and is achieved in *650ms*.

Table 3.3.1: Anthropometric data of human arm from (Diffrient et al. 1978)

	Mass (Kg)	Length (m)	Centre of mass relative to proximal joint (m)	Mass moment of inertia (kg m ²)
Upper arm	1.93	0.29	0.165	0.0141
Forearm	1.52	0.34	0.19	0.0188

The signal-dependent noise torque, τ_N , is modelled using Brownian motion generated by the *randn* function in Matlab. The external dynamics force, $\mathbf{F}_{EX}$, is transformed from Cartesian to joint space using the Jacobian matrix that is defined for the two DoF arm as:

$$\tau_{EX} = \mathbf{J}^T \mathbf{F}_{EX}$$

$$\mathbf{J}(\mathbf{q}) = \begin{pmatrix} \frac{\partial x_i}{\partial q_j} \end{pmatrix} = \begin{bmatrix} -l_1 \sin q_s - l_2 \sin(q_s + q_e) & -l_2 \sin(q_s + q_e) \\ l_1 \cos q_s + l_2 \cos(q_s + q_e) & l_2 \cos(q_s + q_e) \end{bmatrix} \quad (3.13)$$

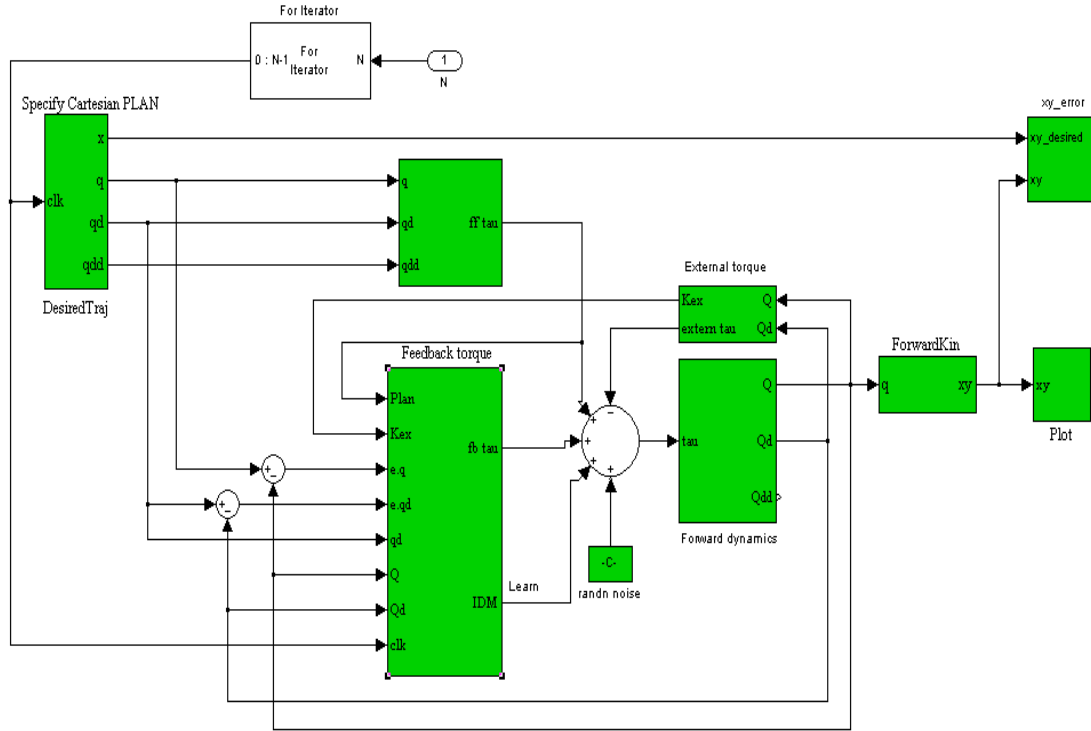


Figure 3.3.2: Feedforward adaptive controller realised in Simulink corresponding to Equations (3.1-8). The torque necessary to make movements is the addition of the feedforward, feedback, noise and the external dynamics torques. Learning is achieved by using the feedback error learning algorithm. Prediction of either the feedforward torque or impedance is achieved using the RBF neural network.

A Simulink block model was implemented, as shown below in Figure (3.3.2). The model is made user friendly through the implementation of pop-up menus where it

is possible to choose the location of the desired target to make reaching movements. The direction of movement is chosen from eight possible targets equally spanned around the workspace from the same starting point. It is also possible to select the nature of the force field (i.e. either stable velocity-dependent or divergent position-dependent) and its intensity, and whether learning should be achieved using the RBF network or the simple feedback error-learning algorithm. Learning could be achieved using either iterative adaptive control as defined in sections (3.2.1 and 3.2.2) or using an RBF network that directly predicts the necessary force or impedance as explained in section (3.2.3). However, prediction of adaptation in a given direction can only be performed when the model has sufficient information about the optimum force or impedance needed in other directions so that it is possible to train the neural network.

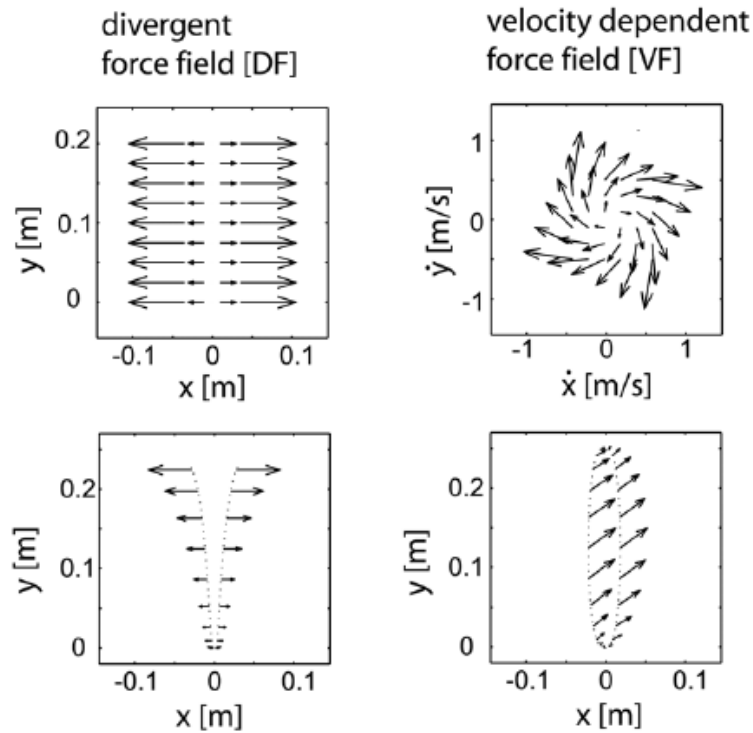


Figure 3.3.3: Position-dependent force field (DF) producing unstable dynamics and velocity-dependent force field (VF) that generates a stable interaction, both shown for a forward movement. Top row depicts field of external force as a function of hand position for DF and hand velocity for VF, while the bottom row shows the external force experienced when movement trajectories deviate left and right of the straight line joining start and finish points in a forward movement.

Movements are performed in novel dynamics and adaptation in any given direction is allowed for 100 learning trials. Two types of force fields, representative of

stable and unstable dynamics were implemented for simulations. The first one was a velocity-dependent field (VF) of the form:

$$\mathbf{F}_{EX} = \mathbf{F}_{VF} = - \begin{bmatrix} -13 & 18 \\ -18 & -13 \end{bmatrix} \mathbf{v} \quad (3.14)$$

Using this force field, a stable interaction with the arm is produced, as can be inferred from the eigenvalues of the linearised coupled system. This external field acting on the arm is always the same, and hence is reproducible (Figure 3.3.3). The force field is switched off inside the $0.0125m$ start circle and when the arm reaches $0.0125m$ radius of the target. The other force field implemented was the position-dependent diverging field (DF):

$$\begin{aligned} \mathbf{F}_{EX} = \mathbf{F}_{DF} &= \begin{bmatrix} 400 & 0 \\ 0 & 0 \end{bmatrix} \mathbf{x} \\ \mathbf{K}_{EX} &= \begin{bmatrix} 400 & 0 \\ 0 & 0 \end{bmatrix} \end{aligned} \quad (3.15)$$

The force generated here is proportional to the hand position as measured from the parallel axis, resulting in an unstable interaction with the arm. The force field is switched off again when the hand reaches $0.0125m$ radius of the target circle. The net stiffness, which is the sum of the negative environmental stiffness and the endpoint stiffness of the arm, has positive eigenvalues before adaptation, leading to instability when a perturbation is produced, and this results in movements diverging either side of the straight line joining start and target points (Figure 3.3.3). To prevent “crashing” the system, particularly during the initial movements, as the hand is unexpectedly pushed extensively to either side, there are virtual boundaries placed at $4cm$ from the centreline to both sides of the movement. When the hand reaches either boundary, the force field is off and a restoring force $\boldsymbol{\tau}_d = \mathbf{J}^T (-50 \dot{\mathbf{x}})$ is applied during the time when the hand is outside the boundaries. However, when the hand is back within, then it is allowed to move freely towards the target.

Transfer of learning between directions could be tested. For instance, joint position and velocity, and achieved force and/or stiffness after adaptation to reaching

movements in two directions are used to train the neural network. The model could then be used to predict a movement trajectory by overcoming field perturbations and compensating for either force or impedance depending on the task requirements as will be shown next.

3.4 Simulations of reaching movements

3.4.1 *Reaching movements in stable and unstable force fields*

Figure (3.4.1A) shows the simulated results for adaptation to the divergent field in one direction. Initial movements diverge to both the left and right sides, but after learning movements follow the straight-line trajectory. Endpoint stiffness ellipse was plotted after adaptation in the null field (NF) when no force field was applied, and after adaptation to the DF. The ellipse is the result of multiplying the stiffness matrix in hand space with a unit circle. Results show that the ellipse size increased significantly after adapting to the DF as compared to the NF, in addition that the elongation of the ellipse was in the direction of instability. The simulation results for adaptation to the VF are shown in Figure (3.4.1B). Initial trials, which correspond to movements exposed to the unexpected onset of the force field, show the effect of perturbation before adaptation to the dynamics. These movements are perturbed to the right, but with a fast reduction of kinematics error over trials due to learning of the dynamics. The resulting stiffness ellipse increased in size after learning in the VF as compared to the stiffness in the NF. These results conform to previous empirical findings by Burdet et al. (2001) and Franklin et al. (2003B).

Overall, the results of making arm reaching movements, one at a time, in various directions show that the implemented algorithm could learn to perform straight line movements in about 25 to 35 trials in any direction. Furthermore, stiffness ellipses are plotted after adaptation to both fields, where the size of the ellipse increases significantly to compensate for the external dynamics. In the DF, there is a significant increase of stiffness in the horizontal axis to counteract the effect of instability, while the superfluous stiffness in the vertical axis is removed after adaptation. These results are similar to findings from past experiments, and illustrate good adaptation of force and impedance to the environment, i.e. force and impedance matching.

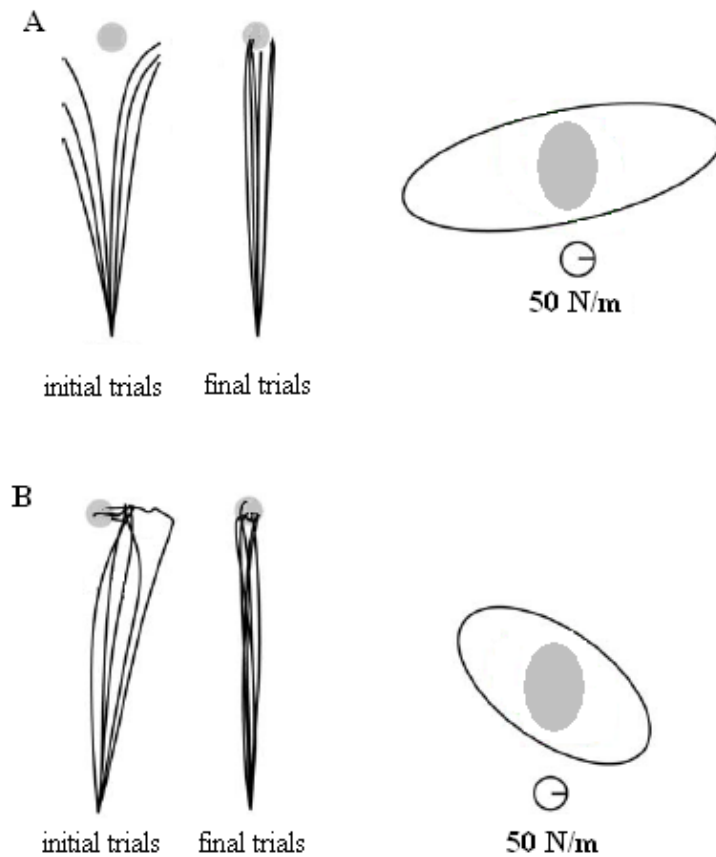


Figure 3.4.1: Simulation of movements shown along forward trajectories during adaptation in a divergent force field (A), and then in a stable force field (B) during another simulation. The figure shows initial and final trials during learning in each field as well as the resulting endpoint stiffness. Corresponding stiffness ellipses are shown before (grey) and after (black) adaptation in each dynamic field. In the DF, stiffness is elongated in the direction of imposed instability.

3.4.2 Testing locality of unstable dynamics learning in multi-directions tasks

In the following set of experiments, locality of learning in the DF was tested. Movements were simulated towards different targets where the force field was always

orthogonal to the direction of movement. First, the model was configured to learn force and impedance in the conventional forward movement (referred to by N for north and is assumed to be at 0°), and then tested the resulting stiffness pattern in another movement reaching to a target at 180° from north (i.e. denoted by S, for south). Results in Figure (3.4.2A) show that the stiffness ellipse in the S movement is elongated in the direction of instability to compensate for disturbance. However, this does not illustrate whether the stiffness produced to counter instability was for movements in direction N or for the test direction S, because the force field is similar between both directions.

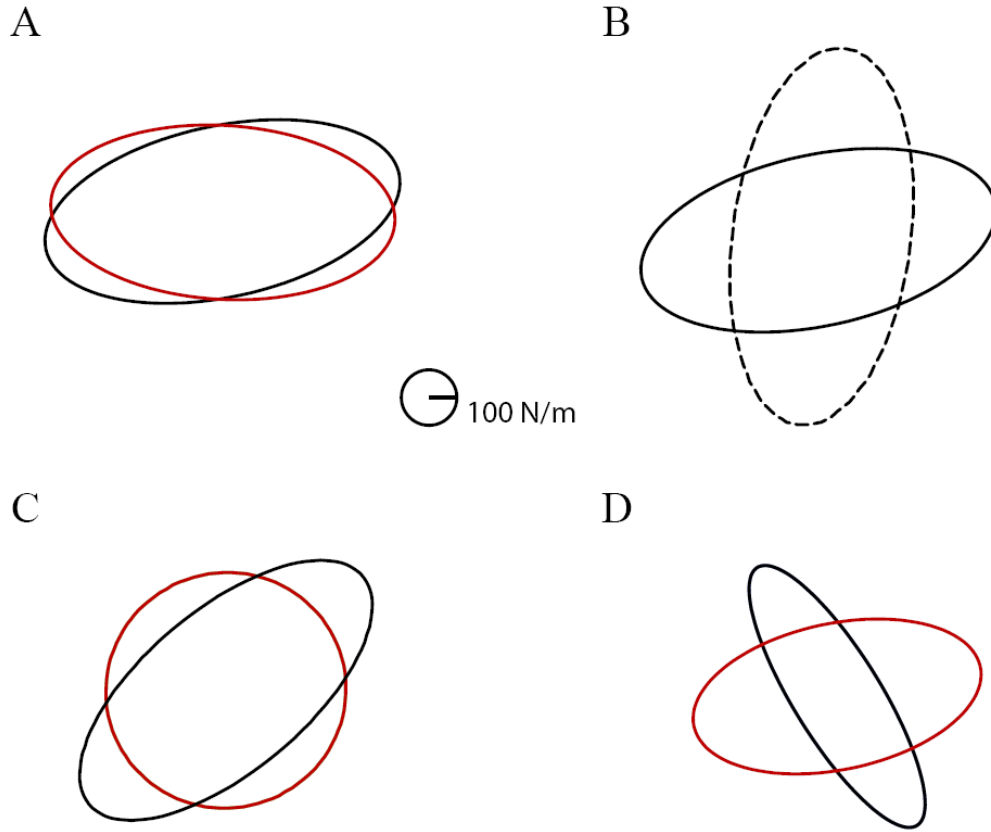


Figure 3.4.2: A: Stiffness is shown after adaptation in direction north (black). Predicted stiffness in south after learning in north only produces similar ellipse (red). B: figure shows endpoint stiffness ellipses after separate adaptation in directions north (black continuous line) then west (black discontinuous line). The elongated ellipses in the direction of instability for each direction, respectively, demonstrate good compensation of the dynamics. C: predicted stiffness in northwest using the RBF network after learning in both north and west (red) compared with stiffness ellipse after learning along the northwest movement only (black). D: learning in northeast only (black) compared with predicted stiffness in northeast after learning in north and northwest (red).

Therefore, in the following tests (Figure 3.4.2B-C), the model was used to learn and then predict endpoint stiffness in different movements. The artificial neural network model would be configured to learn stiffness in the north and west (i.e. denoted by W at 90° anticlockwise from north) directions separately, and then test the ability to generalise stiffness learning to other directions of movement. Learning of the model is achieved by providing one input batch of all positions and velocities that map to one batch of endpoint stiffness, from both the training movements.

Figure (3.4.2B) shows stiffness ellipses after iterative learning in directions N and W. The two ellipses show compensation for instability in each direction respectively. Endpoint stiffness is then predicted in a novel non-visited direction after training the model. Results in Figure (3.4.2C) show that the predicted endpoint stiffness to compensate for instability in direction northwest (i.e. NW at 45° anticlockwise from north) seems to be the interpolation of previously stored stiffness required for adaptation in directions north and west. This does not reflect true learning that should be achieved in NW, because impedance is not countering instability and hence movements would not be stable.

Similarly, after adaptation to movements in north and northwest, endpoint stiffness was predicted for movements in direction northeast (i.e. NE at 45° clockwise from north) (Figure 3.4.2D). The model was not able to predict the necessary endpoint stiffness to compensate for instability in the test direction. The activation fields of the Gaussian basis functions in the RBF were varied in width in order to study how this influences the locality of such interpolation. However, the resulting patterns found did not vary widely from previous results. Therefore, predictions of the model show that learning is local, because the learned impedance in limited space does not seem to transfer to other directions not previously visited.

A third experiment tested the capacity of learning of the neural network model in unstable force fields. In this experiment, impedance was learned in one batch for several movements in various directions simultaneously. The four directions selected were W, NW, N and NE. The stiffness patterns were tested in all these directions, which were identified using a state space of either joint position only or both joint position and velocity. Here, no trial-to-trial learning was performed, so the external stiffness, $\mathbf{K}_{EX}$, from each direction was mapped to its corresponding joint coordinates in the state space (i.e. assuming perfect compensation for instability). For instance, in

direction N, $\mathbf{K}_{EX}=[400 \ 0; 0 \ 0] \text{ N/m}$, which is graphically drawn as a straight-line. In any other direction of movement, the external dynamics matrix, say $\mathbf{K}_{EX2}$, is transformed using the rotation matrix, $\mathbf{Rot}$, where:

$$\begin{aligned} \mathbf{K}_{EX2} &= \mathbf{Rot}^T \mathbf{K}_{EX} \mathbf{Rot} \\ \mathbf{Rot} &= \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \end{aligned} \quad (3.16)$$

Mappings from all movements were gathered in one batch and the RBF network was trained, and then stiffness was tested in each direction separately. The results in Figure (3.4.3) show that the neural network model is able to reproduce the environment impedance in each direction. However, when the state space is based on joint position only, then learning is approximate (Figure 3.4.3A). Note that in this figure only the environment impedance to learn is plotted for comparison, where perfect compensation would result in flat ellipses (i.e. straight-lines). Compensation is much improved and almost perfect when the velocity is added to the state space, as is seen in (Figure 3.4.3B).

Results from the last experiment could be interpreted as the neural network model is capable of using the velocity information to match the environmental impedance, and suggest that humans may use both position and velocity to estimate or learn the necessary force and impedance in various dynamic environments. Results also show that upon successful training, stiffness can be selectively tuned in each direction separately.

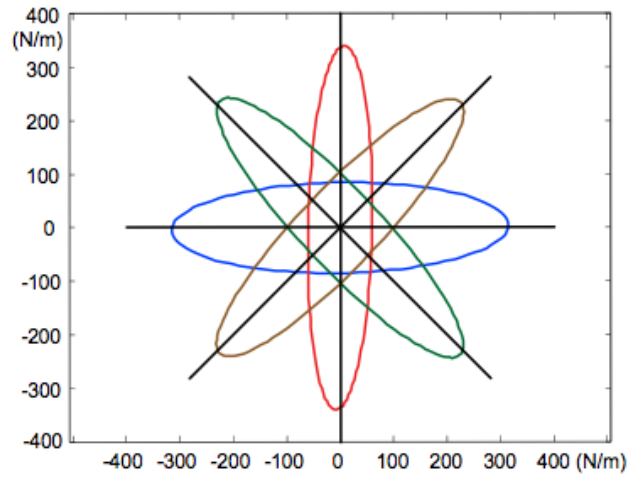
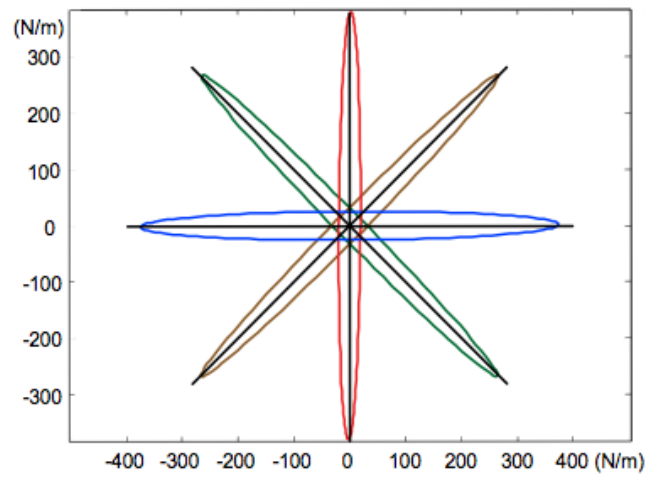
A**B**

Figure 3.4.3: Predicted change of external stiffness in four directions of movement using an RBF neural network. The network mapped either position only (A) or position and velocity (B) to predicted hand stiffness. This is assuming perfect compensation for an unstable divergent force field (DF) with negative stiffness of 400 N/m lateral to each movement (black straight-lines).

3.5 Discussion

This chapter mainly investigated the interference in learning instability across different directions and predicted the external stiffness along that trajectory, in between or outside that task space. The results show that the iterative learning algorithm from Equations (3.1-9) is able to match force and impedance for movements in any direction. Results with the neural network model suggest that learned impedance will be local, thus movements in various directions are necessary to learn a model valid for many trajectories. The neural network has the capacity of learning suitable impedance for movements in various directions. The neural network model that is presented in this chapter to learn force and impedance can be used to forecast generalisation patterns for movements not experienced during learning, which humans may be able to perform.

One disadvantage of the joint space model is that it does not allow for concurrent adaptation in more than one direction of movement. That is, it is only possible to simulate the trajectory and endpoint stiffness of the arm in a novel direction after training the model on previous data from other directions. This drawback will be taken into consideration when designing the muscle space model.

Furthermore, the neural network used in this study was directly implemented from a Matlab toolbox, which did not allow flexibility in choosing the locations and the number of the basis functions, in addition that it was not possible to directly update the weights of the network after each movement trial. These shortcomings will be overcome in the next version of the model, implemented in Chapters 5 and 6, where a novel neural network is derived and used to generalise impedance learning.

Meanwhile, the current model demonstrated several properties that could exist in the CNS. For example, it may not be possible to transfer impedance learnt from a limited experience to a wider workspace in the first instance unless the subject acquires some kinematic (i.e. position and velocity) information about the new space, which conforms to previous findings by Conditt et al. (1997) and Gandolfo et al. (1995). Furthermore, it is worth noting that the CNS has been shown to use proprioceptive information to coordinate multi-joint movement sequences (Cordo et al. 1995). Results from experiments using unpredictable velocity trajectories during hand movements showed that the CNS would extract proprioceptive information related to both angular velocity and position of the joint to trigger a movement in a particular sequence.

However, it is also necessary to emphasise that trying to physiologically interpret position and velocity data and how exactly the information is processed in the brain is beyond this thesis work, which rather focuses on the end-effect learning of the CNS.

The model developed in this chapter assumes that the musculoskeletal system uses a simple joint based approach, and it does not consider complex muscle mechanics and geometry of the limbs. Therefore, this model will probably not adapt to different environments in the same manner and would not reflect the true motor learning observed in humans. This is particularly the case when considering that the coupling of the muscle co-activation (i.e. stiffness) and the reciprocal activation (i.e. force) is more complex than modelled in this chapter (Perreault et al. 2002). The model recently developed by Franklin et al. (2008) and Burdet et al. (2008) proposed a more elaborate version of the learning controller. In addition, another version able to generalise learning across directions at the muscle level will be derived and implemented in this thesis.

What do the results obtained in these simulations suggest for experiments with human subjects? Learning impedance in one direction is local and does not help much for movements in other directions. Hence, it is necessary to perform an experiment to investigate this locality and compare results with the prediction of our RBF based model. Furthermore, human subjects may be able to learn a feedforward model valid for movements in various directions. So, an experiment might explain how subjects are able to learn optimal impedance for movements in several directions and thus explains how humans are able to skilfully use tools. Also, to learn a feedforward model, humans may use the velocity information in addition to position. That is, the CNS might be able to “understand” that the destabilisation is always perpendicular to the movement direction given by the direction of the velocity vector in Cartesian space. If humans were indeed able to learn impedance for movements in various directions concurrently, then experiments would be designed to investigate in which coordinates generalisation is performed.

Finally, the joint-based model developed here was used as an insight to what to expect during the physical experiments. The following chapter will further explore human impedance control and learning in a multiple-directions task involving human subjects.

Chapter 4

IMPEDANCE CONTROL IS TUNED TO MULTIPLE DIRECTIONS OF LEARNING

Abstract

Humans develop an internal model to compensate for instability in the environment. It was demonstrated that the central nervous system (CNS) could selectively control arm stiffness by compensating for the environment instability while making forward movements. In this study, we investigated how the neuromuscular system adapted to instability in two separate movements. On Day 1 of the experiment, subjects performed movements towards a target straight ahead only. On Day 2 they made movements towards another target situated at 35° clockwise from the first target. On Day 3, subjects compensated for the lateral unstable field in both directions concurrently. Results show that i) learning was direction-specific, ii) subjects retained learning gained in each direction across days, iii) subjects directionally tuned stiffness in each direction separately even when making movements in both directions concurrently. The increase in stiffness compensated for the instability for each direction. Further, subjects used different muscles groups to counter perturbations in each direction. Results provide convincing evidence that the CNS can develop and use multiple impedance controllers to stabilise movements with minimum metabolic cost.

4.1 Introduction

4.1.1 *Background*

Humans are capable of controlling their limbs in a skilled behaviour when performing multitude of tasks. We constantly use our upper limbs during an interaction with the surrounding environment where for instance pushing or pulling an object along a defined trajectory involves a stable interaction. Such task requires learning the necessary motor command to counter the external dynamics. Initially, motor command is adapted to define direction of force, its amplitude, friction of the body etc. However, once the task is mastered, the command becomes predictable and hence repetitive.

On the other hand, many common tasks requiring tools such as chiselling, using a screwdriver or a drilling machine, are unstable (Rancourt and Hogan 2001). This instability amplifies motor noise and can lead to unpredictable and unsuccessful action (Burdet et al. 2006). For instance, the hand of an apprentice carpenter will often slip out of the desired track when chiselling a piece of rough wood. However, with practice apprentices will become able to control movements with suitable force and impedance in all directions, and eventually to chisel masterworks.

We have previously studied motion in unstable environments, and shown that the central nervous system learns to deal with instability by co-contracting suitable muscle pairs involved in the movement (Burdet et al. 2001, Burdet et al. 2006, Franklin et al. 2003). The mechanism of this impedance control (Hogan 1985) and the associated learning of optimal muscle activation have been investigated in recent studies (Burdet et al. 2006; Franklin et al. 2008, Burdet et al. 2008).

All the studies investigating impedance control in movements performed so far examined impedance only along one repeated movement (Burdet et al. 2001; Takahashi et al. 2001, Franklin et al. 2003, Franklin et al. 2004, Franklin et al. 2007). This is due in particular to the many trials necessary to estimate impedance with sufficient accuracy despite noise in the force measurement and motor output variability (Burdet et al. 2000). However this does not help us to understand how sculptors have learned to compensate for instability in all directions, as they need to produce three-dimensional objects.

Learning to compensate for a novel force field when performing movements in several directions has been studied in a series of experiments over the last 15 years (Conditt et al. 1997, Conditt and Mussa-Ivaldi 1999, Kawato and Wolpert 1998, Shadmehr and Mussa-Ivaldi 1994). The results demonstrated that the CNS gradually forms an internal representation of the novel dynamics required to perform successful movements optimally, and generalises to neighbouring states. However, these studies involved a stable interaction, which did not require modifying impedance, while behavioural data indicates that distinct mechanisms may be used to control force and impedance (Osu et al. 2003). Therefore the patterns observed in stable interactions may not be representative of the learning necessary to master unstable tasks.

4.1.2 Aim of this study

This study examines the learning of reaching movements in several directions in the presence of instability. We studied reaching movements with lateral instability to two distinct targets (Figure 4.1.1A). Are subjects able to succeed in this task, and if yes, by which mechanism? Learning unstable tasks seems more difficult than stable tasks, because the former need longer learning (Franklin et al. 2003B). Further, impedance adaptation for different postures may be difficult where the effective force produced by a given muscle activation level will be different. This is due to several factors including moment arms and force length relationships of the muscle, in addition to the effects of different limb geometry. Therefore, different levels of muscle activation would need to be produced throughout a movement. The CNS has to deal with all these factors in order to learn performing successful movements to different directions in unstable dynamics.

Figure (4.1.1A) illustrates possible impedance learning strategies to perform successful movements during concurrent learning. First, the CNS may co-contract all muscles of the same amount (Figure 4.1.1B). However, this means a large physical effort to compensate for the external instability, as illustrated by the large ellipse size. So, instead the CNS may use the average of optimal impedance to deal with simultaneous directions while it could barely stabilise both movements (Figure 4.1.1C). Finally the CNS might be able to selectively co-contract muscles pairs to tune impedance to the environment instability for every movement direction (Figure 4.1.1D). To analyse the strategy actually used by the CNS, experiments were performed

while measuring and analysing the trajectories, force and impedance during movement and across learning to two distinct targets.

This chapter will initially present the simulations performed before commencing the experiments in order to predict the possible outcomes, followed by the methods, experimental procedure and data analysis methods, after which the results will be presented, and finally an elaborate discussion will follow.

4.1.3 Simulations of potential stiffness learning strategies

In order to predict the effect of co-activating different muscle pairs on the endpoint stiffness of the arm, simulations were performed to evaluate the effects of co-contracting antagonistic pairs of muscle groups on endpoint stiffness geometry. The prediction was that in each case, the endpoint stiffness would increase in the corresponding direction and that an increase in the activation of the corresponding muscles would be observed.

Endpoint stiffness is composed of both joint stiffness and geometric stiffness (Franklin and Milner 2003). Although the contribution of geometric stiffness to endpoint stiffness is a function of endpoint force and geometry of the limb, the contribution of joint stiffness is purely a function of muscle activation. The joint stiffness ($\mathbf{R}$) is composed of four elements that in turn can be expressed in terms of three muscle stiffness parameters (McIntyre et al. 1996):

$$\mathbf{R} = \begin{bmatrix} R_{ss} & R_{se} \\ R_{es} & R_{ee} \end{bmatrix} = \begin{bmatrix} k_s + \frac{r_1}{r_2} k_d & k_d \\ k_d & k_e + \frac{r_2}{r_1} k_d \end{bmatrix} \quad (4.1)$$

where R_{ss} is the stiffness at the shoulder produced by muscles crossing the shoulder joint, R_{se} is the stiffness at the shoulder produced by the biarticular muscles, R_{ee} is the stiffness at the elbow produced by muscles crossing the elbow joint, R_{es} is the stiffness at the elbow produced by the biarticular muscles, k_s is the single-joint shoulder muscle stiffness, k_d is the double-joint muscle stiffness, k_e is the single-joint elbow muscle stiffness, r_1 is the moment arm of the biarticular muscles at the shoulder, and r_2 is the moment arm of the biarticular muscles at the elbow. This formulation is only valid

when considering stiffness attributable to intrinsic muscle properties. In general, stiffness measurements will also include reflex contributions, which can result in the off-diagonal terms of the joint stiffness matrix being unequal. With the assumption that the moment arms at the shoulder and elbow of the biarticular muscles are equal, an increase in co-contraction of muscle pairs relative to that of null field (NF) movements would produce changes in joint stiffness that can be modelled as follows:

$$\mathbf{R}_{cc} = \begin{bmatrix} R_{ss}^{NF} + \delta k_s + \delta k_d & R_{se}^{NF} + \delta k_d \\ R_{es}^{NF} + \delta k_d & R_{ee}^{NF} + \delta k_e + \delta k_d \end{bmatrix} \quad (4.2)$$

where the δk_s , δk_d , and δk_e terms indicate a change in the joint stiffness produced through the cocontraction of the muscle pairs. The means of the joint stiffness terms in the NF for five subjects were used as the baseline to compute the torque-dependent joint stiffness $\mathbf{R}^{NF}$ (Gomi and Osu 1998, Tee et al. 2004):

$$\mathbf{R}^{NF} = \begin{bmatrix} R_{SS}^{NF} & R_{SE}^{NF} \\ R_{ES}^{NF} & R_{EE}^{NF} \end{bmatrix} = \begin{bmatrix} 10.8 + 3.18 |\tau_s| & 2.83 + 2.15 |\tau_e| \\ 2.51 + 2.34 |\tau_e| & 8.67 + 6.18 |\tau_e| \end{bmatrix} \quad Nm / rad \quad (4.3)$$

where τ_s and τ_e are elbow and shoulder torques respectively measured at midpoint of movement. Torque applied was different between the two directions.

Simulations were performed to examine how the CNS may adapt endpoint stiffness of the arm when lateral instability is applied on the hand during movements to two directions separated by an angle of 35° (Figure 4.1.1A). Endpoint stiffness depends on limb geometry, and stiffness was computed here only in the middle of the movement. Figure (4.1.1B) shows co-activation of all muscle pairs simulated by concurrently setting k_s , k_d , and k_e to 30 Nm/rad . Joint stiffness $\mathbf{R}$ was then transformed to hand space stiffness $\mathbf{K}$ using the relationship $\mathbf{R} = \mathbf{J}^T \mathbf{K} \mathbf{J}$ (assuming zero forces) where $\mathbf{J}$ is the (position-dependent) jacobian matrix transforming between hand and joint coordinates (Craig 1989). Then, the endpoint stiffness ellipse was plotted using singular value decomposition (Gomi and Osu 1998).

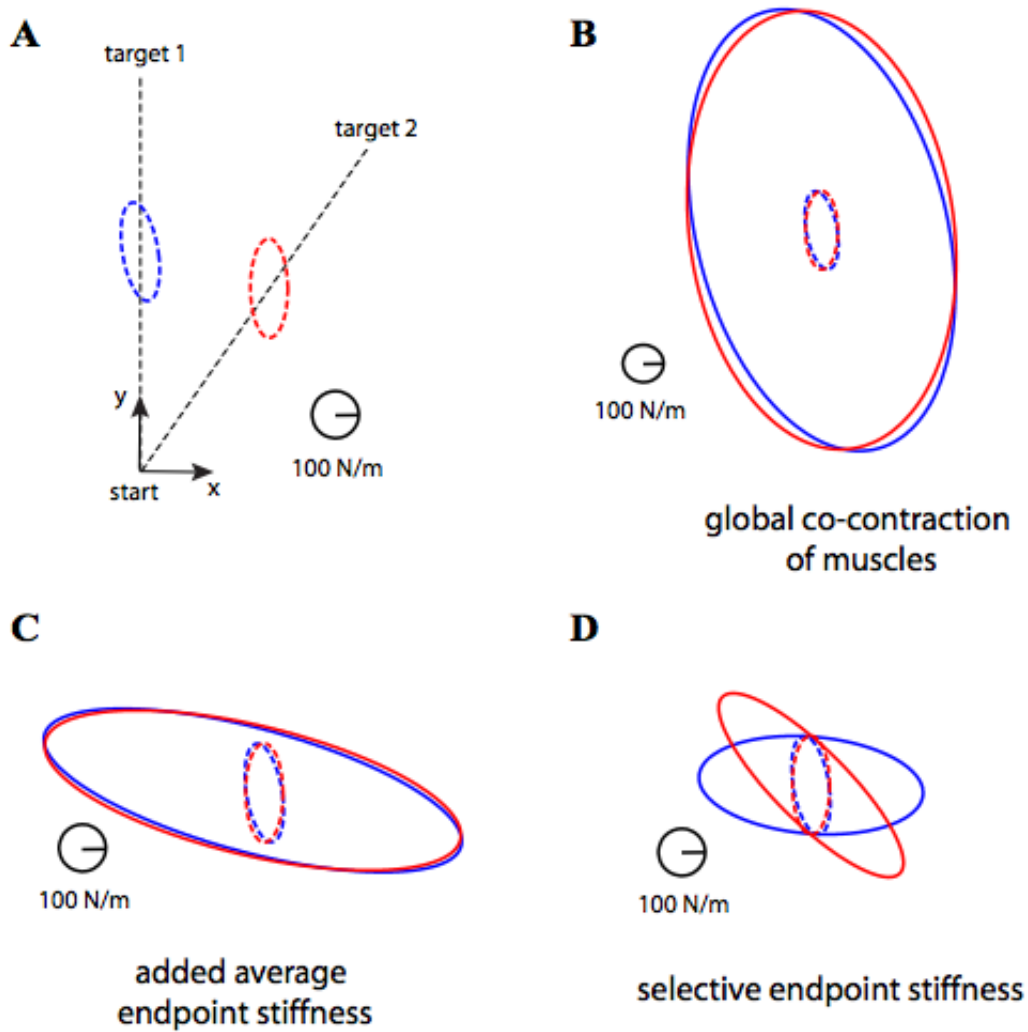


Figure 4.1.1: A: Learning of impedance necessary to compensate for orthogonal instability is considered in two reaching movements to targets separated by 35° . Simulated endpoint stiffness ellipses in the middle of the movement are plotted in both directions. B-D: Illustration of possible strategies for impedance adaptation to succeed in both configurations. B: Uniform co-contraction of all muscle pairs. C: Average of optimal stiffness in each direction. D: Selective co-contraction tuned to the required direction.

Alternatively the CNS may be able to learn isotropic stiffness (Burdet et al. 2001) when lateral instability is applied on the hand, and the mean over the visited directions is used to perform movements in both directions. In this simulation, the intensity of the lateral field affecting forward movement in Cartesian space is $\mathbf{K}_{EX}=[400 \ 0; \ 0 \ 0] \text{ N/m}$. In the second arm configuration, the external dynamics matrix is transformed using the rotation matrix, $\mathbf{Rot}$, where:

$$\begin{aligned} \mathbf{K}_{EX2} &= \mathbf{Rot}^T \mathbf{K}_{EX} \mathbf{Rot} \\ \mathbf{Rot} &= \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) \\ \sin(\alpha) & \cos(\alpha) \end{bmatrix}, \alpha = 35^\circ \end{aligned} \quad (4.4)$$

Figure (4.1.1C) shows stiffness ellipse during null field (discontinuous line) and after adding the mean stiffness across $\mathbf{K}_{EX}$ and $\mathbf{K}_{EX2}$ (continuous line) in both arm configurations.

Finally, another possibility is that the CNS adapts endpoint stiffness to the instability, optimally specifically in each direction. To simulate this strategy, stiffness of the external force field was added according to the direction specific instability (Figure 4.1.1D).

Furthermore, simulations were performed to investigate the effects of co-contracting pairs of muscles in a forward movement. Individual terms of the joint stiffness matrix Rcc as in Equation (4.2) were then selectively increased by changing δk_s , δk_d , and δk_e to simulate the co-contraction of specific muscle pairs. To simulate co-activation of a more dominant double-joint biarticular muscles, δk_d was set to 30 *Nm/rad*, while δk_s and δk_e were set to 0 *Nm/rad* (Figure 4.1.2A). The figure shows that the stiffness ellipse is elongated along the horizontal axis, which is also defined as the 0° axis. To simulate selective co-activation of more dominant single-joint shoulder muscles, δk_s was set to 30 *Nm/rad*, while the other parameters δk_d and δk_e were set to 10 *Nm/rad* and 0 *Nm/rad*, respectively (Figure 4.1.2B). The figure shows that the resulting stiffness ellipse is elongated in the direction of the 45° axis, which is half-way between horizontal and orthogonal axes. Finally, δk_e , was set to 30 *Nm/rad* while parameters δk_d and δk_s were set to 10 *Nm/rad* and 0 *Nm/rad*, respectively (Figure 4.1.2C) in order to simulate stiffness after co-contraction of single-joint elbow muscles.

The figure shows that stiffness ellipse is elongated mainly along the orthogonal -90° axis.

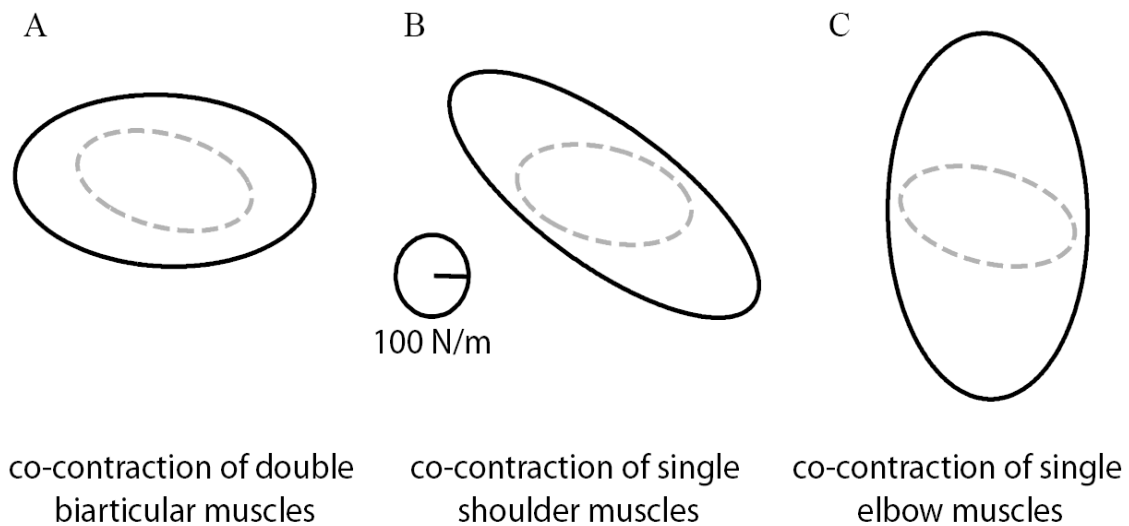


Figure 4.1.2: Simulations of endpoint stiffness resulting from an increase in co-contraction of a particular pair of muscles in a forward movement. The null field (dashed-grey) ellipse was obtained using data from averaged performance of five subjects (Gomi and Osu 1998) and is the same in all three cases. A: co-contraction of the double-joint biarticular muscles only results in an ellipse elongated along the horizontal axis along the 0° plane. B: when single-joint shoulder muscles are co-activated only, then corresponding stiffness ellipse is elongated around the -45° axis. C: finally, stiffness ellipse resulting from co-contracting single-joint elbow muscles is elongated in the direction of the 90° axis.

4.2 Materials and methods

4.2.1 *Subjects*

Ten right-handed male subjects without any known neurological problem aged between 19 and 34 years old participated in the study, which was performed at ATR International, Kyoto Japan. The institutional ethics committee approved the experiments and subjects gave informed consent.

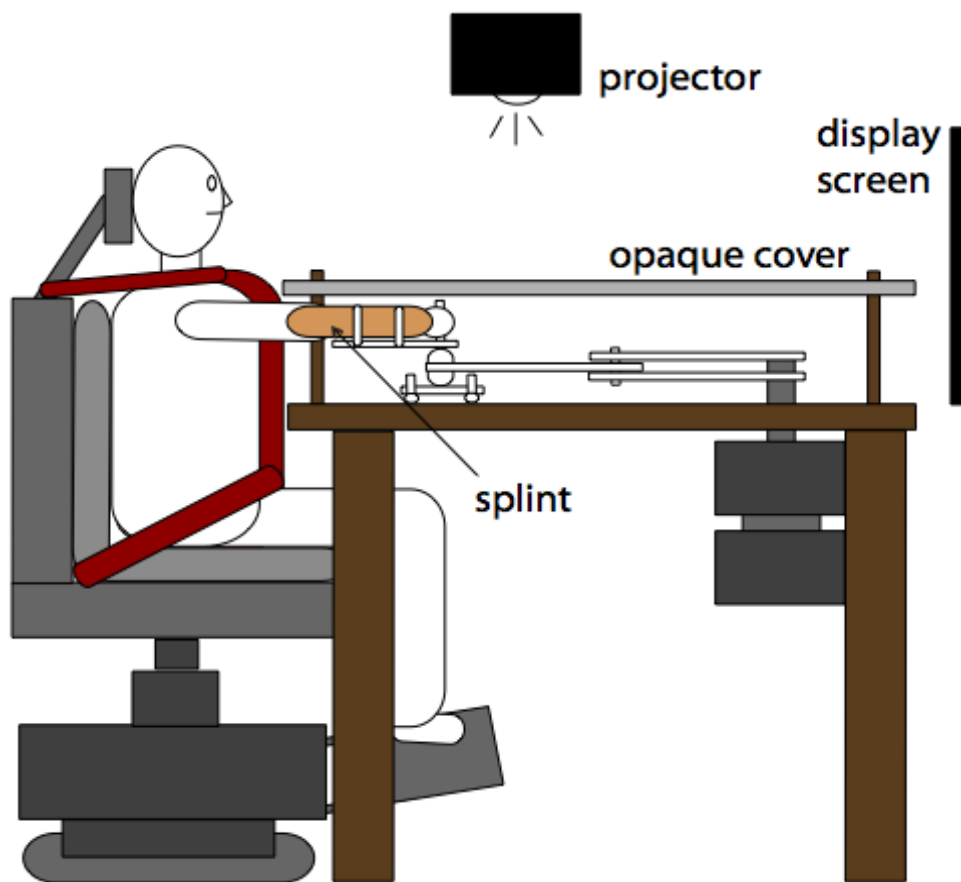


Figure 4.2.1: Experimental setup to investigate adaptation to unstable dynamics in multiple directions. Subjects were seated in an adjustable chair with their shoulder restrained by a harness and their hand and forearm firmly attached to the parallel-link direct drive air-magnet floating manipulandum (PFM) with a thermoplastic splint. A projector from the ceiling shows hand position in actual time whereas an opaque cover prevents direct visual feedback of the hand. A display screen gives subjects feedback on their performance after each trial.

4.2.2 Apparatus

Subjects sat on an adjustable chair with harness over their upper trunk, which prevented movement of the trunk (Figure 4.2.1). A subject custom-moulded thermoplastic cuff was used to restrict motion of the wrist and firmly attach the subject's hand to the manipulandum. The forearm and cuff were coupled to the handle of the parallel-link direct drive air magnet floating manipulandum (PFM) (Burdet et al. 2000). The robotic arm consists of two thin and two large driving plates. The driving plates are connected to two large torque motors placed under the table. The two degrees-of-freedom (DoF) PFM is sliding in the horizontal plane as the effect of gravity is removed using air bearing (Gomi and Kawato 1997). Subjects grab the handle, which uses a magnetic mechanism to prevent the handle from tilting or bending the thin plates of the PFM. The arm was restricted to planar motion of the shoulder and elbow, where the positive x and positive y directions correspond to the right and forward of the subject, respectively. Hand position was estimated from the PFM joint encoders (409 600 pulse/rev), and force exerted on/by the hand was measured using a force sensor (resolution 0.006 N) placed between the handle and the manipulandum's links. Both force and position signals were sampled at 500Hz. The maximum speed, force and acceleration are $4m/s$, $50m/s^2$ and $150N$, respectively.

4.2.3 Task

Subjects were instructed to perform point-to-point movements from a starting circle centred at $(0, 31)cm$ relative to the shoulder and towards two targets denoted by N and E35 respectively. Each target was a $2.5cm$ -diameter circle that was $25cm$ distant from the starting point. Subjects had to make the movement within $600 \pm 100ms$. N movements were performed to a target at $(0, 56)cm$ straight-ahead of the shoulder, and E35 movements towards a circle centred at $(14, 52)cm$, which was at 35° clockwise rotation from the first target (Figure 4.2.2A). A cursor, beamed from a projector mounted on the ceiling, represented the actual hand position while an opaque cover prevented subjects from seeing their hands or the robot. Start circle and the selected target circle were displayed before and during each trial in order to indicate the movement subjects needed to make. A screen in front of subjects displayed feedback about successful and non-successful movements after each trial.

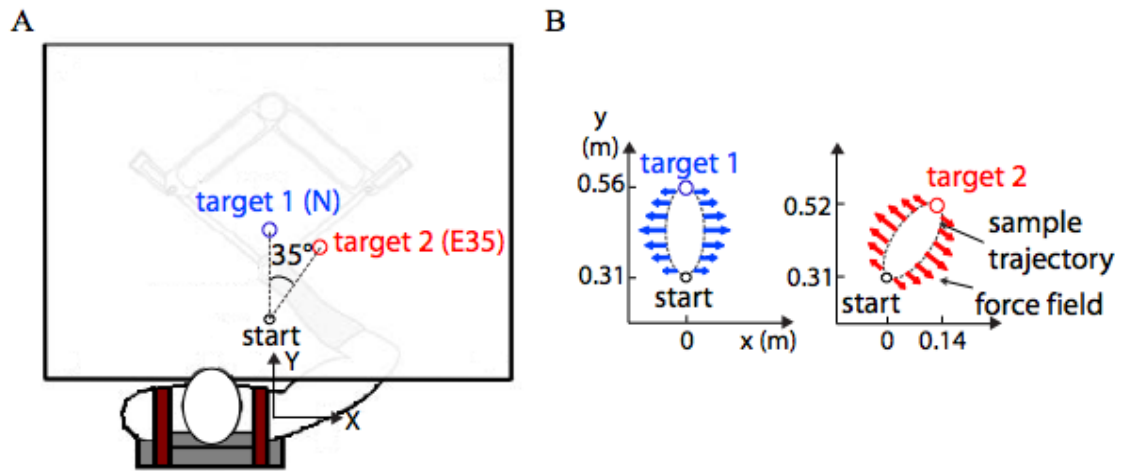


Figure 4.2.2: Experimental procedure to investigate adaptation to unstable dynamics in multiple directions. A: reaching movements were performed towards two targets in the workspace. The first target circle was straight ahead on the same y-axis as the start circle and was denoted as N. The second target circle was 35° clockwise to the first target and was denoted as E35. Both targets were at a 25cm distance from the starting point. B: position-dependent force fields applied in each movement were perpendicular on the straight-line joining start to finish points. The divergent force field (DF) is a linear function of the hand position error. The force fields stimulated instability like that experienced in real-life tasks such as carving and chiselling.

Subjects were asked to make movements within the required time and bring the cursor inside the 2.5cm in diameter target circle for the trial to be deemed successful. An unsuccessful trial was indicated by “out of target”, “too slow” or “too fast” on a monitor placed in front of the subject after the trial. All movements were recorded during the experiment, whether successful or not. In all sessions of the experiment, there was no time constraint as to when the following trial should start and so subjects could rest between trials. Subjects were required to bring the cursor inside the start circle before a beep sound signalled start of the movement. Each time the cursor was brought within the start circle, a trial was initiated by three beeps at 500ms intervals. Subjects were instructed to start moving their hand at the third beep and reach the specified target circle by the fourth beep, 600ms later. After reaching the target or the 600ms elapsed between the third and fourth beeps, there were another two beeps, 500ms apart, to indicate time needed to record success information about the trial.

4.2.4 Force field

Subjects produced movements in either a null-field (NF) environment where only the robot own dynamics were felt, or in a divergent force field (DF) where the robot applied a hand position-dependent unstable force on the hand, which was lateral to the movement (Figure 4.2.2B) and defined by:

$$\begin{bmatrix} F_{\perp} \\ F_{\parallel} \end{bmatrix} = \begin{bmatrix} Bp_{\perp} \\ 0 \end{bmatrix} \quad (4.5)$$

where $F_{\perp}$ and $F_{\parallel}$ indicate the force components normal and parallel to the straight line from start to end points, respectively. $p_{\perp}$ is the lateral deviation of the hand from this straight line and $B=300N/m$. A virtual safety barrier was implemented when the hand deviated by more than $\pm 5cm$ from the straight line between start and finish points, consisting of large damping replacing the negative stiffness of Equation (4.1). Beyond these boundaries, the force field was ceased and the trial deemed non-successful. There was no force field inside the start and end circles.

4.2.5 Experiment procedure

Subjects started by familiarising themselves with the PFM and the task by performing NF reaching movements. They had to practice on the robot at least one day prior to starting the experiment, by performing movements in N and E35 directions. Targets were randomly mixed, and subjects had to achieve 30 successful trials in each direction. The experiment was then conducted on three separate days for each subject. On Day1, subjects learned movements in one direction, while they performed movements towards the other direction on Day2, and on Day3 they practiced in both directions concurrently (Table 4.2.1).

On each of Day1 and Day2, first subjects had to perform 20 successful NF trials. After that, stiffness of the arm was estimated while subjects had to make an additional 100 successful trials in the NF. Then, subjects had to learn the DF by performing 100 successful trials. After this learning phase, stiffness was estimated

while subjects made 148 successful trials. On Day3, the target was selected randomly between directions N and E35. Subjects performed trials with the same phases as on Day1 and Day2, but had to make an equal number of successful trials in each direction. For example, in the first phase, subjects had to produce 20 successful trials in the N direction and 20 successful trials in the E35 direction.

In order to study any possible confound associated with a particular direction, subjects were separated into two groups of five (Table 4.2.1). Directions of learning were alternated between the two groups. In other words, in one group subjects learnt in direction N on Day1 and in direction E35 on Day2, whereas in the other group subjects learnt in E35 on Day1 and in N on Day2.

Table 4.2.1: Number of successful trials required for each subject

	Group I subjects	Group II subjects
Day 1	$\left\{ \begin{array}{l} 20 \text{ in } NF \\ 100 \text{ for stiffness} \\ 100 \text{ in } DF \\ 148 \text{ for stiffness} \end{array} \right\} N$	$\left\{ \begin{array}{l} 20 \text{ in } NF \\ 100 \text{ for stiffness} \\ 100 \text{ in } DF \\ 148 \text{ for stiffness} \end{array} \right\} E35$
Day 2	$\left\{ \begin{array}{l} 20 \text{ in } NF \\ 100 \text{ for stiffness} \\ 100 \text{ in } DF \\ 148 \text{ for stiffness} \end{array} \right\} E35$	$\left\{ \begin{array}{l} 20 \text{ in } NF \\ 100 \text{ for stiffness} \\ 100 \text{ in } DF \\ 148 \text{ for stiffness} \end{array} \right\} N$
Day 3	$\left\{ \begin{array}{l} 40 \text{ in } NF \\ 200 \text{ for stiffness} \\ 200 \text{ in } DF \\ 296 \text{ for stiffness} \end{array} \right\} \text{directions } N \text{ and } E35$	

4.2.6 Stiffness Measurement

Stiffness measurement had to be performed without any contribution of damping. Therefore, during the hold period of the perturbation, the hand was displaced with the same predicted velocity as in unperturbed movements, which should result in no difference in velocity between perturbed and unperturbed trials. The method developed

by Burdet and colleagues (2000) was based on a previous method proposed by Bennett et al. (1993) where the hand was displaced relative to a predicted undisturbed trajectory. This method was used to predict joint stiffness during elbow movements using a few trials only and stiffness was simply calculated as force divided by displacement. Hence, Bennett's method was used for linear one-joint movements and using the mean of past movements to predict the undisturbed trajectory was acceptable. However, this is not the case with multi-joints movements where the error becomes reasonably large between movements because they are less constrained.

Therefore, the method developed by Burdet et al. (2000) was used to estimate stiffness. Subjects first completed 20 successful trials in whichever force field was being tested. As the velocity profile is roughly the same for these movements then the average profile was taken for the current predicted trajectory. Before that, the velocity profiles of these movements were low-pass filtered at 50Hz, scaled to produce the same amplitude and truncated at both ends using a 0.03m/s velocity threshold. The mean for the acceleration and deceleration were computed separately in order to avoid distortion of the template profile due to differences in the times of the peak velocity. The template velocity was scaled over a range of 11 amplitudes and 11 time shifts (i.e. 11x11=121 candidate velocity profiles were generated), chosen to minimise the prediction error over 20 unperturbed movements. The candidate best matching the current trajectory was then selected, and used for predicting the unperturbed trajectory. The best match was determined by minimising the following recursive function once the velocity had crossed a threshold of 0.03m/s:

$$d_{l,k} = (\mathbf{v}_k - \mathbf{w}_{l,k})^2 + \alpha d_{l,k-1} \quad (4.6)$$

where $\mathbf{v}_k$ is the velocity of the current time sample k , $\mathbf{w}_{l,k}$ is the l^{th} velocity candidate at time k and $\alpha=0.94$ is a forgetting factor which limits matching to the last 100ms. The movement was decomposed parallel and perpendicular to the main movement direction and candidate velocity profiles were selected independently in the x - and y - directions. The template velocity profile was updated after each trial and the standard deviation was computed with the most recent trial replacing the earliest of the 20 stored trials. If the standard deviation was larger than 1.05 times the previous standard deviation, then the most recent trial was excluded. The speed and acceleration were obtained from the

position signal using second and third order Butterworth filters, respectively, with a cut-off frequency of 50Hz , such that differentiation and filtering were realised simultaneously.

Before each stiffness estimation session started, subjects were readapted to the field for 20 trials to ensure subjects retained learning. Then, half of the additional trials were randomly selected for stiffness estimation. On each of these trials, the movement was perturbed in one of eight equally spaced directions, encompassing the full 360° (i.e. 0° , 45° , 90° , 135° , 180° , 225° , 270° , 315°), in order to account for any artefacts that could arise from different configurations of the hand during movements (i.e. using all possible degrees of freedom, because stiffness is present in all directions of hand configuration). The perturbation of amplitude of 8mm was applied near the midpoint of the movement and the displacement lasted for 300ms . Displacement phase consisted of a smooth 100ms ramp-up, 100ms hold, and a smooth 100ms ramp-down segment. Transition phases of up to 100ms were necessary to minimise vibration. The effect of vibration was avoided by restricting the stiffness identification to a 50ms interval centred at the midpoint of the plateau phase. Note that the measured stiffness corresponds to a temporal mean over these 50ms . Stiffness estimation was conducted between 140ms and 190ms after the onset of perturbation to account for reflexes (Burdet et al. 2000). Prediction was not perfect, but the errors were found to be small and the average over a number of trials made the error negligible, which meant that distorting forces due to damping or acceleration did not affect stiffness estimation.

4.2.7 Electromyography (EMG) measurement

During all sessions, surface EMG was recorded from two monoarticular shoulder muscles: pectoralis major and posterior deltoid; two monoarticular elbow muscles: brachioradialis and lateral head of the triceps; and two biarticular muscles: biceps brachii and long head of the triceps. EMG was recorded using pairs of silver-silver chloride surface electrodes. The electrode locations were chosen to maximise the signal from a particular muscle while avoiding cross talk from other muscles. The skin was cleansed with alcohol and prepared by rubbing electrode paste into it. The paste was then removed with a dry cloth, and the pre-gelled electrodes were attached to the skin and secured with tape. The electrode spacing was $\sim 2\text{cm}$. The impedance of each electrode pair was tested to ensure that it was less than $10\text{k}\Omega$. The EMG signals were

Butterworth bandpass filtered between 25Hz (high pass) and 1.0kHz (low pass) and sampled at 2.0kHz. Muscle activity was recorded for 700ms, starting 70ms before the onset of movement and 630ms during execution of the movement. EMG activity was averaged over a number of trials to better analyse the signal from each session. The same electrodes were kept during NF and DF learning on the subjects for each day. This way it was possible to measure the net EMG after adaptation to the divergent force field.

The electrodes were placed at the centre of the muscle in order to maximise the signal detection. They were placed before starting the experiment when subjects were asked to maintain horizontal arm posture, as they would be in the experiment. The elbow was maintained at 90° flexion and subjects were asked to contract each muscle in turn before cleaning the skin and placing the electrodes. The pectoralis major electrodes were placed approximately 5cm proximal and 5cm inferior to the glenohumeral joint. The posterior deltoid electrodes were placed approximately at the centre of the posterior side of the glenohumeral side. The biceps brachii electrodes were placed around the middle of the two heads of the biceps muscle. The long head triceps electrodes were placed about 15cm away from the shoulder joint on the posterior inferior edge of the arm. The brachio-radialis electrodes were placed approximately 5cm distant from the elbow joint along the superior-medial edge. Finally, the triceps lateral head electrodes were placed along the superior posterior edge of the arm 10cm away from the elbow joint.

4.2.8 Data analysis

Learning

Two measures were used to analyse learning. First we used the *hand-path error*

$$E = \int_0^T |p_{\perp}(t)| |\dot{p}_{\parallel}| dt \quad (4.7)$$

where $p_{\perp}$ is the perpendicular position relative to the straight line from start to target, and $\dot{p}_{\parallel}$ is the parallel velocity component. The hand-path error is the area between the realised path and the straight line from start to target. Error was calculated from time 0 (75ms before crossing a hand-velocity threshold of 0.05ms⁻¹) to time T (when curvature

exceeded $0.07mm^{-1}$) (Pollick and Ishimura 1996). For movements deviating more than $5cm$ from the straight line, it was assumed that the position of the hand followed the $5cm$ parallel line until movement end.

The moving average of *success rate* was used as second measure, and was computed using:

$$\mathbf{m}(n) = \left(\frac{1}{F}\right) \sum_{i=n}^{n+F-1} c(i) \quad (4.8)$$

$$n \in \{1, 2, 3, \dots, (N - F)\}$$

where $c(i)=1$ for a successful trial and $c(i)=0$ otherwise, N is the total number of (successful and unsuccessful) trials for a particular session, and $F=10$ is the number of sample trials averaged at each iteration.

Both hand-path error and success rate data were fitted using a power series model of the form:

$$\mathbf{y}(k) = a\mathbf{x}(k)^b + c \quad (4.9)$$

where a is the gain of the power model, b the growth rate, c the steady-state value and k the trial number.

When performing statistical analysis, absolute error and success rate were quantified by comparing the first 10 trials against the last 10 trials from the average data across subjects. Furthermore, an analysis of variance (ANOVA) was used to verify any effect of, dividing subjects into two groups, force field (i.e. comparing performance in NF and DF), learning between directions N and E35, and learning in one direction only as compared to learning in multiple directions concurrently. Random effect was subjects in each test.

Endpoint force

Force produced by subjects was measured using the force sensors attached to the PFM. Data was collected during training in both NF and DF on each day of the experiment. End-point force was measured from the first 20 successful trials in the stiffness measurement session.

Mean endpoint force, over the 50ms stiffness measurement interval, for each subject at the midpoint of movement was determined. This is to assess whether subjects used endpoint force while compensating for the dynamics in either direction of movement. The time interval corresponding to stiffness estimation time was chosen so that, if found, direct relation could be established between change in endpoint stiffness and change in endpoint force.

Statistical tests were used to determine any significant change in the force produced in both *lateral*- and *parallel*-axes. ANOVA was used with main effect of direction of movement, force field, single or multiple directions learning, group of subjects and the difference between *lateral*- and *parallel*-axes forces. Random effect was subjects.

Cartesian and joint stiffness

End-point force was measured from the first 20 successful trials in the stiffness measurement session. The average force and displacement measured during the final 50ms of the hold period were used to estimate the two-by-two endpoint stiffness matrix **K**:

$$\begin{bmatrix} \delta F_{\perp} \\ \delta F_{\parallel} \end{bmatrix} = \mathbf{K} \begin{bmatrix} \delta p_{\perp} \\ \delta p_{\parallel} \end{bmatrix}, \quad (4.10)$$

$$\mathbf{K} = \begin{bmatrix} K_{\perp\perp} & K_{\perp\parallel} \\ K_{\parallel\perp} & K_{\parallel\parallel} \end{bmatrix}$$

using a linear regression model, where $\delta F_{\perp}$, $\delta F_{\parallel}$, $\delta p_{\perp}$ and $\delta p_{\parallel}$, are the mean changes in endpoint force and displacement, in *normal* and *parallel* directions respectively. $K_{\perp\parallel}$, for instance, refers to the amount of force change in the *normal* direction after the hand is displaced along the *parallel*-axis. The endpoint stiffness can be represented as an ellipse (Mussa-Ivaldi et al. 1985). Singular value decomposition of the stiffness matrix **K** was used to determine the size, shape, and orientation of the stiffness ellipses (Gomi and Osu 1998).

The joint stiffness matrix **R** (Nm/rad) was derived from the endpoint stiffness **K** using:

$$\mathbf{R} = \mathbf{J}^T \mathbf{K} \mathbf{J} + \frac{\partial \mathbf{J}^T}{\partial \theta} \mathbf{F}$$

$$\mathbf{R} = \begin{bmatrix} R_{ss} & R_{se} \\ R_{es} & R_{ee} \end{bmatrix} \quad (4.11)$$

where $\mathbf{J}$ is the Jacobian matrix relating hand and joint angular coordinates. The second term on the right is the change in hand force due to change in geometry of the arm that depends on displacement (Franklin et al. 2003A; McIntyre et al. 1996). R_{ss} is the joint stiffness relating shoulder torque to shoulder displacement, R_{se} relates shoulder torque to elbow displacement, R_{es} relates elbow torque to shoulder displacement and R_{ee} relates elbow torque to elbow displacement.

Statistical difference in stiffness was first quantified by analysing ellipse shape, size, orientation and the ratio of shoulder joint stiffness to elbow joint stiffness (i.e. R_{ss}/R_{ee}).

In order to examine whether stiffness increased in either *lateral*- or *parallel*-axis after learning in the divergent field, all four elements of the Cartesian stiffness matrix were analysed with particular emphasis on $K_{||}$ and $K_{\perp}$. Similarly, joint stiffness matrix components were analysed for any significant differences in learning. Analysis was through the use of an ANOVA to compare subject performance with main effect of force field, group of subjects, direction of movement, and single or multiple directions learning. Random effect was subjects.

Electromyography

To examine muscle activity after adaptation to the force field, electromyography signals were analysed during learning in NF as well as in DF. The EMG in the final 20 successful NF trials and the final 60 successful DF trials during learning were analysed. EMG data for each subject was rectified, averaged across trials, and then Butterworth low-pass filtered with a cut off frequency of 100Hz. Before taking the relative difference between DF and NF, smoothened activity was freed from any baseline noise using:

$$SA_m = EMG_m - \min(EMG_m), \quad m \in \{1, 2 \dots 6\} \quad (4.12)$$

where EMG_m is the filtered muscle activity for each muscle m and SA_m is the noise-free EMG. The relative change between DF and NF was computed as:

$$\begin{aligned}\Delta SA_m &= \frac{SA_m^{DF} - SA_m^{NF}}{\overline{SA}_m^{NF}} \\ \overline{SA}_m^{NF} &= \frac{1}{700} \int_{t=0}^{700} SA_{mi}^{NF}(t) dt\end{aligned}\tag{4.13}$$

where $\overline{SA}_m^{NF}$ is the average NF activity over each muscle m for 700ms. Then, any resultant negative values were assumed to be zero muscle activity.

In order to compare EMG across days and directions, the total relative change of agonist/antagonist muscle activity of each pair (single-joint shoulder, biarticular, and single-joint elbow) was represented as a percentage of the total activity from all three pairs on each day. Ratios were averaged every 10ms from onset of movement until the end of recording. Note that agonist/antagonist pairs were added because co-contraction of muscles at one joint provides direct relation to stiffness orientation (Franklin et al. 2007). Therefore, differences in stiffness between N and E35 directions may be related to increased co-contraction of specific muscles pairs.

EMG for all muscles was assessed using ANOVA for any significance at the 0.05 levels. Analysis considered looking for main effects of pair of muscles, change in force field from NF to DF, direction of movement, and the difference between single- and multiple-direction learning. Random effect was subjects.

Data was analysed using Matlab R2007a (The Mathworks), while statistical analysis was performed using the general linear model in SPSS 16.0.1 (Chicago, IL) to perform ANOVA.

4.3 Results

Results were first analysed for the two groups separately, where the subjects from group I started by training in direction N on Day1 and then in direction E35 on Day2, and conversely for the subjects of group II. However, statistical analysis showed that subjects from the two groups performed similarly in the same direction on Day1 and Day2, and that they also performed similarly on Day3. ANOVA showed that there was no main effect of group factor in hand-path error ($p=0.333$) or success rate ($p=0.681$). Orientation of stiffness ellipse did not change between groups I and II ($p=0.1$), nor did the ellipse's size ($p=0.228$). Neither Cartesian endpoint stiffness K ($p=0.789$) nor joint stiffness R ($p=0.489$) changed between groups. Additionally, there was no effect of the group parameter in endpoint force applied by subjects ($p=0.373$). Based on these results, data from both groups were used together and the following analysis presents the results across all subjects.

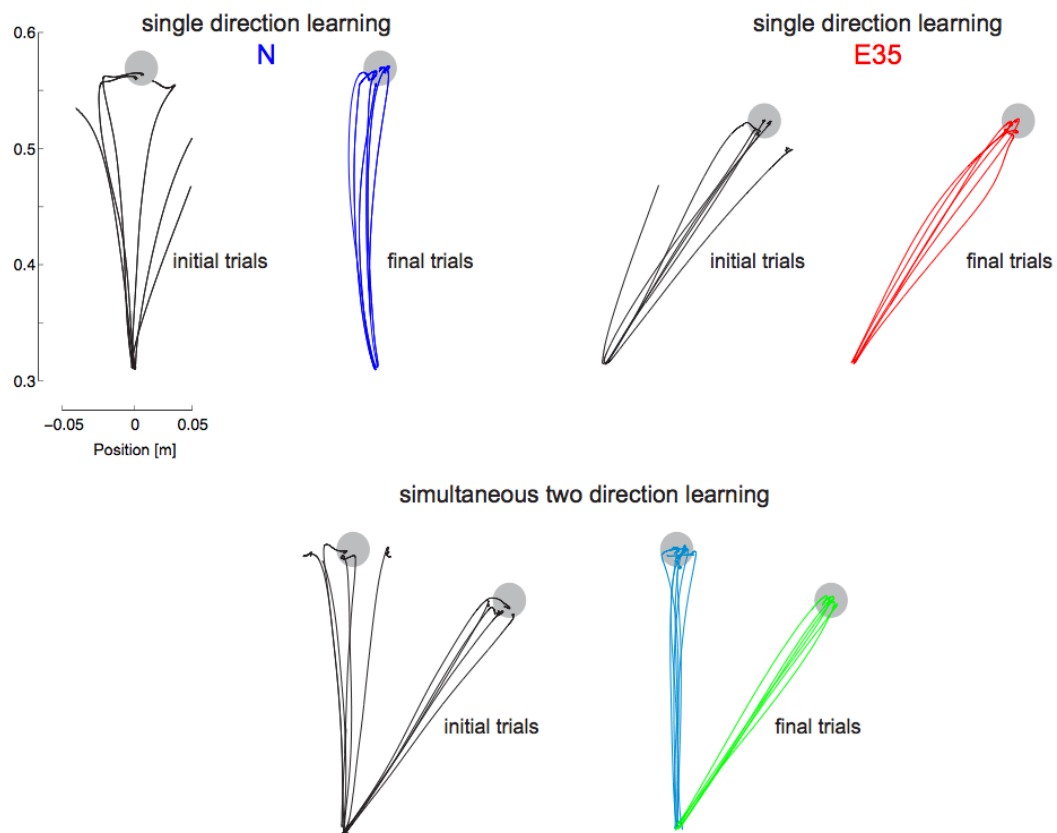


Figure 4.3.1: Reaching movements towards both targets on all 3 days of the experiment, for one representative subject. The figure shows initial and final trajectories in directions N and E35. A virtual barrier stops the deviation at $\pm 5\text{cm}$ normal to the straight-line trajectory. Movements were diverged to either right or left of the straight-line joining start and finish points, in each direction respectively. Movement divergence at first exposure to the force field was larger in direction N than in E35. Subject made straighter movements towards the end of learning on each day, which were similar to movements made after adaptation in NF.

4.3.1 *Learning*

Hand-path error

In both N and E35 directions, initial hand trajectories made by subjects in the divergent field deviated widely from the straight line joining start and finish points (Figure 4.3.1). However, with repeated trials trajectories became gradually straighter and similar to those in the null-field.

Hand-path error, representing the area between the hand movement and the straight-line between start and target points, was examined during repeated trials in NF and DF. The mean error over the subjects decreased after repeated trials in DF (Figure 4.3.2), as shown by the significant decrease of mean error between the first five and last five trials in both directions and on every day ($p < 0.001$). This suggests that there was learning on every day and in both directions. Note that on Day3, where movements were performed both in N and E35 directions, the error decreased in each of these directions.

Subjects were required to produce 100 successful movements in each direction and on each day. The average $\pm$ SD number of trials performed by subjects was 197 ± 44 when learning the DF in direction N only, and 151 ± 25 trials when learning in direction E35 only. Only 174 ± 38 (56%) and 136 ± 20 (44%) were needed on Day3 in directions N and E35, respectively. This may suggest that learning in the two single directions on Day1 and Day2 facilitated performance in these directions on Day 3, and that movements were easier in the E35 direction.

This prompted to further investigate any difference in learning across movement directions and across days. ANOVA showed a significant effect of direction on hand path error even on Day3 when learning was in both directions together ($p < 0.001$). An interpretation would be that adaptation was direction-specific, as subjects produced less error in direction E35 than they did in direction N. There was also a significant difference in error between learning in one direction only and learning in two directions concurrently ($p = 0.006$). This demonstrates that error dropped even further on the final day in the two directions.

However, it was necessary to distinguish between initial and final learning across directions and days. ANOVA showed that initial error was different between directions ($p = 0.001$) and also for a given direction it was different between single and multiple directions learning ($p = 0.009$). This shows that subjects not only retained but

improved learning from the first two days going into the third day of the experiment. Final error was significantly different across directions of movement ($p=0.001$) while it was not different between single and multiple direction learning ($p=0.452$). This shows that subjects reached the same level of adaptation to the force fields when learning in one direction only as compared to learning in two directions concurrently.

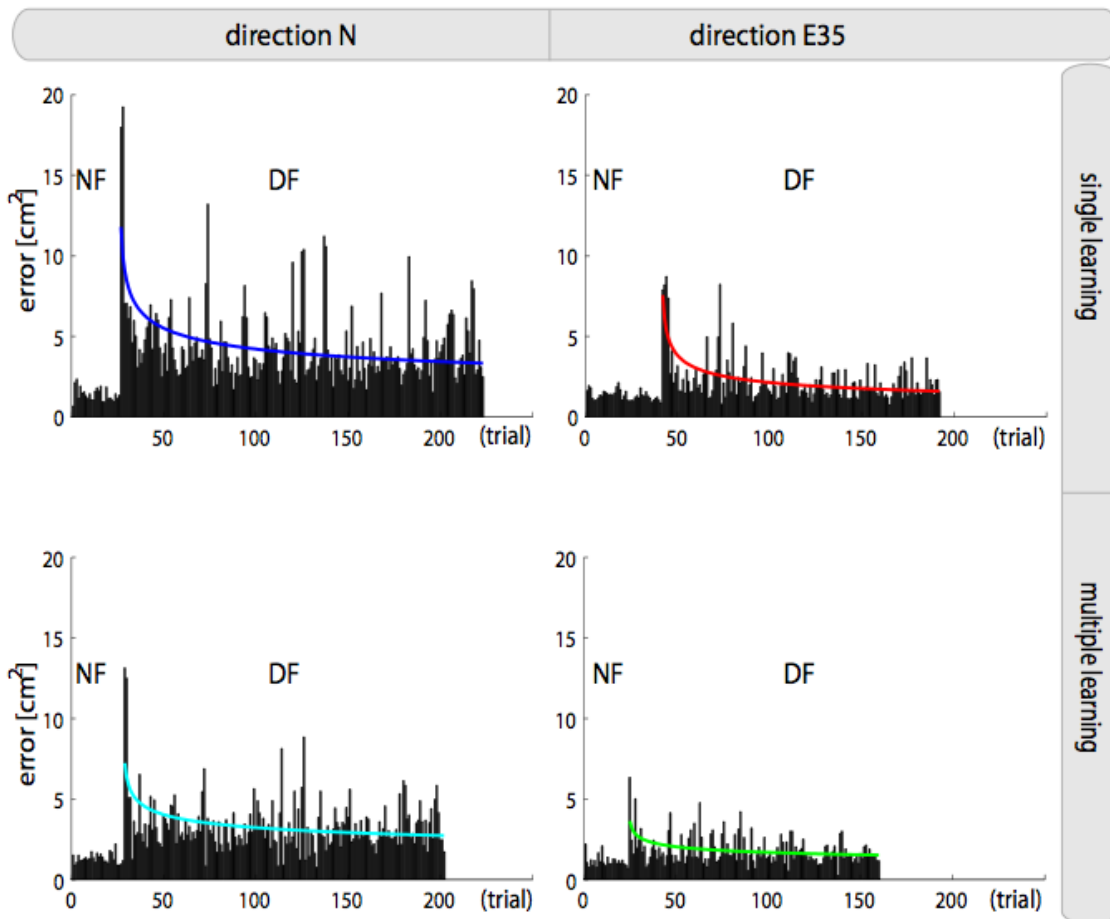


Figure 4.3.2: Mean across subjects of absolute hand-path error in NF and DF on all days of the experiment. Plots show that error dropped during training in the DF on all days of the experiment. Error was calculated as the area separating measured position and a straight-line joining start to finish points. Error is displayed for all successful and non-successful trials. Subjects needed to make 20 successful trials in NF and 100 successful trials in DF. The thin-lines dropping in the graphs represent the power-model fit to the data. Subjects produced more error in direction N than in E35 whether learning in a single direction only or in both directions concurrently. The figure also shows that hand-path error dropped on Day3 as compared to the two previous days in the same direction.

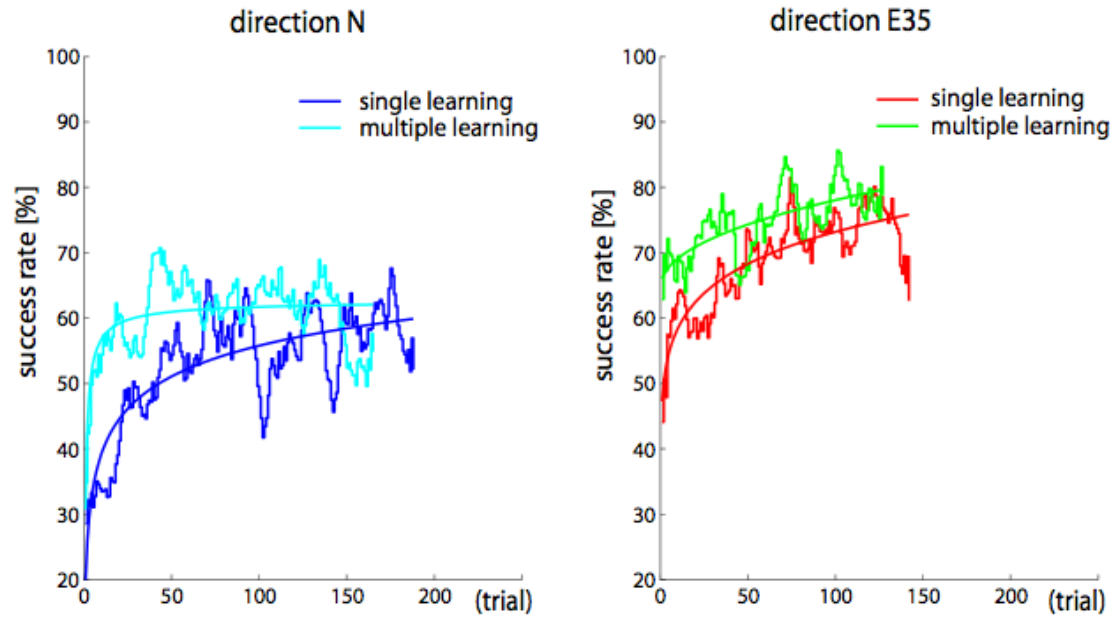


Figure 4.3.3: Evolution of success rate during adaptation to the divergent field on all days of the experiment. Plots show the mean across subjects of success rate that was smoothened using a normal moving average then fitted with a power-model fit to the data (continuous thin line in the graph). Success rate was the ratio of successful movements in any batch of 10 trials. Success rate during adaptation to the divergent field dynamics increased on all days of the experiment. Graph on the left depicts single-direction (blue) against multiple-directions learning (cyan) during training in DF in direction N. Plots on the right show single-direction (red) and multiple-directions learning (green) during adaptation in DF in direction E35. Subjects were less successful in direction N than they were in direction E35 whether learning in a single direction only or in both directions concurrently. The figure also shows that success rate was mostly higher on Day3 as compared to the previous two days in each direction respectively.

Success rate

The rate of successful trials achieved by subjects confirmed the results on the error evolution analysis. Figure (4.3.3) shows the average rate across all subjects during learning in direction N only, in direction E35 only and when learning in both directions together. It shows that subjects learnt the tasks on all days regardless of their complexity. Subjects had a relatively low success rate at the beginning of each session, but gradually became more successful. ANOVA validated that success rate increased significantly between the first ten and last ten trials in each direction of movement ($p < 0.001$).

Comparing data across directions shows that learning was better in direction E35 than it was in direction N, even on Day3 when subjects had to make movements towards both targets concurrently. Indeed, there was a significantly larger proportion of successful trials in direction E35 than in the N direction ($p < 0.001$). Therefore, similar to hand-path error results, learning assessed through success rate of the movement was direction-specific.

When comparing performance in the same direction across days, it can be seen that success rate was better when learning in two directions together than when learning in one direction only ($p = 0.013$). Hence, although that the task was more complex when making concurrent movements towards both targets, subjects had no particular difficulty in performing movements towards two directions concurrently.

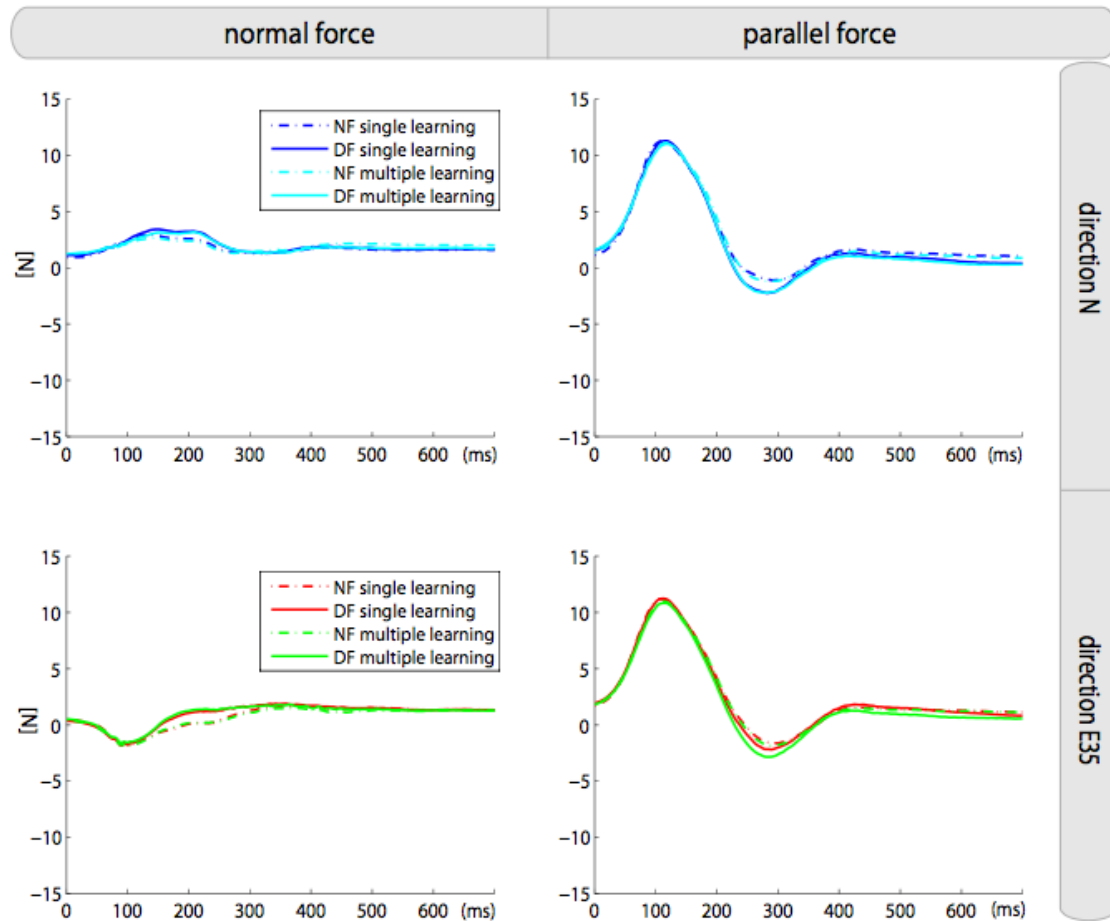


Figure 4.3.4: Mean across subjects of force profiles in normal- and parallel-axes in both directions N and E35. Force was similar before (dotted lines) and after (continuous lines) learning in the divergent field in both directions. Force profiles were also similar between single and multiple learning across directions of movement.

4.3.2 End-point force

Analysis of endpoint force showed that adaptation to the DF is not due to a change of force. The mean endpoint force of the last 20 trials when learning the DF was studied, where Figure (4.3.4) shows the average force profiles across all subjects. Forces in *normal* and *parallel*-axes were plotted separately to find any difference in learning between the two directions. Forces are similar in NF and DF and in the two directions, on every day, extending the finding of (Franklin et al. 2003A). These results show that the decrease of movement error cannot be due to a change of endpoint force.

Figure (4.3.5) shows the mean endpoint force and standard deviations at the midpoint trajectory, i.e. where stiffness was estimated, averaged over the last 20 trials in NF and DF for each subject. These results show that, for each subject, adaptation to the divergent field did not require any change in force. Using force data in the first 10 trials during stiffness measurement, an ANOVA showed that there was no main effect of force field ($p=0.931$). There was also no difference between single and multiple direction learning ($p=0.424$). Recorded force was not different between the two directions of movement in neither the *normal*-axis nor the *parallel*-axis ($p>0.456$).

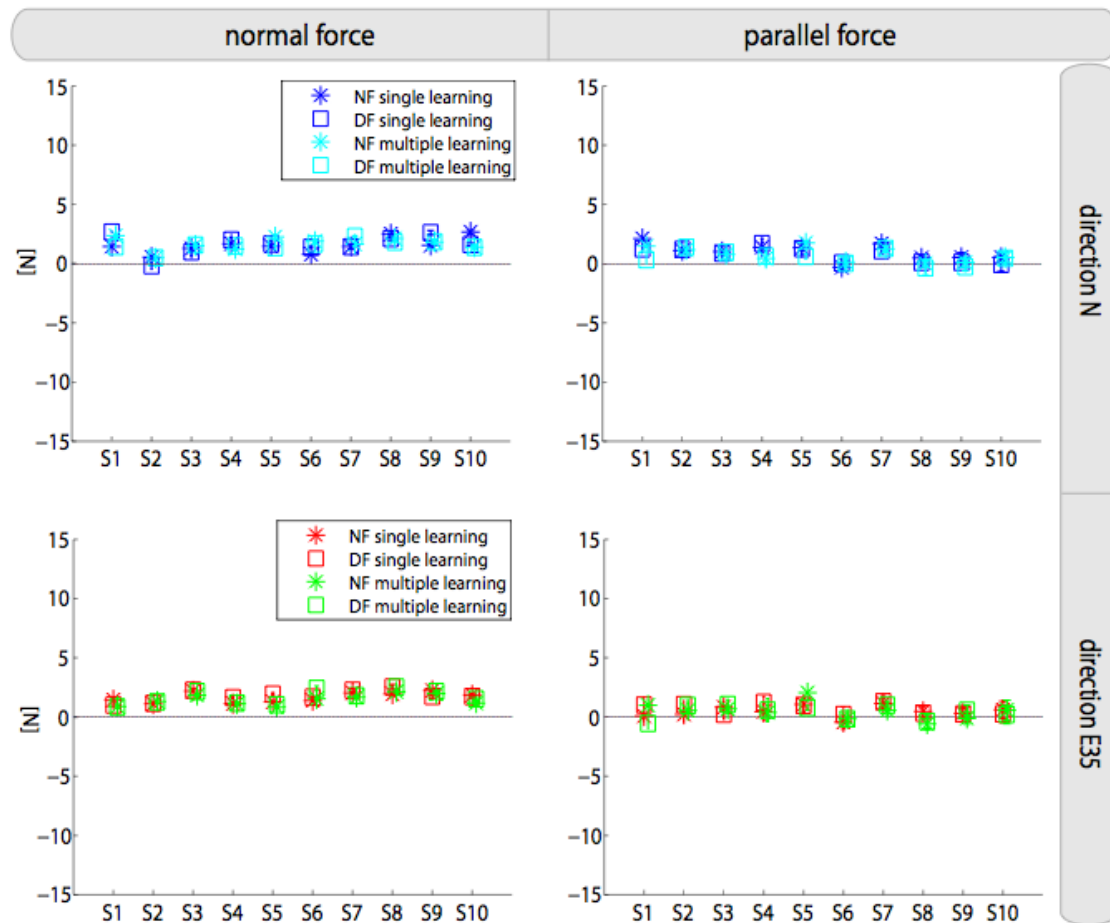


Figure 4.3.5: Endpoint force exerted during stiffness measurement period for each subject separately. The figure shows the mean and standard deviation of normal- (left column) and parallel-force (right column) for all ten subjects in directions N (top draw) and E35 (bottom row). Endpoint force was calculated at the midpoint interval over 50ms, which is the same time when stiffness was measured. There was no change between force applied after training in NF (star) and DF (square) in both directions.

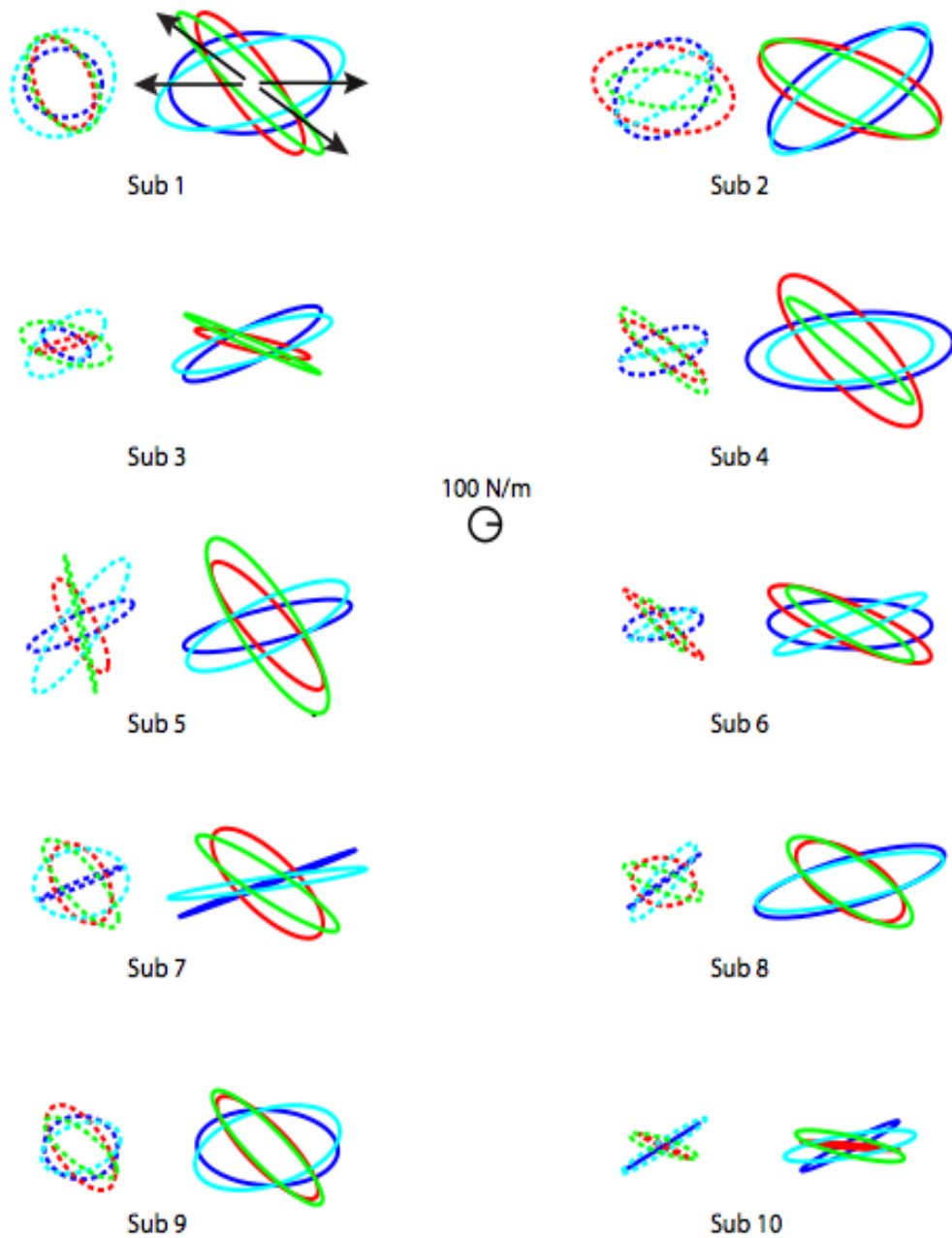


Figure 4.3.6: Endpoint stiffness ellipse plotted from all three days of the experiment. The figure shows the endpoint stiffness ellipse from all ten subjects in both NF (discontinuous line) and DF (continuous line). Ellipse is plotted after single direction adaptation in N (blue) and E35 (red), and then multiple directions learning in N (cyan) and E35 (green). Stiffness ellipse after learning in the divergent field was larger than in the null field. The figure shows that adaptation was different between directions N and E35. Additionally, stiffness increased in the same direction for similar movements across days. These directions of stiffness increase are close to the directions of instability (represented by the black arrows) in the environment for each movement respectively.

4.3.3 *Stiffness*

Stiffness ellipse properties

In order to further examine how subjects adapted to the instability in both directions, endpoint stiffness was estimated by displacing the hand relative to a prediction of the trajectory, and then the restoring force was measured relative to displacement (Burdet et al. 2000). Figure (4.3.6) illustrates endpoint stiffness geometry, averaged over the subjects, in NF and DF and in both directions N and E35. The stiffness ellipses appear to be elongated orthogonal to the movement, in particular after adaptation to the instability of the divergent force field.

The geometric characteristics of the ellipse were further analysed. First, the shape of stiffness ellipse, i.e. the ratio of smaller to larger singular value, was significantly larger in the NF than in the DF ($p=0.023$) (Figure 4.3.7A). On the other hand, shape was similar in the same direction across days ($p=0.401$), and there was no difference between single- and multiple-direction learning ($p=0.202$).

Further, the size of the ellipse (proportional to the product of the singular values) was significantly larger in DF than in NF for both movement directions ($p<0.001$), despite the large variability (Figure 4.3.7B). Size of ellipse was the same in a given direction of movement across days ($p=0.208$). Stiffness ellipse size was not different between single- and multiple- direction learning ($p=0.522$).

Finally, in Figure (4.3.7C), the orientation of the ellipse is shown to have increased in the direction of instability of each movement. Orientation of ellipse did not change after adaptation to DF in either direction as compared to the NF ($p=0.555$). Subjects maintained the same stiffness orientation in the same direction across days ($p=0.362$). However, orientation was different between directions N and E35 in either DF or NF ($p<0.001$).

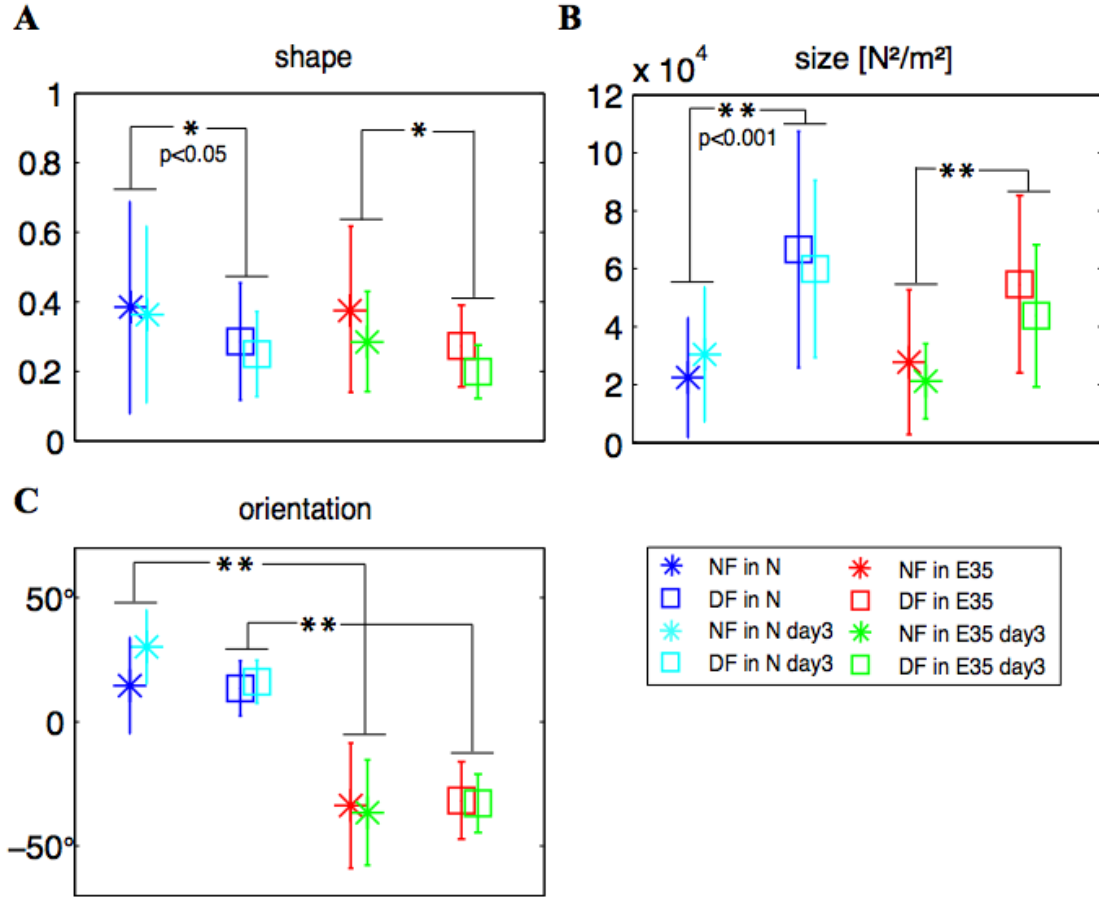


Figure 4.3.7: Properties of the endpoint stiffness ellipse in NF and after exposure to the dynamics of the unstable fields. The figure shows the mean across subjects of ellipse change in shape, size and orientation between NF and DF in directions N and E35. The vertical bars represent the standard deviation across subjects. **A:** mean shape of ellipse was higher in NF than in DF for both directions respectively. There was no difference in shape between single and multiple learning in the same direction. The change in shape between NF and DF reflects how stiffness ellipse increased anisotropically in the direction of instability. **B:** mean size of ellipse increased after adaptation to the divergent field as compared to the null field stiffness in both directions. This shows that subjects increased their stiffness more in DF in order to counter the dynamics of the environment. **C:** mean orientation of ellipse was similar between force fields but different across directions of movement, though less variance across subjects in the DF. Subjects, as seen in the previous figure, rotated their stiffness differently between directions N and E35. The orientation of the ellipse was closely in the same direction as the trend of instability of each direction. (* $p < 0.05$, ** $p < 0.001$).

Hand stiffness components

The four components of the end-point stiffness matrix averaged across subjects are plotted in Figure (4.3.8). Statistical analysis of the four-components matrix shows that there was an increase in endpoint stiffness in DF as compared to NF in both directions N and E35 ($p < 0.001$), while there was no change in the same direction across days ($p = 0.490$) (Figure 4.3.8). However, stiffness was different between the two directions ($p = 0.002$).

This prompted an analysis of each of the stiffness matrix elements separately. Using ANOVA in direction N, $K_{\perp\perp}$ changed significantly between NF and DF ($p < 0.001$), but none of the other three elements changed ($K_{\perp\parallel}$: $p = 0.327$; $K_{\parallel\perp}$: $p = 0.072$; $K_{\parallel\parallel}$: $p = 0.267$). Stiffness, in direction E35, changed between DF and NF in $K_{\perp\perp}$ ($p < 0.001$) and in $K_{\perp\parallel}$ ($p = 0.001$) but not in $K_{\parallel\perp}$ ($p = 0.584$) and $K_{\parallel\parallel}$ ($p = 0.052$). These differences suggest that learning occurred by specifically tuning the $K_{\perp\perp}$ component in direction N and both $K_{\perp\perp}$ and $K_{\perp\parallel}$ in direction E35. In fact, Figure (4.3.9) shows that the net stiffness, when the force field was subtracted, was similar to the NF stiffness in all directions of learning. This demonstrates that the subjects succeeded in moving in the divergent force field by compensating for the imposed instability.

The next step was to look for any differences in the matrix elements between the two directions. $K_{\perp\perp}$ and $K_{\parallel\parallel}$ did not change between the two directions in NF ($p = 0.733$, $p = 0.135$) nor did they in DF ($p = 0.113$, $p = 0.14$). However, both $K_{\perp\parallel}$ and $K_{\parallel\perp}$ changed significantly between directions N and E35 in NF and DF ($p < 0.001$).

These findings extend previous results from Burdet et al. (2001), Franklin et al. (2004) and Franklin et al. (2007). The stiffness ellipses were selectively tuned towards the direction of instability. Both in directions N and E35, we observed similar tendencies where stiffness selectively increased in the lateral axis after adaptation to the force field. The difference in stiffness between directions N and E35 was in the asymmetric values $K_{\perp\parallel}$ and $K_{\parallel\perp}$, however the difference in adaptation to the force field occurred in $K_{\perp\parallel}$ component only.

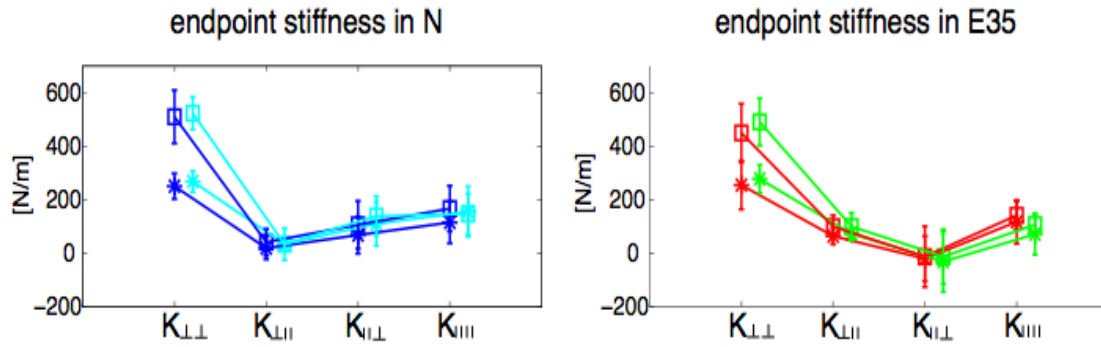


Figure 4.3.8: Hand stiffness components across subjects. Plotted is the stiffness in NF (star) and DF (square) from all days of the experiment. Vertical bars show the 90% confidence intervals. Endpoint stiffness for single learning is shown in blue for direction N and in red for direction E35. Stiffness for multiple directions learning is shown in cyan for direction N and in green for direction E35. In both directions stiffness increased mainly in $K_{\perp\perp}$, while $K_{\parallel\perp}$ and $K_{\perp\parallel}$ are different between the two directions. No difference is noticed between single and multiple learning in neither of directions N and E35.

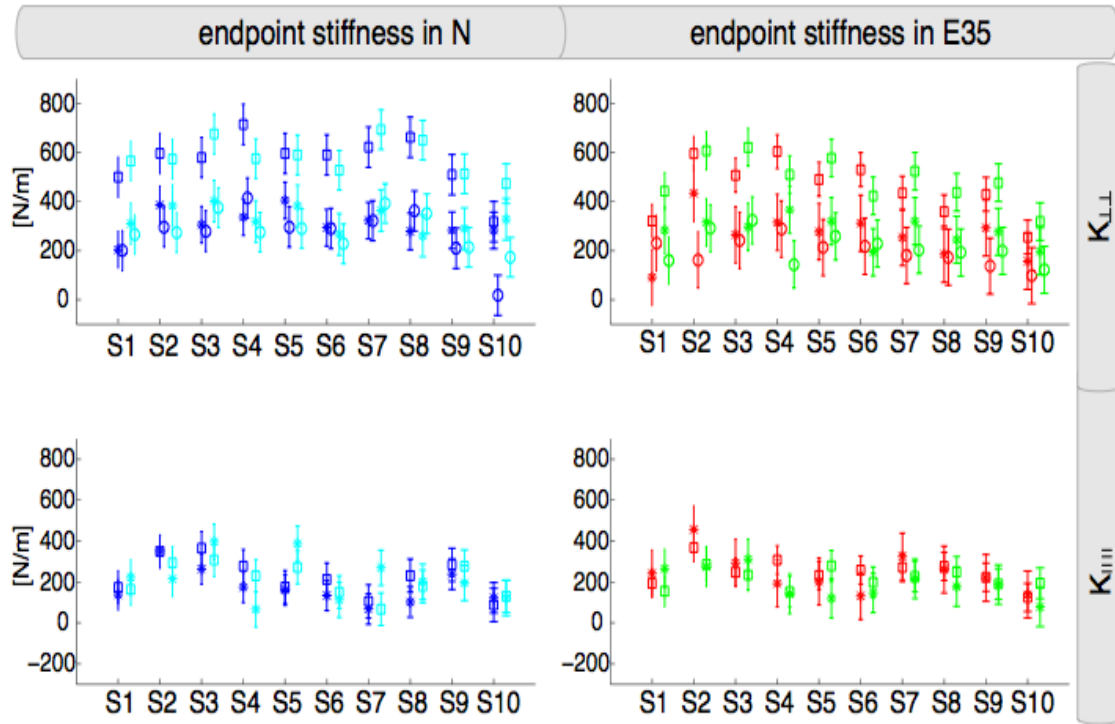


Figure 4.3.9: Normal, $K_{\perp}$, and parallel, $K_{\parallel}$, hand stiffness components for each subject separately. Vertical bars show the 90% confidence intervals after stiffness matrix estimation using SVD. Endpoint stiffness for single learning is shown in blue for direction N and in red for direction E35. Stiffness for multiple directions learning is shown in cyan for direction N and in green for direction E35. Plotted is the stiffness in NF (star) and DF (square) from all days of the experiment. The net stiffness in DF (i.e. the difference of learned stiffness in DF and the force field $F_{EX}=[300\ 0; 0\ 0]$), plotted as circle, is similar to the NF stiffness, suggesting that a similar stability margin is maintained in all conditions. No difference is noticed between single and multiple learning in neither of directions N and E35.

Joint stiffness components

Joint stiffness was computed from Cartesian stiffness using Equation (4.11). The matrix consists of four components that represent the amount of stiffness in shoulder, elbow, and cross-joints. Figure (4.3.10) shows that joint stiffness, after adaptation to the divergent field, increased in both N and E35 directions. Using ANOVA, we found that there was main effect of force field ($p < 0.001$), of the movement direction ($p < 0.001$) as well as element of joint stiffness ($p < 0.001$). However, joint stiffness did not vary in the same direction whether learning was in a single direction or in the two directions concurrently ($p > 0.186$).

In order to examine which joints were used to learn the task in each direction, the four stiffness elements were analysed for differences between NF and DF. The relative increase in stiffness was primarily in R_{ss} compared to the other three elements. In direction N, all joint stiffness components, i.e., R_{ss} , R_{se} , R_{es} and R_{ee} , increased significantly after learning in the DF ($p < 0.001$). In direction E35, the elements R_{ss} , R_{se} and R_{es} changed significantly between NF and DF ($p < 0.002$), but not R_{ee} ($p = 0.110$).

The following step was to analyse differences in each element between directions N and E35. Figure (4.3.10A-B) shows that the level of stiffness after learning in DF was greater in direction N than in direction E35. Using ANOVA for every component revealed that there was no significant difference in shoulder stiffness R_{ss} in NF between the two directions ($p = 0.390$). There was, on the other hand, a difference in R_{ss} between the two directions after learning in DF ($p = 0.001$). In R_{se} , there was an effect of direction of learning in NF ($p = 0.018$) and in DF ($p < 0.001$). There was also a significant effect of direction in both R_{es} and R_{ee} in NF ($p < 0.001$) and DF ($p < 0.001$).

In order to further interpret how the limb stiffness was tuned, the ratio of shoulder to elbow stiffness was calculated during different days of the experiment. This ratio provides information on the muscle pairs crossing either joint that were used to control stiffness. However, this information does not explain which muscles were required to stiffen the arm in either direction, because the biarticular muscles contribute variably to both elbow and shoulder joints. Figure (4.3.10C) illustrates the mean across subjects of the R_{ss}/R_{ee} ratio in NF and DF in both directions of movement. Subjects increased joint stiffness between DF and NF in both directions ($p = 0.003$), but more noticeably in direction E35 than in N ($p < 0.001$). Additionally, the relative ratio was drastically higher in direction E35 than in direction N. This means that the difference

between shoulder and elbow joint stiffness was higher in E35 than in N, despite that shoulder stiffness was higher in N than in E35 as shown in Figure (4.3.10A-B). As expected, there was no difference in the ratio calculated for the same direction whether learning was in a single direction or in two directions together ($p=0.913$).

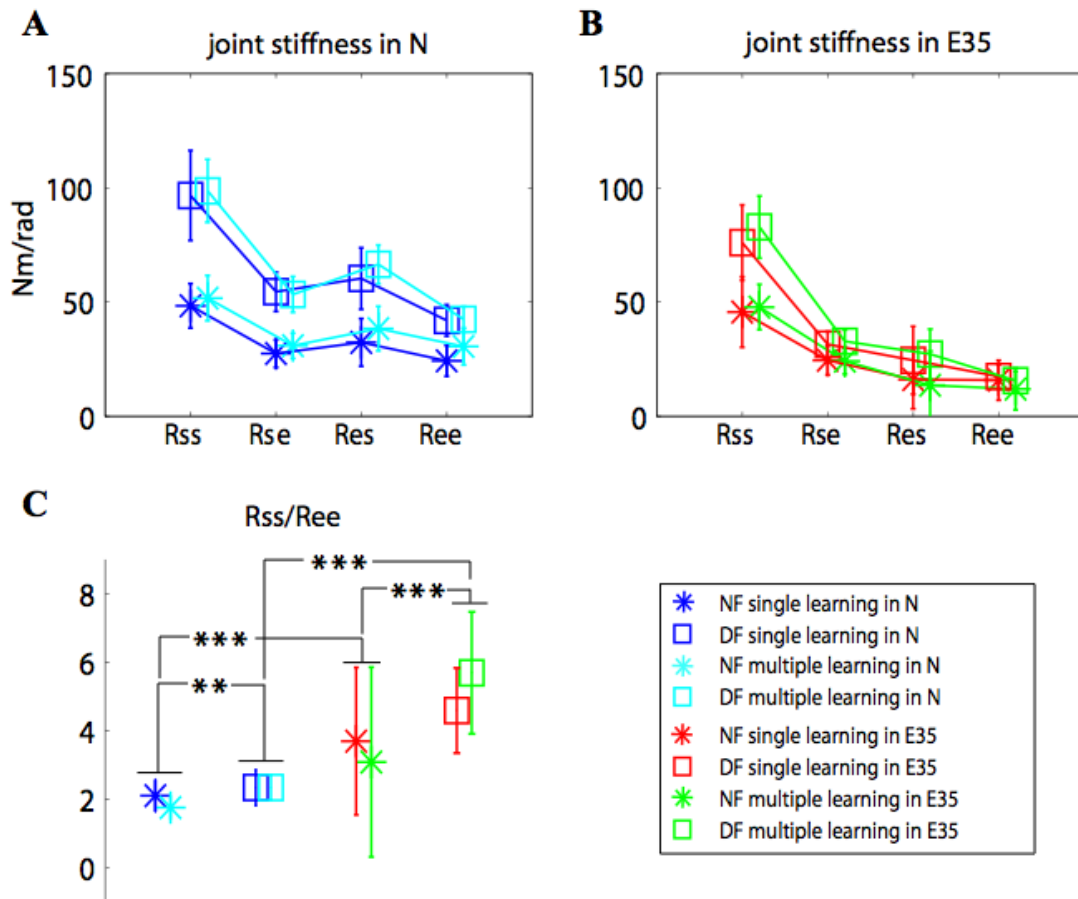


Figure 4.3.10: The mean over subjects of joint stiffness components increased noticeably after adaptation to the divergent field in both directions. A: joint stiffness increased in pure shoulder joint between DF and NF than the other three components in direction N. In the cross-joint stiffness, there was dependence on R_{es} than on R_{se} . Joint stiffness components were closely similar between single and multiple directions learning. B: joint stiffness increased more in R_{ss} than the other components, but R_{se} was higher than R_{es} in both forms of learning in direction E35. C: the ratio of shoulder to elbow joint stiffness is plotted in NF and DF in both directions and across days of the experiment. There was a higher shoulder than elbow joint stiffness in all cases. The proportion was more significant in DF than in NF for both directions N and E35. The fraction R_{ss}/R_{ee} was higher in direction E35 than it was in direction N. This shows that subjects tended to increase more shoulder stiffness than elbow in direction E35 as compared to direction N. (** $p<0.01$, *** $p<0.001$)

4.3.4 Muscle activity

The mean across subjects of EMG from each day of the experiment is plotted in Figure (4.3.11). In the three muscle pairs, there was a significant effect of force field in both directions ($p < 0.001$), as well as a significant effect of direction of movement ($p < 0.001$). From Figure (4.3.11), the biarticular muscles were more dominant in direction N; while in direction E35 subjects used their shoulder muscles more than biarticular and elbow muscles ($p < 0.001$ for effect of muscle pairs on all days).

Consistently, subjects used predominantly biarticular muscles in direction N and shoulder muscles in direction E35 on the last day of the experiment even though they made movements towards both targets concurrently Figure (4.3.11). There was no effect of single-to-multiple direction learning in shoulder ($p = 0.563$) and biarticular ($p = 0.089$) pairs, but there was an effect in elbow ($p = 0.027$) pair. The interaction between direction and single-to-multiple learning in elbow muscles was highly significant ($p = 0.009$), which means that the change in elbow activity was in one direction only. In order to investigate in which direction this occurred, ANOVA was used in each direction separately. We found no significant effect in direction N ($p = 0.583$), but an effect in direction E35 ($p < 0.001$). Hence, the change in elbow activity was significant in direction E35 but not in N.

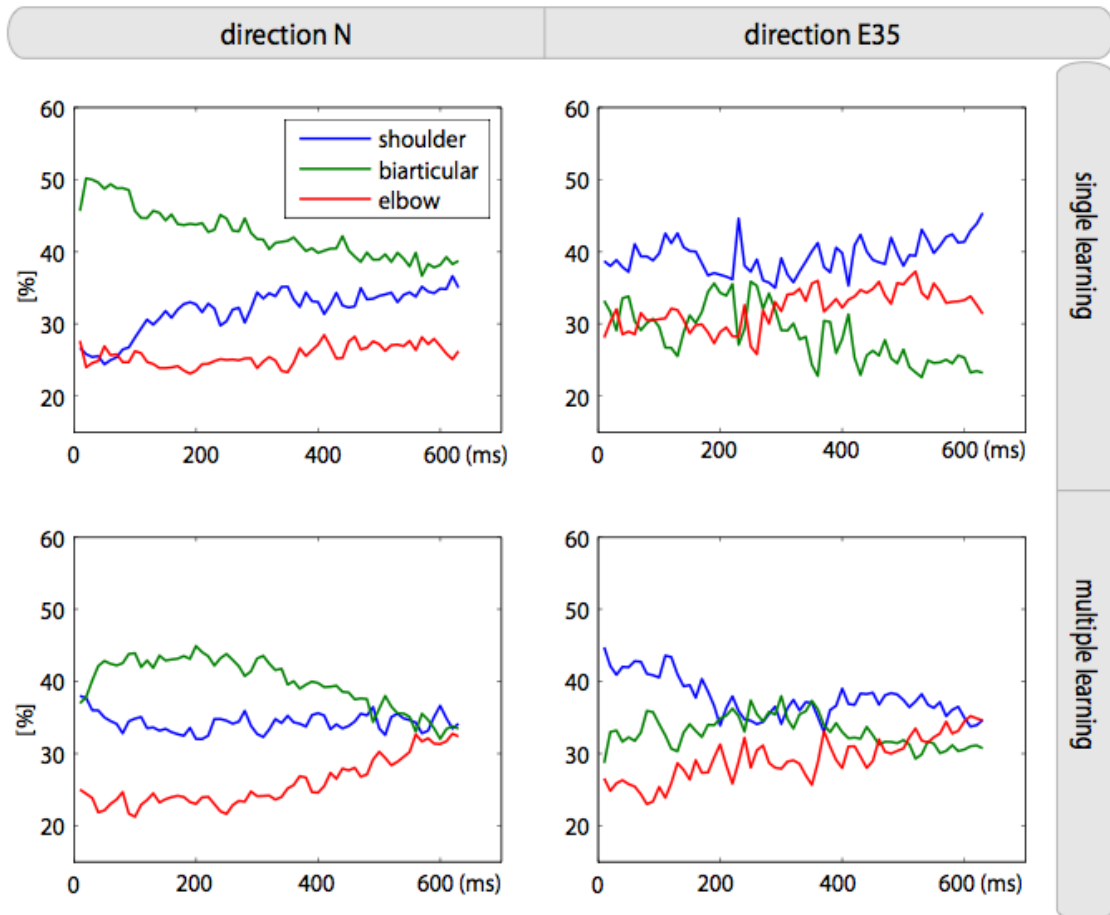


Figure 4.3.11: EMG level in directions N and E35 during single and multiple learning schemes. Plotted is the mean over subjects of the relative increase in muscle activity between DF and NF, in each of the agonist/antagonist muscle pairs: single-joint shoulder (blue), single-joint elbow (red) and double-joint biarticular (green) muscles. Subjects made use of the shoulder muscles more when training in direction E35 while they used the biarticular muscles more in direction N.

4.4 Discussion

The current study investigated adaptation to an unstable force field amplifying lateral deviations, when reaching movements were performed to either of two targets, resulting in movements separated by 35° . In contrast, previous studies (Burdet et al. 2001, Takahashi et al. 2001, Franklin et al. 2007) had investigated the adaptation to unstable or unpredictable dynamics along a single movement only. Our study is the first to show that subjects are able to learn performing movements in unstable dynamics in several directions concurrently. This was demonstrated by a significant decrease in the kinematic error relative to the straight-line trajectory to the target, and resulted in increasing the proportion of successful trials. Independent internal models were acquired and consolidated in memory, as no interference was found between movements performed in different directions and stiffness was selectively tuned in each respective direction. These results were consistent when assessing adaptation through hand-path error, success rate of the movement, hand and joint stiffness, and muscle activity (EMG). Findings from this study could explain the mechanisms undertaken by humans to perform unstable tasks in multiple directions such as required for carving.

Before performing this experiment, it was not clear whether subjects would be able to compensate for the instability in multiple directions, for several reasons. First, studies involving learning of movements in several kinematic or dynamic conditions have generally found interferences between simultaneous learning with distinct conditions (Brashers-Krug and Shadmehr 1996, Caithness et al. 2004, Tong et al. 2002). Second, learning and the estimation of stiffness during movement required a large number of trials and several hours of experiment, in particular when it was necessary to perform movements in all directions on the same day in order to compare EMG. Further, a pilot study with movements in two directions separated by an angle of 70° was found to exhaust subjects, probably because subjects needed to adapt using different postures that required heavy change in arm dynamics. Therefore, in our experiment the investigation was limited to two directions of movements with a specific separation angle. Using a method based on random perturbations during motion, like that by Perreault et al. (1999), may enable to reduce the number of necessary trials for impedance estimation in future studies.

Preliminary results indicated that naïve subjects might be able to learn compensating for the lateral instability directly by alternating movements in these two directions on a single day. However we preferred to let the subjects learn the individual directions separately in two prior days in order to ensure good performances for this first study on multiple impedance learning. Indeed, tasks involving motor learning have been shown to improve with sleep (Stickgold et al. 2005, Walker et al. 2003, Walker et al. 2004) and several hours between multiple conditions (Shadmehr et al. 1997). Therefore, prior adaptation on Day1 and Day2 could have participated in improving performance on Day3, even though the two directions were trained concurrently on that day. Meanwhile, the author did not investigate the effect of fatigue during the experiment. It was assumed that subjects performed to their peak and that they did not suffer from muscle fatigue, because their performance did not seem to drop towards the end of the sessions (particularly on the last day). This shows that subjects maintained a good adaptation level after acquiring the necessary dynamics to overcome instability in both directions.

Similar to the results obtained when motion was performed in a single direction (Burdet et al. 2001), in the present study with movements to multiple directions, adaptation to the lateral instability was not produced by a modification of force, as the force in DF was not different than in NF. However, stiffness was increased to compensate for the unstable environment. Results showed that there was no global stiffening of the arm or isotropic increase of stiffness, even when alternating reaching movements to both directions in the same session. In contrast, stiffness after learning was elongated selectively in the respective direction of instability. Subjects were able to produce different arm impedance while the arm posture was different when making reaching movements towards each target.

As in the one movement case, impedance was modified during learning in a way to produce the same stability margin in all conditions. This required modifying the contributions of the multiple muscles involved in these movements. In particular, all muscle pairs increased their activity, but the increase was different in the two directions. The EMG signals indicated a larger contribution to the change of activity from the shoulder muscles for movements in direction E35 and a larger contribution of the biarticular muscles in the N direction, while elbow muscles were less dominant on all days. Further, joint stiffness estimation showed a larger shoulder to elbow ratio in E35 than in N.

Interestingly, our results show that subjects retained learning in a given direction across days. Despite that subjects had to adapt to a distinctively different perturbation on Day2 than that had experienced on Day1, initial learning started with better performance in both directions on Day3. On Day3, subjects could further improve their performance relative to Day1 and Day2, starting almost immediately from their best performance level on Day1 or Day2. This retention of learning may have been facilitated by the long interval (Shadmehr et al. 1997) or sleep (Stickgold et al. 2005, Walker et al. 2003, Walker et al. 2004) between the two conditions or by the absence of biased wash-out trials (Caithness et al. 2004, Wigmore et al. 2002) as adaptation to the divergent force field does not require modification of force.

Finally, how did the subjects become able to perform successfully in the two directions? One possibility is that subjects could have gradually formed an inverse model of the external dynamics, i.e. a mapping from a state space to muscle tension (Conditt et al. 1997), while compensating for the force and instability encountered during movements. When the state space contains velocity, the direction of instability, normal to the intended movement, could be inferred from its velocity. In fact, simulation of such mapping (Figure 3.4.3 in Chapter 3) demonstrates that having velocity information enables nearly perfect compensation of the instability, in contrast to a state space relying solely on position.

Alternatively, the central nervous system might acquire two distinct inverse dynamic models and switch between them using contextual information (Haruno et al. 2001, Kawato et al. 1998). While it is not clear whether cues such as target background colour (Osu et al. 2004) or a fixed sequence of movements (Karniel and Mussa-Ivaldi 2002) enable learning different conditions along the same movements, this study shows that distinct movements with specific conditions can be learned simultaneously, similar to results by Tong et al. (2003). The CNS may have learned different internal models corresponding to the two different movements on Day1 and Day2, which it could separately recall when prompted on Day3.

Chapter 5

A UNIFIED MOTOR LEARNING SIMULATOR

Abstract

This chapter investigates the generalisation properties of a novel computational model of human motor adaptation that is able to learn both force and impedance control and to succeed in unstable tasks typical of tool use. Appropriate muscle activation is learned movement after movement through minimisation of feedforward and feedback, where feedback is a V-shape function of muscle length error. The learning law is derived mathematically, and then implemented using a neural network enabling generalisation over movements defined in the whole state space. Simulations in Chapter 6 show the efficiency of the learning algorithm, and expose patterns similar to past experimental results, thus demonstrating its plausibility as a model of human motor learning and generalisation.

5.1 Introduction

5.1.1 *Background*

Humans have exceptional capabilities to perform tasks with various tools, however it is not clear how we learn using these tools and always adapt to new tasks with different tools and conditions. For example, successful carving requires moving the chisel skilfully in all directions while compensating for the force and the instability arising from the interaction with the material. In such unstable tasks it is not sufficient to produce a suitable force, because the instability will amplify motor noise and unexpected perturbations due to material irregularities, and result in unpredictable and unsuccessful movements (Burdet et al. 2006). To succeed in unstable tasks, the central nervous system (CNS) needs to coordinate suitable muscles, thus stiffening the limbs in specific directions and compensating for the instability (Burdet et al. 2001, Franklin et al. 2003B).

When learning a novel task such as carving, it is not possible to store all commands necessary to produce movements in every situation, therefore the CNS has to generalise learning from trained movements at its disposal. Producing successful movements in all directions requires generalisation of muscle activations in order to produce suitable limb force and impedance (the resistance to mechanical perturbations). Past studies have investigated the generalisation of force in stable novel environments (e.g. Shadmehr and Mussa-Ivaldi 1994, Conditt et al. 1997, Thoroughman and Taylor 2005), but do not explain how humans learn to perform unstable task in various directions.

Our goal is to understand how the CNS learns novel tasks with stable or unstable dynamics using a constructive approach, by developing a computational model of motor learning. This model should learn suitable endpoint force and impedance, as well as correct muscle activation transients, and generalise learned patterns to untrained movements. It must, as humans do, learn to produce appropriate muscle activation trial after trial, by learning from the experience in previous trials and using sensory signals available to the CNS. The adaptive control algorithm should be efficient that a robotic implementation can learn appropriate force and impedance for succeeding in manipulating objects.

Which experimental results can constrain this model? Psychophysical experiments investigating the adaptation to stable dynamics first demonstrated, through after effects illustrating the memory of learned dynamics, that an internal representation of the motor commands necessary to succeed in external force field is formed during the movements (Lackner and Dizio 1994, Shadmehr and Mussa-Ivaldi 1994). Further, learning affects neighbouring regions of the trained movements, suggesting some generalisation (Shadmehr and Mussa-Ivaldi 1994, Gandolfo et al. 1996). Generalisation arises also when other dynamic conditions (Goodbody and Wolpert 1998) or movements (Conditt et al. 1997) are performed in the same workspace of the trained movements, showing that the internal representation depends on a state space, and motor learning is not achieved through rote memorisation. Furthermore, the granularity of the internal model has been shown to vary with varying force field complexity (Donchin et al. 2003, Thoroughman and Taylor 2005).

More recently, the adaptation to unstable dynamics has been investigated in a series of studies (Akazawa and Milner 1983, Burdet et al. 2001, Scheidt et al. 2001, Franklin et al. 2003A, Franklin et al. 2003B, Franklin et al. 2007), which demonstrated that the CNS produces force and impedance to compensate for the environment dynamics. We have recently examined concurrent learning of movements to several directions when lateral instability is encountered during motion (Kadiyallah et al. 2008). The results show that subjects learned optimal impedance tuned to the instability in each direction, and would be compatible with an internal task representation using muscle position and velocity as state space.

Mainly two kinds of motor adaptation models have been proposed so far. Optimisation provides a powerful tool to predict the internal model after learning (Stroeve 1999) as well as the adaptation of trajectory (Todorov and Jordan 2002, Trainin et al. 2007, Guigon et al. 2007, Izawa et al. 2008) and bimanual coordination (Diedrichsen et al. 2007). However, such models cannot predict the trial-by-trial adaptation of motor command. In this regard, gradual adaptation is present in models based on iterative learning or adaptive control (Kawato et al. 1987, Slotine 1991, Burdet et al. 1998, Gribble et al. 2000, Donchin et al. 2003, Thoroughman and Taylor 2005, Emken et al. 2007), however these models do not have a mechanism to acquire the stability required for successful action in unstable dynamics, nor do they predict correct muscle activity transients with initial increase and gradual decrease (Franklin et al. 2003B).

5.1.2 Motivation and aim

Recent work by (Franklin et al. 2008, Burdet et al. 2008) introduced a computational model, based on experimental data, to predict adaptation of muscle activation in stable and unstable dynamics throughout learning. This model, which considers the nonlinear dynamics of multi-joints arm movements, as well as inherent signal dependent noise and reflexes, could predict the trial-by-trial changes in muscle activation and trajectory when adapting to various stable and unstable dynamics (Burdet et al. 2008). However, this computational model was formulated for a single repeated movement only, in the form of a simple difference equation.

The present work extends this model to more general movements in various directions, in a formulation encompassing force fields (Shadmehr and Mussa-Ivaldi 1994) and muscles synergies (d'Avella et al. 2003). The learning algorithm is now derived from an optimisation principle, using a cost function of motion error and effort. The learned feedforward is implemented as a neural network enabling systematic investigation of the input signals used to compute this feedforward. This enables us to simulate adaptation to various stable and unstable novel dynamics with generalisation over movements. We can thus compare our results with those obtained in previous experimental studies, and predict the outcome of future experiments in a simple way.

Our goal is to understand how the CNS learns novel tasks with stable or unstable dynamics using a constructive approach, by developing a computational model of motor learning. This model should learn suitable force and impedance and generalise learned patterns to untrained movements. It must, as humans do, learn to produce appropriate muscle activation trial after trial, by learning from experience in previous trials. The adaptive control algorithm should be efficient that a robotic implementation can learn appropriate force and impedance for succeeding in manipulating objects.

5.1.3 Concept of the model

The theory of the model is based on feedback-error-learning (FEL) at the muscle level in order to compensate for both stable and unstable interactions. In other words, feedback-error-learning interacts with the environment dynamics on repeated trials to learn suitable force and impedance to successfully accomplish the task. This model of motor adaptation is compatible with the internal model hypothesis, where stretch

reflexes due to trajectory error contribute to the formation of an inverse dynamics model and to an increase of muscle impedance.

Let us consider how FEL interacts with unstable dynamics at one joint during a goal-directed reaching movement task as instability is applied (Figure 5.1.1A). When a muscles-generated torque is applied, then any perturbation (in a positive direction) will lead to a large deviation in the same direction (Franklin et al. 2003C) (Figure 5.1.1B). Using FEL, the following trial would lead to an increase in torque in the opposite direction (i.e. negative direction). Subsequent trial would see the torque increase in the positive direction, etc. Therefore, it seems that the inverse dynamics model using FEL will tend to null when the number of trials is equal in both positive and negative directions (Tee 2003). This interaction at the joint level clearly would not solve the unstable task problem.

But, what if the same mechanism as feedback-error-learning is considered at the muscle rather than the joint level? At one joint, it is considered that there is a simple agonist-antagonist muscle pair (Figure 5.1.1C). As the joint is destabilised by a small perturbation, this will lead to a large (positive) deviation that would eventually trigger the agonist muscle to stretch. As the agonist muscle is stretched, the muscle tension increases, and the movement is deviated towards that direction. This would lead to a stretch in the antagonist muscle too. As a result, in the following trial both agonist and antagonist muscles are activated. Hence, it seems that when using FEL at the muscle level together with instability, this would lead to co-contraction of muscles. Because impedance increases with muscle activation (Hunter and Kearney 1982), then impedance is increased at the joint to counter instability.

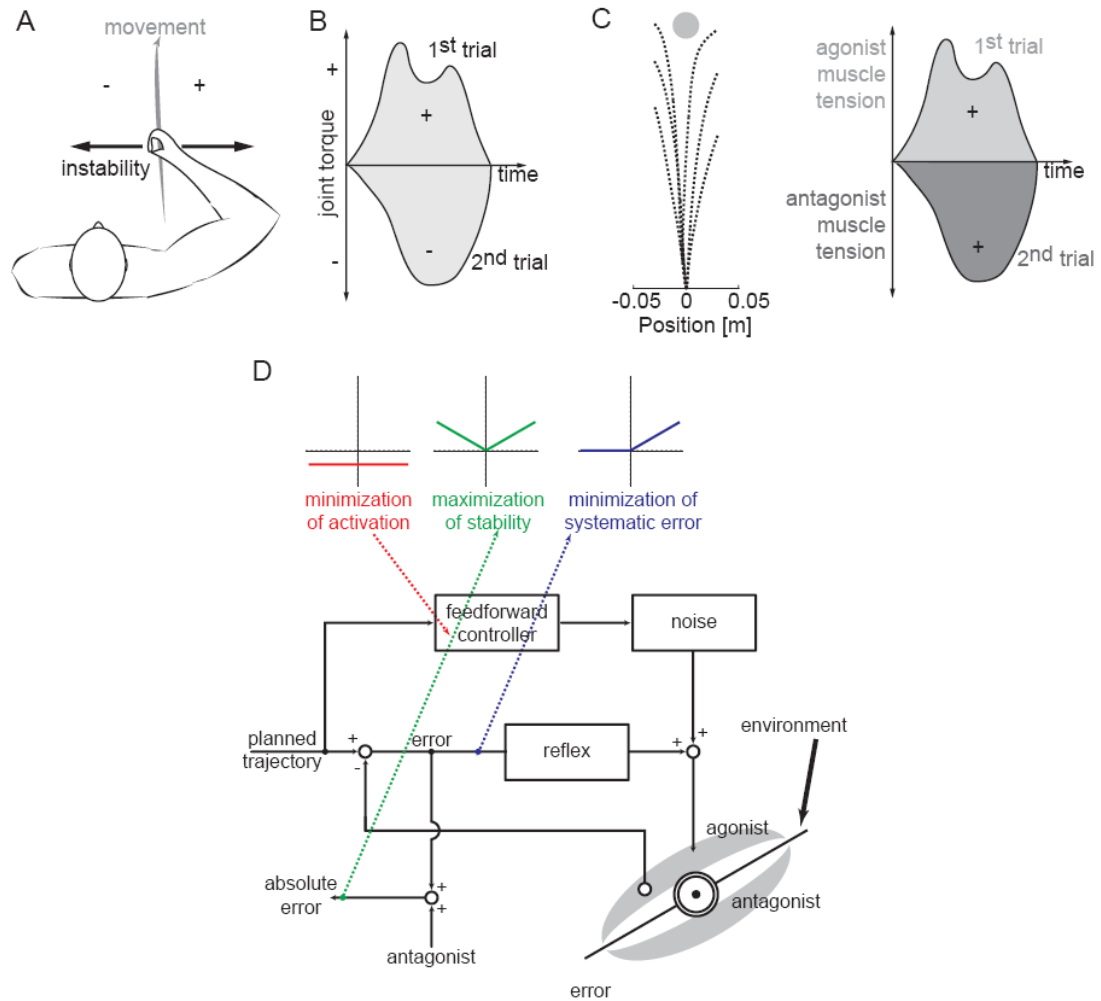


Figure 5.1.1: Concurrent minimisation of movement error at the muscle level used in the model.
A: subject making movement in an unstable environment. **B:** at joint level FEL cannot compensate for unstable dynamics, because the mean torque after an equal number of trials that deviate left and right of wanted trajectory is zero. **C:** while making initial alternating movements, at the muscle level activation from both agonist and antagonist muscles add together to create a co-contraction of both muscles. **D:** schema of the muscle space feedback-error-learning algorithm used to update the feedforward command using feedback that stems from controlling both agonist and antagonist muscles.

The model developed and presented here stems from observations in experimental data and is based on the following principles (Figure 5.1.1D):

1. Motor command to perform a desired action is the addition of feedforward and feedback
2. Humans learn to produce suitable motor command trial-after-trial. The feedforward is updated in a muscle space or in neural activations corresponding to muscle activation
3. This modification of feedforward minimises motion error experienced in a movement
4. Both muscle stretch and shortening lead to augmentation of muscle activity in the next movement. This produces necessary force in the novel dynamics and impedance to compensate for instability
5. Muscle activation is minimised with learning
6. Muscle deactivation removes co-contraction not necessary for stability

5.2 Learning Controller

This section will derive a mathematical model fulfilling these principles using optimisation. In the following mathematical descriptions scalars s are italic, (column) vectors $\mathbf{v}$ are bold and matrices $\mathbf{M}$ are bold capitals.

5.2.1 Concurrent minimisation of feedforward and feedback

Translating above principle 1, we assume that the motor command $\mathbf{u}$ is composed of a feedforward term $\mathbf{u}_f$, corresponding to learned dynamics, and a feedback term $\boldsymbol{\varepsilon}$:

$$\mathbf{u} = \mathbf{u}_f + \boldsymbol{\varepsilon} \quad (5.1)$$

Corresponding to above principle 2, these variables are expressed in muscle coordinates, as well as all variables of this section.

Motor learning consists of adapting feedforward to insure successful and optimal performance. Experimental evidence (e.g. Franklin et al. 2003A, Franklin et al. 2003B) suggests that motor learning minimises movement error and effort (above

principles 3&5). Correspondingly we formulate motor learning as follows: the feedforward $\mathbf{u}(\mathbf{p})$ depends on activation parameters $\mathbf{p}$, which have to minimise the function:

$$V(\mathbf{p}) = \frac{1}{2} \boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon} + \xi \sum_{j=1}^n p_j, \quad \xi > 0 \quad (5.2)$$

where $\boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon}$ is a cost for movement feedback, and $\sum p_j$ is a cost for the activation (i.e. for feedforward), while n is the reference number of the activation parameters.

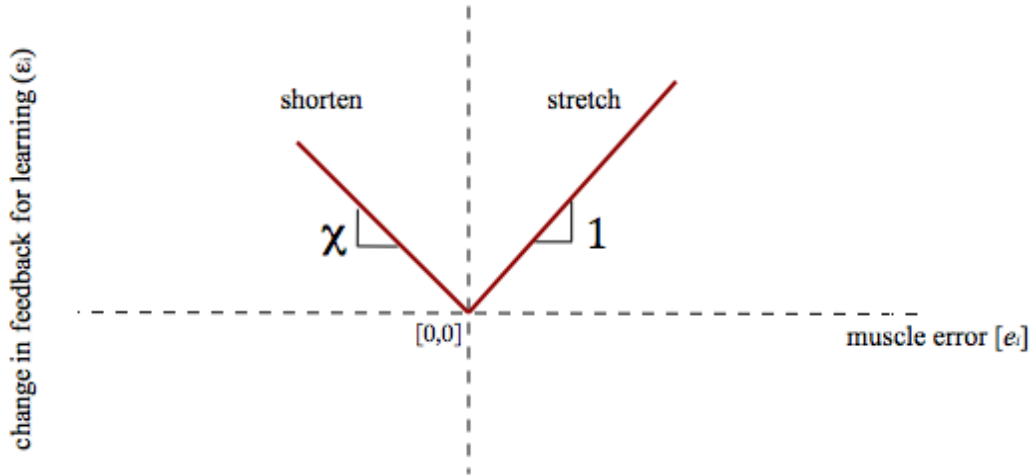


Figure 5.2.1 The V-shaped learning function corresponding to Equation (5.3). The slope $0 < \chi < 1$ enables modification of motor command and co-contraction with movement error.

Corresponding to above principle 4, for each muscle i , e_i is an increasing function of both stretch and shortening (Franklin et al. 2008) (Figure 5.2.1). For simplicity we assume that this function is linearly increasing in both directions, i.e.

$$\begin{aligned} \varepsilon_i &= e_{i,+} + \chi e_{i,-} & 0 < \chi < 1 \\ e_i &= e_{l,i} + g_d \dot{e}_{l,i} & g_d > 0 \end{aligned} \quad (5.3)$$

where $[\cdot]_+ = \max(\cdot, 0)$ is the positive part and $[\cdot]_- = -[\cdot]_+$ is the negative part. Franklin et al. (2008) showed that a deviation to one direction is compensated-for by a force in the opposite direction in the next trial (principle 3), hence, we set $\chi < 1$. Also, e_i is a linear term of the stretch/shortening $e_{l,i}$ and its time derivative.

We assume that learning corresponds to the gradient descent minimisation of the cost function in Equation (5.2), i.e. activation is updated proportionally to the gradient of this function:

$$\Delta \mathbf{p} = \mathbf{p}^{k+1} - \mathbf{p}^k \doteq -\frac{dV}{d\mathbf{p}} \quad (5.4)$$

where k is a trial index. The gradient descent update, using Equation (5.1) with $\partial u_i / \partial p_j = 0$, yields:

$$\Delta \mathbf{p}^k = \alpha \left(\frac{\partial u_{l,i}}{\partial p_j} \right)^T \boldsymbol{\varepsilon} - \gamma \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_n, \quad \alpha, \gamma > 0, \quad (5.5)$$

The second term, $-\gamma \mathbf{1}$, producing the same decrease of activation in all parameters p_j , is minimising the overall activation in a subtle way. If activation i is larger than activation j , then the smaller, p_j , is decreasing relatively faster than the larger, p_j . This enables learning law (6) to realise a winner-take-all scheme selecting the activation directions that were increased most with $\alpha(\partial u_{l,i} / \partial p_j)^T \boldsymbol{\varepsilon}$. In the initial trials the error $\boldsymbol{\varepsilon}$ is large and most of the activation modification results from $\alpha(\partial u_{l,i} / \partial p_j)^T \boldsymbol{\varepsilon}$. Later in the learning, optimisation of impedance is performed from the term $-\gamma \mathbf{1}$, producing large decrease of impedance in the directions less activated. As the simulations will show, this feature realises selective co-contraction in the direction of instability.

5.2.2 Learning law

We focus on the case that the motor command is linear in the activity parameters:

$$\mathbf{u}_l(\mathbf{p}) \equiv \Psi \mathbf{p} \quad (5.6)$$

which is sufficiently general to represent the results of previous experiments. For example, Ψ can be in the form of (possibly nonlinear) *force fields* $\Psi(q, \dot{q})$ (Shadmehr and Mussa-Ivaldi 1994). Alternatively, $\Psi \mathbf{p}$ can represent synergies (D'avella et al. 2003). $\Psi \mathbf{p}(t)$, where t is the time, corresponds to time dependent synergies and $\Psi(t) \mathbf{p}$ to time invariant synergies. The structure of Equation (5.6) could also include radial basis function network models, for which the activations parameters correspond to the weights of this network. With this structure the learning law yields:

$$\Delta \mathbf{p} \equiv \Gamma \Psi(\mathbf{s})^T \boldsymbol{\varepsilon} - \gamma \mathbf{1} \quad (5.7)$$

where $\mathbf{s}$ is the state. We recognise the term $\Gamma \Psi^T \boldsymbol{\varepsilon}$ of traditional nonlinear adaptive control (Burdet and Milner 1998), which is now in muscle space (instead of non-redundant joint or hand space for traditional adaptive control). Note that updating each activation depends on the respective error only, and is independent of the other activations, i.e. no explicit dependence between the activations is needed to regulate endpoint force and impedance with the coupled and highly nonlinear dynamics of a redundant multi-neurons, multi-muscles, and multi-joints system. Using gradient descent, the minimisation of Equation (5.7) may converge to a local minimum, but motor noise could provide tunnelling to the global minimum.

How does the force vary in this scheme? For simplicity we consider an agonist-antagonist muscle pair acting at the same joint. The update of reciprocal activation $\mathbf{ru} = \mathbf{u}_+ - \mathbf{u}_-$, the difference between agonist motor command $\mathbf{u}_+$ and antagonist motor command $\mathbf{u}_-$ then corresponds to:

$$\begin{aligned} \mathbf{u}_{l+}^{k+1} - \mathbf{u}_{l-}^{k+1} &= \Psi(\mathbf{p}_+^k + \Delta \mathbf{p}_+^k) - \Psi(\mathbf{p}_-^k + \Delta \mathbf{p}_-^k) \\ &= \Psi(\mathbf{p}_+^k - \mathbf{p}_-^k) + \alpha \Psi \Psi^T (\boldsymbol{\varepsilon}_+^k - \boldsymbol{\varepsilon}_-^k) \\ &= \mathbf{u}_+^k - \mathbf{u}_-^k + \Gamma \Psi \Psi^T (\boldsymbol{\varepsilon}_+^k - \boldsymbol{\varepsilon}_-^k) \\ \text{or} \quad \Delta \mathbf{ru} &= \mathbf{ru}^{k+1} - \mathbf{ru}^k = \Gamma \Psi \Psi^T \boldsymbol{\varepsilon}^k \end{aligned} \quad (5.8)$$

as $e = e_+ - e_-$. We see that this force regulation is similar to algorithms of nonlinear adaptive control (Slotine and Weiping 1991), iterative control (Bien and Xu 1998), and previous models of motor learning (Sanner and Kosha 1999, Kawato et al. 1987). This shows that our scheme is extending these algorithms to simultaneous regulation of force and impedance.

As we consider the adaptation of activation determining whole discrete movements, the motor command, activation and state vector in above equations are all functions of the time: $\mathbf{u} \equiv \mathbf{u}(t)$, $\mathbf{p} \equiv \mathbf{p}(t)$, $\mathbf{s} \equiv \mathbf{s}(t)$, $t \in [0, T]$. Equation (5.8) describes the adaptation of activation in the descending motor signal between consecutive trials indexed by k , corresponding to iterative control. For (nonlinear) adaptive control (Slotine and Weiping 1991), Equation (5.8) has to be replaced by its continuous time version.

5.3 General Model Implementation

In the following, let the motor command correspond to muscle tension: $\mathbf{u} = \mathbf{m}$, and we adopt the notations $\mathbf{u}_I = \mathbf{m}_{FF}$ and $\mathbf{e} = \mathbf{m}_{FB}$. However, the motion dynamics are easier to compute in joint space, as muscles tension $\mathbf{m}$ as well as Cartesian forces $\mathbf{F}$ applied on the hand can be transformed into joint space torque using suitable Jacobian transformations:

$$\begin{aligned}\boldsymbol{\tau} &= \mathbf{J}_m^T \mathbf{m} \\ \boldsymbol{\tau} &= \mathbf{J}(\mathbf{q})^T \mathbf{F}\end{aligned}\tag{5.9}$$

where the components of the muscle Jacobian $\mathbf{J}_m$ are composed of moment arms, and $\mathbf{J}(\mathbf{q})$ is the Jacobian relating joint to Cartesian endpoint velocity (Burdet et al. 2008).

Muscles generate forces to move the limb and to counter the external force, $\boldsymbol{\tau}_E$, due to the interaction with the environment:

$$\boldsymbol{\tau} = \boldsymbol{\tau}_{RB} + \boldsymbol{\tau}_E\tag{5.10}$$

where τ_{RB} are the rigid body arm dynamics. We assume that the motor command is composed of a feedforward term τ_{FF} corresponding to learned dynamics (which can contain feedback), signal-dependent noise τ_N , resistance from the mechanical impedance produced by stiffening muscles τ_{IMP} as well as feedback τ_{FB} due to unexpected or unlearned perturbations (Figure 5.3.1):

$$\tau = \tau_{FF} + \tau_N + \tau_{IMP} + \tau_{FB} \quad (5.11)$$

This equation can be integrated numerically to determine the movement of the arm in interaction with the environment.

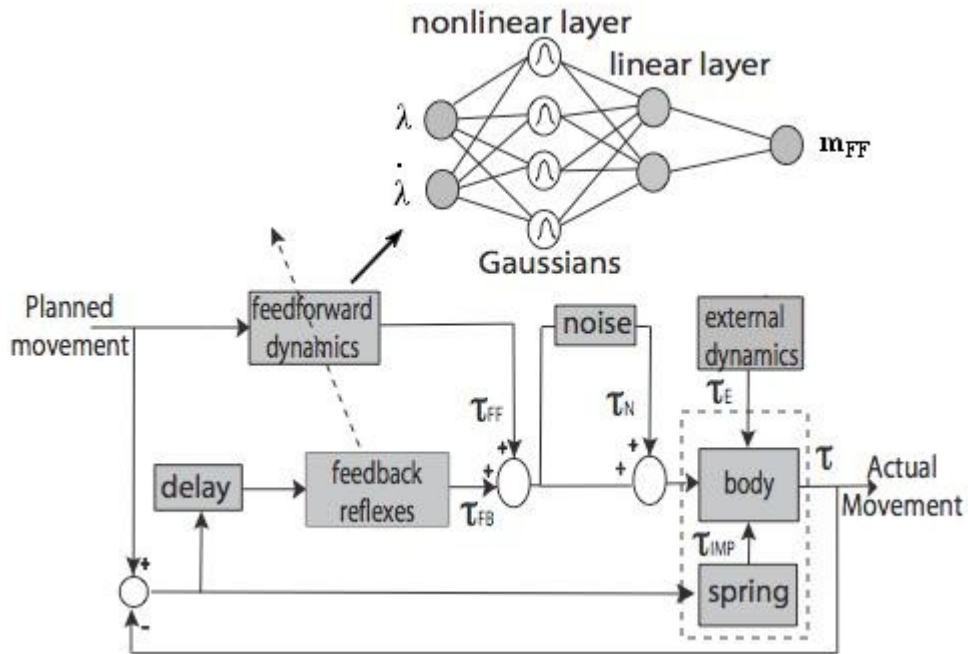


Figure 5.3.1: Model implementation. Figure shows control diagram of the neural control and learning in novel dynamics. The feedforward term is implemented as radial-basis function network.

5.3.1 RBF neural network feedforward model

A Radial basis function (RBF) network consists of modelling an input-output mapping as a linear combination of non-linear radial basis functions (Figure 5.3.1). RBF has been proved a reliable approximation and interpolation tool for simulations and experimental functions (Poggio and Girosi 1990, Park and Sandberg 1991). The main advantage of using RBF networks is their speed of training as compared to multi-layer-perception (MLP) networks. Also, each neuron (or basis function) in an RBF network is a multi-input to a scalar output mapping. This represents an advantage over other basis function networks, because the number of neurons in the hidden layer does not need to increase as the number of input variables increases. The network is characterised by three main parameters that are the centres, the widths of neurons and weights connecting each neuron.

In our model, the RBF network is used to calculate the feedforward according to:

$$\begin{aligned}\mathbf{m}_{FF} &= \mathbf{W}\boldsymbol{\varphi} \\ \boldsymbol{\varphi} &= (\varphi_1, \varphi_2, \dots, \varphi_n)^T \\ \varphi_j(\mathbf{s}_d) &= \exp\left[-\frac{\|\mathbf{s}_d - \mathbf{s}_j\|^2}{2\sigma_j^2}\right]\end{aligned}\tag{5.12}$$

where $\boldsymbol{\varphi}(\mathbf{s}_d)$ are the nonlinear functions of the hidden layer comprising n neurons. The input to the RBF is a vector with component in a state space, e.g. desired position or both position and velocity data $\mathbf{s}_d \equiv (\lambda_d, \dot{\lambda}_d)$. Each neuron φ_j is centred on a different element $\mathbf{s}_j$ of the state space and has an activation field defined by the deviation σ_j , which is differently set for each neuron. The difference between the input vector to the network $\mathbf{s}_d$ and a predefined neuron centre $\mathbf{s}_j$ is passed through a Gaussian function φ_j , then the output of the network arises is the multiplication of the weight parameters matrix $\mathbf{W}$ with the vector of outputs from the Gaussian functions.

To derive the learning law, we first need to set the neural network of Equation (5.12) in the format of the linear model of Equation (5.6), as the following:

$$\begin{aligned}
\mathbf{m}_{FF} &= \mathbf{W}\boldsymbol{\varphi} \equiv \boldsymbol{\Psi}\mathbf{p} \\
\mathbf{p} &\equiv (w_{1,1}, \dots, w_{1,m}, w_{2,1}, \dots, w_{2,m}, \dots, w_{m,n})^T \\
\boldsymbol{\Psi} &\equiv \begin{bmatrix} \varphi_1 & \varphi_2 & \dots & \varphi_m & 0 & \dots & 0 & \dots & 0 & \dots & 0 \\ 0 & \dots & 0 & \varphi_1 & \varphi_2 & \dots & \varphi_m & \dots & 0 & \dots & 0 \\ & & & & & & & \ddots & & & \\ 0 & \dots & 0 & 0 & \dots & 0 & \dots & \dots & \varphi_1 & \varphi_2 & \dots & \varphi_m \end{bmatrix}
\end{aligned} \tag{5.13}$$

where m is the muscle number and n the number of neurons. Setting $\Gamma \equiv \alpha \mathbf{1}$, the learning law in Equation (5.7) yields:

$$\begin{aligned}
\mathbf{W}^{k+1} &= \mathbf{W}^k + \Delta \mathbf{W}^k \\
\Delta \mathbf{W}_{ij}^k &= \alpha \mathbf{m}_{FB,i} \boldsymbol{\varphi}_j - \gamma
\end{aligned} \tag{5.14}$$

where superscript k is the trial number, α is the learning factor, and γ is a deactivation constant that removes superfluous co-contraction (Franklin et al. 2008, Burdet et al. 2008). Therefore, the weights of the network are updated after each trial related to feedback muscle force.

Data clustering

Choosing the locations ($\mathbf{s}_i$), the number of neurons and activation fields (σ_i) of the network is important for a good representation of the feedforward. For example, using too many neurons can lead to over-fitting and too few neurons to under-fitting.

A number of algorithms have been developed to determine the centres and widths of neurons in an RBF (Moody and Darken 1989, Billings and Chen 1998, Saha and Keeler 1989). We used a simple unsupervised learning algorithm called the *k-means* (McQueen 1967, Duda et al. 2001) to assign neurons to a group of data. The *k-means* algorithm minimises the sum of the square distances to the neurons centres:

$$f = \sum_{c=1}^K \sum_{s_j \in z_c} (\mathbf{s}_j - \mathbf{v}_c)^2 \tag{5.15}$$

where K is the number of clusters, z_c the vector of clusters where each cluster is assigned a centroid v_c , which represents the mean point of (s_j) points. The k-means algorithm is suitable for multi-dimensional data and works by assuming that the number of clusters K is known and there is an initial guess of the centre of each cluster. The conventional k-means clustering algorithm can usually only achieve a local optimal solution, which depends on the initial locations of cluster centres. In this case, however, the algorithm is run over a number of times, where each time the centres have different locations. Hence, the performance of clustering is improved by taking the optimal solution that minimises f .

Data is clustered using the k-means algorithm in order to assign centroids to each cluster and determine the width of their corresponding activation fields. After calculating the number and centres of neurons, the activation fields of all neurons (σ_i) are chosen to include all data within the cluster and so that the Gaussian from one neuron overlaps with adjacent neurons in order to ensure a smooth transition across data (an example of clustering data is shown in the following chapter). Making different widths for neurons in a generalised RBF has been used and proved to be useful for handling several real and simulations problems (Billings et al. 2007).

5.4 Summary

This chapter has introduced a novel algorithm of motor adaptation and generalisation of learning using the kinematic error to modulate the feedforward muscle activation and uniform deactivation to decrease superfluous agonist-antagonist co-activation. The new algorithm extends work from previous studies enabling simulations of movements, for instance, to various directions during simultaneous learning of the endpoint force and impedance necessary to perform stable motion. The algorithm was implemented using a radial-basis-function artificial neural network, which allows transfer of feedback error across different workspace configurations, and thus should allow for broader and better compensation for external dynamics. The multi-variables state space information is appropriately clustered and the widths of the basis functions suitably determined for broader generalisation of learning.

Our new model of motor learning regulates force and impedance by adapting the feedforward muscle force using less behavioural data directly extracted from

experiments, as in previous models. The trial-to-trial adaptation was realised using a V-shape function of muscle error, which triggers an increase in activity as the muscle is stretched, a lower increase when the muscle is shortened and a decrease when the error is small. Further, another feature of the model is its capacity to regulate reciprocal activation and co-activation in redundant muscle limbs (mechanisms), while still regulating energy cost.

The newly developed algorithm represents a global frame of motor adaptation under various dynamic conditions, which enables generalisation of learning and is different from previously proposed models. Previous models based on optimisation of muscle activation and endpoint variance (Stroeve 1999, Trainin et al. 2007, Guigon et al. 2007, Todorov and Jordan 2002, Izawa et al. 2008), which do not explicitly reflect the trial after trial learning seen in real experiments. Other models, based on feedback error learning, proposed to solve iterative and adaptive control problems such as those associated with robotic implementations (Kawato et al. 1987, Sanner and Kosha 1999, Burdet and Milner 1998, Donchin et al. 2003). Such models could only be used to examine adaptation of force or torque control, but could not be implemented to compensate for unstable tasks that require high level of impedance tuning observed in tool tasks for instance.

Many of the existing computer models implemented learning algorithms that modify joint torque or endpoint force to oppose the interaction force in the dynamic environment (Kawato et al. 1987, Burdet et al. 2005, Donchin et al. 2003, Thoroughman and Taylor 2005). However, our model is implemented to simulate the evolution of muscle activity in limb movements, and is able to demonstrate increase of muscle co-contraction in response to a perturbation. This would lead to observing impedance control and changing muscle transients that contribute towards stabilising unstable tasks, which was not possible with joint space models before.

In order to test the usefulness and limitations of the novel algorithm, it is important to compare simulations with past experimental motor learning studies. In this regard, adaptation of reaching arm movements is ideal, because many motor learning studies have investigated generalisation of learning in the past. Hence, the next chapter will demonstrate how the new algorithm can be implemented for a two degrees-of-freedom and six muscles human arm. The model will be simulated during various reaching tasks and results compared with past experimental studies.

Chapter 6

SIMULATIONS OF PAST EXPERIMENTS & MODEL PREDICTIONS USING A MUSCLE SPACE ARM MODEL

6.1 Introduction

In order to investigate the control and learning behaviour resulting from the general algorithm described in the previous chapter, it is necessary to implement the model so that the simulations would reveal its plausibility and robustness. Therefore, in this chapter the model is implemented in a two degrees-of-freedom (DoF) and six muscles rigid arm moving horizontally and interacting with various stable and unstable force fields (Figure 6.1.1).

The decision to choose a simple two DoF six muscles arm for simulations was compliant with many past experimental procedure involving human subjects. This way, it is possible to simulate a minimum number of degrees-of-freedom and muscle that allow simpler interpretation of results and would be less computationally expensive. Furthermore, the choice of the six muscles is based on the fact that stiffness (which is torque dependent) acts on shoulder and elbow joints as well as the muscles in between i.e. multi-joint muscles, which are required to achieve synergistic activation of all the muscles (Hogan et al. 1985). Also, it is necessary to include a pair of agonist-antagonist muscles for each joint where the pairs are chosen to represent muscles in respective regions (i.e. coupling), and where they would contribute most during planar movements as reported in McIntyre et al. (1996).

The model to develop should encompass mechanisms that enable simultaneous adaptation of force and impedance produced by modulation of muscle reciprocal-activation and co-activation (Osu et al. 2003). In reaching movement tasks, the model would enable adaptation to instability of various strengths (Franklin et al. 2004) and in different directions (Franklin et al. 2007, Kadiallah et al. 2008), which is achieved through continuous adjustment of the level of co-activation in the antagonist muscles. Thus, the main question is whether the algorithm presented in the previous chapter could be implemented to produce the necessary muscle transients to compensate for the dynamics in different arm reaching tasks.

In order to validate the muscle-space learning model, simulations of previous results obtained during psychophysical studies in both stable and unstable environments are reproduced. Furthermore, the novel model is used to predict future experiments that require multiple directions impedance control and track what intrinsic information the central nervous system (CNS) would ideally employ for the generalisation of learning.

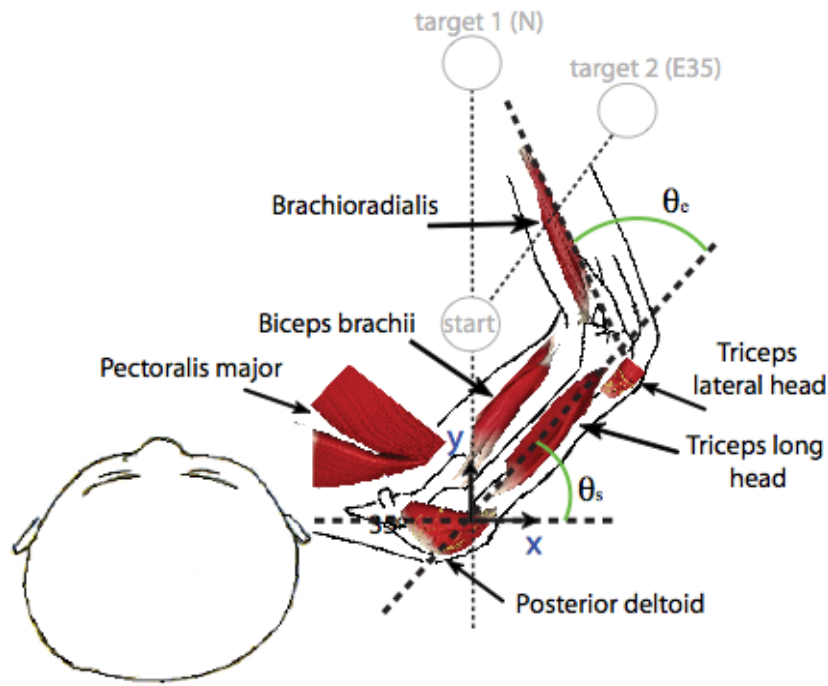


Figure 6.1.1: The two DoF and six muscles human arm that was modelled. The arm was assumed to produce horizontal movements at shoulder height similar to the real experiments. The muscles chosen were two shoulder monoarticular muscles; two elbow monoarticular muscles and two biarticular muscles between the two joints. As an example, the figure is depicting arm configuration for a subject making movements towards either of two targets.

6.2 Model of motor adaptation in muscle coordinates

6.2.1 Rigid body kinematics and dynamics

The kinematics and dynamics transformations between the hand, joint and muscles spaces are summarised in Table (6.2.1). In Cartesian (or hand) space, $\mathbf{x}$ is the hand position, and $\mathbf{F}$ is the force exerted on the hand. In joint space, $\mathbf{q}$ is the joint position, $\dot{\mathbf{q}}$ is the joint velocity, and $\boldsymbol{\tau}$ is the joint torque. In muscle space, $\boldsymbol{\lambda}$ is the vector of muscles lengths, $\dot{\boldsymbol{\lambda}}$ is the velocity in muscles lengths and $\mathbf{m}$ represents the muscle tensions.

Table 6.2.1: Kinematics and dynamics transformations between hand, joint and space coordinates

Hand		joint		muscle	
$\mathbf{x}$	$\xleftarrow{\text{forward kin.}}$	$\mathbf{q}$	$\xrightarrow{\mathbf{J}_m \mathbf{q}}$	$\boldsymbol{\lambda}$	position
$\dot{\mathbf{x}}$	$\xleftarrow{\mathbf{J} \dot{\mathbf{q}}}$	$\dot{\mathbf{q}}$	$\xrightarrow{\mathbf{J}_m \dot{\mathbf{q}}}$	$\dot{\boldsymbol{\lambda}}$	velocity
$\mathbf{F}$	$\xrightarrow{\mathbf{J}^T \mathbf{F}}$	$\boldsymbol{\tau}$	$\xleftarrow{\mathbf{J}_m^T \mathbf{m}}$	$\mathbf{m}$	force
$\mathbf{K}_x$	$\xrightarrow{\mathbf{J}^T \mathbf{K}_x \mathbf{J} + (d\mathbf{J}^T/d\mathbf{q})\mathbf{F}}$	$\mathbf{R}$	$\xleftarrow{\mathbf{J}_m^T \boldsymbol{\kappa} \mathbf{J}_m}$	$\boldsymbol{\kappa}$	stiffness

The horizontal movements at shoulder height use a two-link mechanical structure, whose anthropometric parameters were obtained from (Diffrient et al. 1978) and summarised in Table (3.3.1). The rigid body dynamics are obtained using:

$$\boldsymbol{\tau}_{FF} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}}$$

$$\mathbf{M}(\mathbf{q}) = \begin{bmatrix} J_1 + J_2 + M_1 l_{m1}^2 + M_2 (l_1^2 + l_{m2}^2 + 2l_1 l_{m2} \cos q_e) & J_2 + M_2 (l_{m2}^2 + l_1 l_{m2} \cos q_e) \\ J_2 + M_2 (l_{m2}^2 + l_1 l_{m2} \cos q_e) & J_2 + M_2 l_{m2}^2 \end{bmatrix}$$

$$\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} = \begin{bmatrix} M_2 l_1 l_{m2} \dot{q}_e (2\dot{q}_s + \dot{q}_e) \sin q_e \\ M_2 l_1 l_{m2} \dot{q}_e^2 \sin q_e \end{bmatrix} \quad (6.1)$$

For the two links and six muscles model, $\mathbf{x}$, $\mathbf{q}$, $\boldsymbol{\tau}$, $\mathbf{F}$ are 2x1 vectors, $\mathbf{J}$ and $\mathbf{K}$ are 2x2 matrices. Muscle force $\mathbf{m} = [m_1 \ m_2 \ m_3 \ \dots \ m_6]^T$, $\boldsymbol{\lambda}$ and $\dot{\boldsymbol{\lambda}}$ are a 6x1 vector, where $_1$ and $_2$ stand for shoulder monoarticular muscles, $_3$ and $_4$ for elbow monoarticular muscles, then $_5$ and $_6$ for biarticular muscles. $\mathbf{J}_m$ is a 6x2 matrix transforming between joint space and muscle space that corresponds to the moment arms ρ_1 to ρ_8 of the six muscles at the two joints:

$$\mathbf{J}_m = \begin{bmatrix} \rho_1 & -\rho_2 & 0 & 0 & \rho_5 & -\rho_6 \\ 0 & 0 & \rho_3 & -\rho_4 & \rho_7 & \rho_8 \end{bmatrix}^T \quad (6.2)$$

The moment arm values used in the simulations are assumed to be constants. In addition, given that the number of neurons is 32 for instance, then the weights matrix of the neural network is 6x32 dimensional.

6.2.2 Motion integration

The desired trajectory in Cartesian space, $\mathbf{x}_d$, is smoothened using minimal jerk trajectory as defined in Equation (3.10). The planned trajectory is transformed into joint coordinates using inverse kinematics (Equation 3.11), and from joint angles to muscles lengths using the moment-arms Jacobian defined in Equation (6.2).

In order to curb oscillations after reaching the target, a high damping force is implemented when parallel displacement relative to the movement has reached more than 95% of the distance, $\boldsymbol{\tau}_d = \mathbf{J}^T (-60 \dot{\mathbf{x}})$. Furthermore, a virtual safety wall was implemented at $\pm 4cm$ parallel to the straight-line trajectory joint start and target points. At this point, the force field is ceased and an adjusting force of $\boldsymbol{\tau}_p = \mathbf{J}^T (30 \dot{\mathbf{x}})$ is applied to restore movement, but when the hand is within the boundaries again then it is allowed to move freely towards the target.

Motion control is realised according to the diagram depicted in Figure (5.3.1). Re-writing the movement control equation from previous chapter:

$$\boldsymbol{\tau} = \boldsymbol{\tau}_{FF} + \boldsymbol{\tau}_N + \boldsymbol{\tau}_{IMP} + \boldsymbol{\tau}_{FB} \quad (6.3)$$

where the rigid body dynamics, $\boldsymbol{\tau}_{FF}$, and motion planning have been described above and the rest of terms will be explained individually in details in the following subsections. Motion calculation is achieved at the joint level, after transforming muscle dynamics to joint torques using equations in Table (6.2.1). In order to obtain the movement resulting from the interaction of the arm and the environment, Equation (6.3) is Euler integrated at 1Hz according to:

$$\begin{aligned} \ddot{\mathbf{q}}(t) &= \Pi(\mathbf{q}(t - \Delta t), \dot{\mathbf{q}}(t - \Delta t), \mathbf{m}(t - \Delta t)) \\ \dot{\mathbf{q}}(t) &= \dot{\mathbf{q}}(t - \Delta t) + \ddot{\mathbf{q}}(t) \Delta t \\ \mathbf{q}(t) &= \mathbf{q}(t - \Delta t) + \dot{\mathbf{q}}(t - \Delta t) \Delta t + \frac{1}{2} \ddot{\mathbf{q}}(t) \Delta t^2 \end{aligned} \quad (6.4)$$

where t is the movement time, Δt is the sampling time, and Π represents the dynamics of the interaction depending on joint position $\mathbf{q}$, joint velocity $\dot{\mathbf{q}}$, and muscle activation $\mathbf{m}$ of the previous time.

6.2.3 Feedforward RBF network learning

The number of neurons and their corresponding activation fields (i.e. widths) are determined using the k-means algorithm. First, joint position and velocity data are collected for several movements that cover the workspace where simulations are performed. The data collected does not necessarily represent the trajectories of movements that would be simulated. Then, to determine clusters and assign a centroid to each of these clusters in the task space, the k-means algorithm was run for 2000 iterations while the number of neurons was allowed to vary between 3 and 80. The activation field of each neuron was the area covered by its cluster, which means different activation fields would be obtained for each neuron and each time the algorithm is run. For instance, Figure (6.2.1) shows how joint position data was clustered using the described method. In fact, the number of neurons selected was in the range 22-40 in all the experiments in this study.

To check that data was clustered effectively, the Matlab built-in *silhouette* function was used. The purpose of this function is to verify how similar the value of each point to other points within the same cluster as compared to other points in other clusters. The plot obtained using the *silhouette* function shows bars in the range -1 to +1 for each neuron. The more the values for each neuron tend towards +1, the better clustering that was achieved. *Silhouette* uses the squared Euclidean distance between data points. K-means and *silhouette* were run to create a new RBF network before performing each simulation. After the artificial neural network is initialised, then training is realised by updating the weights parameters trial after trial using feedback muscle force (Equation 5.14). This learning directly updates the feedforward muscular force for each movement (Figure 5.3.1).

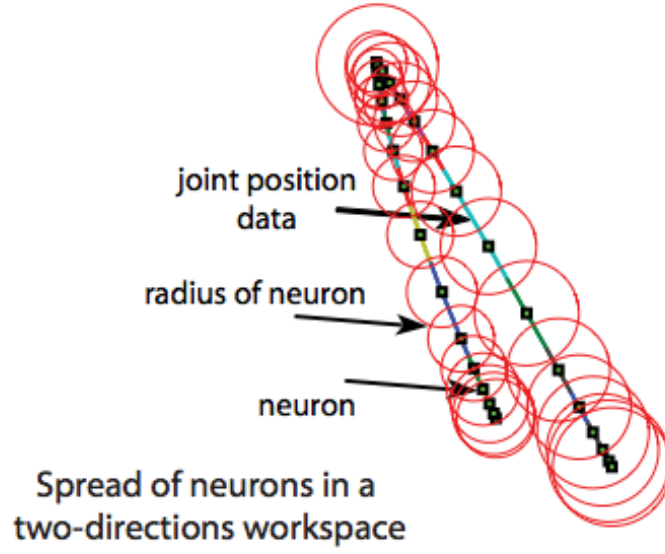


Figure 6.2.1: Clustering of joint position data for two movements in a workspace using the k-means algorithm. Two-dimensional joint position data only is shown for illustration purposes since four-dimensional data using position and velocity is not possible to visualise. The green squares are the centres of different clusters and are also termed centroids, while the radii are the red circles that encompass data from each cluster.

6.2.4 Noise

Previous experimental findings in isometric force production (Jones et al 2002) and in movement (Nakano et al. 2002) suggest that variability in the force produced by muscles is a linear function of the mean force. Hence, noise increases with the motor command and is modelled as Brownian motion. The noise series μ is obtained through the Matlab random generator *randn*. Noise series is generated for each muscle over time and is then multiplied with the feedforward force of each muscle:

$$\mathbf{m}_N(t) = \mathbf{J}_m^T \left[(\mu_0 + \mu_1 \mathbf{m}_{FF}(t)) * \mu(t) \right] \quad (6.5)$$

where μ_0 and μ_1 are noise parameters.

6.2.5 Feedback reflexes

Feedback force stems from the muscle reflexes that cause stretch after exposure to external disturbance. Both muscle stiffness and reflex gain increase with muscle force (Sinkjaer et al. 1988), while reflex EMG increases roughly linearly with muscle stretch velocity (Eng and Hoffer 1997, Nakazawa et al. 2001). In addition, reflex activity of the antagonist increases even though only the agonist muscle is stretched (Milner et al. 1995, Franklin et al. 2003B). Therefore, elastic force and stretch reflex are modelled as linear functions of muscle stretch $\Delta\lambda(t)$ and stretch velocity $\Delta\dot{\lambda}(t)$. Both of these variables are transforms of Cartesian hand error (Burdet et al. 2006). The reflexes $\mathbf{m}_{FB}$ in the agonist and antagonist muscles are modelled as:

$$\mathbf{m}_{FB}(t) = \mathbf{G}_m [\Delta\lambda(t - \xi) + g_d \Delta\dot{\lambda}(t - \xi)] I_{\{\Delta\lambda(t) > 0\}} \quad (6.6)$$

where g_d a reflex gain and ξ is the reflex delay. I is the Kronecker indicator function defined by $I_{\text{condition}} \equiv 1$ when the *condition* is fulfilled and 0 otherwise. Error signal, $\mathbf{m}_{FB}(t)$, of the agonist or antagonist muscle is linearly dependent on stretch and stretch velocity. The stretch, $\Delta\lambda = \lambda_d - \lambda$, is computed relative to the planned trajectory in muscle coordinates. $\mathbf{G}_m$ is reflex gain assumed to increase linearly with muscle activity (Hunter and Kearney 1982, Sinkjaer et al. 1988), and is modelled as:

$$\mathbf{G}_m(t) = \text{diag} \left[g_0 + g_1 * (\mathbf{m}_{FF}(t) + \mathbf{m}_{FB}(t) + \mathbf{m}_N(t)) \right] \quad (6.7)$$

and g_0, g_1 are scalar reflex parameters.

6.2.6 Muscle Impedance

The learning controller used in this study corresponds to a nonlinear adaptive controller in muscle space coupled with a radial-basis-function neural network, where both impedance and reflex terms depend on the proportional and derivative terms of the imposed muscle stretch. The muscle spring-like property stems from muscle elasticity as well as from the stretch reflex. Muscle elasticity is modelled as (Burdet et al. 2006):

$$\mathbf{m}_{IMP}(t) = \mathbf{K}_m [\Delta \boldsymbol{\lambda}(t) + \kappa_d \dot{\Delta \boldsymbol{\lambda}}(t)] * I_{\{\Delta \boldsymbol{\lambda}(t) > 0\}} \quad (6.8)$$

where $\mathbf{K}_m$ is the muscle stiffness. The intrinsic stiffness $\mathbf{K}_m$ is assumed to increase linearly with muscle activity (Hunter and Kearney 1982):

$$\mathbf{K}_m(t) = \text{diag} \left[\kappa_0 + \kappa_1 * (\mathbf{m}_{FF}(t) + \mathbf{m}_{FB}(t) + \mathbf{m}_N(t)) \right] \quad (6.9)$$

where κ_0 , κ_1 and κ_d are stiffness parameters.

6.2.7 External dynamics

Movements are performed during novel external dynamics that perturb the hand in various ways. The external torque, $\boldsymbol{\tau}_E$, is configured differently depending on the purpose of each experiment. Hence, a more detailed description is given at each simulation in the results section.

On the other hand, the external force consists not only of the perturbing dynamics, but also of the friction and inertia of the PFM used in many past experiments (Burdet et al. 2001, Franklin et al. 2003A, Franklin et al. 2007, Kadiallah et al. 2008). The PFM dynamics are coded based on findings from Franklin et al. (2002), and according to:

$$\begin{aligned} \boldsymbol{\tau}_{PFM} &= \mathbf{J}^T \left[\mathbf{M} \mathbf{x}_a + \mathbf{D}_d \mathbf{x}_v + \tanh(200 \mathbf{D}_s \mathbf{x}_v) \right], \\ \mathbf{M}_{PFM} &= \begin{bmatrix} 1.516 & 0 \\ 0 & 1.404 \end{bmatrix}, \quad \mathbf{D}_d = \begin{bmatrix} 10.247 & 0 \\ 0 & 7.592 \end{bmatrix}, \quad \mathbf{D}_s = \begin{bmatrix} 0.102 & 0 \\ 0 & 0.356 \end{bmatrix} \end{aligned} \quad (6.10)$$

where $\mathbf{x}_v$ is the hand velocity and $\mathbf{x}_a$ is the acceleration, $\mathbf{M}_{PFM}$ is the PFM mass, $\mathbf{D}_d$ is damping and $\mathbf{D}_s$ is the static friction. The static friction dynamics are smoothened by the hyperbolic tangent function. When testing past experiments in the next chapter, we assume that the same friction and inertia dynamics of the PFM were exposed in other robotic arms.

6.2.8 Selection of physiological parameters

The nonlinear adaptive controller described uses neural feedback, modelled as a proportional derivative term of the muscle stretch, to learn the required dynamics. It has been demonstrated that in nonlinear adaptive controllers applied in a robotic arm, convergence occurs with positive proportional or derivative terms of the error (Bayard and Wen 1998). Hence, our model is able to successfully perform any task in the field free movements. However, different sets of parameters can produce dissimilar behaviour. Therefore, default parameters for the model have to be initially chosen, so they correspond to experimental data. The objective is to use reflex, impedance and noise parameters corresponding to experimental values and producing deviation similar to that of real movements. The parameters values chosen in this implementation were largely determined based on previous work from Tee (2003) and then adapted to the needs of this work.

The reflex delay in was set to $\xi=30ms$ corresponding to the experimental data (Franklin et al. 2003B). Considering that we are working with muscle forces and not EMG, there is an additional latency of 25-50ms to account for excitation-contraction coupling and time to reach maximum muscle contraction. Further muscle elasticity is mainly position dependent while reflexes are mainly velocity dependent, so the corresponding ratios are set to $\kappa_d=1/12$ and $g_d=0.2$ respectively. The selection of parameters for reflex and impedance ensured a reflex contribution of 20-35% of the total restoring response, similar to the physiological range of 18-44% (Carter et al 1990). Also, in the impedance modelling, the following stiffness parameters are selected: $\kappa_0=3360Nm^{-1}$, $\kappa_1=3360*0.035m^{-1}$, producing stiffness ellipse in NF similar to what is measured in experiments (Franklin et al 2003, Burdet et al 2001, Gomi and Kawato 1997). The reflex gains were selected as: $g_0=114Nm^{-1}$, $g_1=114*0.035m^{-1}$, $g_d=0.2$.

The noise is an additive component of the muscle tension with parameters set to emulate the movement variability observed in experimental data of NF movements and initial movements in the VF and DF (Franklin et al. 2008). Noise parameters were set to $\mu_0=7$ and $\mu_1=0.04$.

The learning parameters were chosen to achieve a steady state similar to experimental observations in the NF. Therefore:

$$\alpha = 1, \quad \gamma = \frac{2e_{ss}\zeta\beta}{\zeta + \beta} = 6.43 * 10^{-4} \quad (6.11)$$

where $e_{ss} = 7.8 * 10^{-4}$ is the steady state error based on data from NF trials, $\zeta = 9800$ and $(\beta/\zeta) = 0.7$ are learning and physiological factors used in the model of (Franklin et al. 2008).

We select moment arms producing stiffness similar to measured movements. To visualise impedance geometry, we use stiffness ellipses corresponding to the restoring force to a unit displacement. The change of endpoint stiffness $\Delta \mathbf{K} \mathbf{x}$ resulting from a trajectory perturbation $\Delta \mathbf{x}$ through feedback error learning at muscle level depends on the moment arms $\mathbf{p}$ and on the learning factor α . For simplicity it was assumed that the agonist and antagonist muscles acting at a same joint have equal moment arms. Co-activation of the shoulder or elbow muscles pair causes endpoint stiffness to increase in a fixed direction by a magnitude depending on the moment arm. The direction of the stiffness ellipse corresponding to the double-joint muscles depends on the ratio of the two moment arms used, which enables to vary the orientation of the impedance. A moment arm ratio of 1.4 was selected between the shoulder and elbow joints, such that a deviation $\Delta \mathbf{x} = (1, 0)$ produces stiffness increase approximately in the same direction (Franklin et al. 2003B). Finally, moment arms corresponding to the three muscles pairs are tuned to produce a stiffness ellipse similar to the measurement in the middle of NF movements, slightly elongated along the movement direction. The moment arms used in simulation are $0.03m$ for the shoulder muscles, $0.021m$ for the elbow muscles, and $0.044m$ and $0.0338m$ for the double-joint muscles acting at shoulder and elbow joints, respectively.

6.3 Simulations of past experimental results

The simulations of the model are based on previous experimental conditions similar to the real experiments. The methods used in the simulations for choosing parameters such as the length of the trajectory, time required to accomplish the movement, the nature of the force field and its intensity are defined independently before each simulation. Concerning movement planning, the minimum jerk trajectory is used in the model to

generate the desired trajectory positions in Cartesian space, which are then transformed to joint and muscle space coordinates as required. Dynamics of the arm are also transformed using forward and inverse methods.

The neural network model developed in the previous section was simulated and used to predict major experiments investigating generalisation in the last 15 years. In order to check the prediction of the model against experimental data, it is used to simulate horizontal arm movements analysing different hand trajectories, endpoint stiffness and muscle activity throughout.

6.3.1 Generalisation over movements (Conditt et al 1997)

Generalisation over movements was investigated in a prominent study by (Conditt et al.1997). The experiment involved adapting to a velocity depending force field (VF) (Figure 6.3.1A) of the form:

$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} -13 & -13 \\ -13 & 12 \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} (N) \quad (6.12)$$

The subjects were separated into two groups. The first group learned the VF by performing reaching movements to randomly selected targets in eight directions separated by 45° , after which possible transfer of learning to circular movements performed in the same force field was tested. The second group of subjects learned to perform movements in VF directly along the 10cm radius circle.

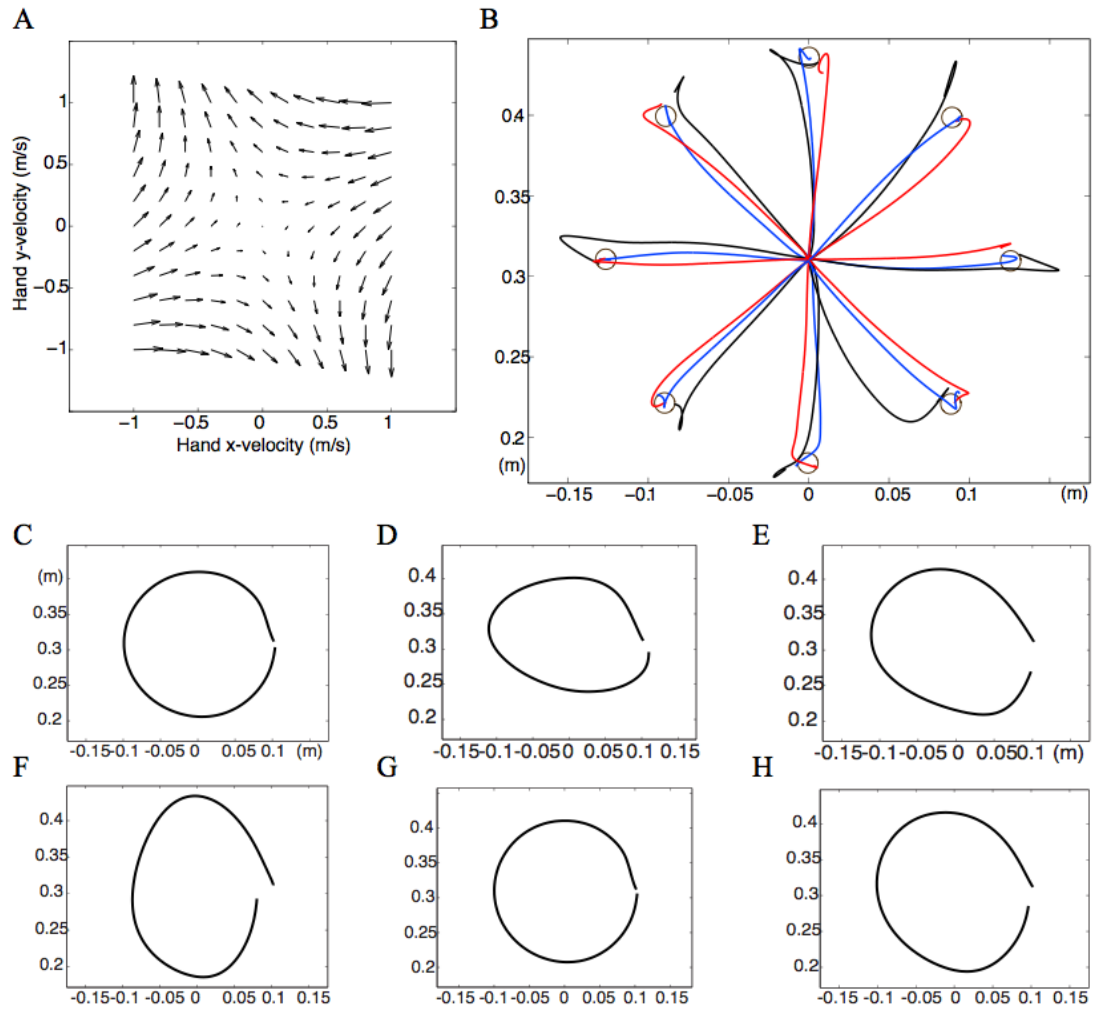


Figure 6.3.1: Simulation of transfer of learning to other movements as in Conditt et al. (1997). Learning directly on a circle or training reaching movements in all directions results in similar performance and after effects. A: velocity-dependent force field B: reaching movements in eight directions before (black) and after (blue) learning in the force field, while after-effects are shown in red. C: drawing a circle in the null field. D: initial circular movements a velocity-dependent (VF) force field. E: circle made after adaptation to the VF. F: after-effects after adaptation to making circles in the VF. G: transferred learning tested by making circles after adaptation of reaching movements towards 8 directions. H: after-effects in making circular movements after adaptation to reaching movements in all directions as shown in B.

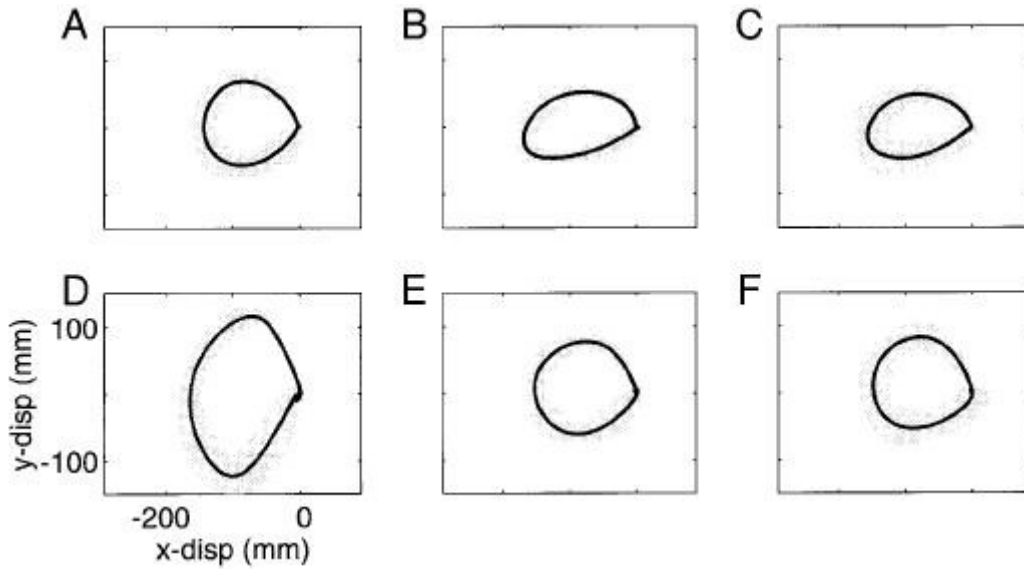


Figure 6.3.2: Experimental results showing the transfer of learning and after-effects from reaching movements to circular movements. The figure was taken from Conditt et al. (1997). Results in panels A-C correspond to panels C-H in Figure (6.3.1), respectively.

In order to simulate the experiment by (Conditt et al. 1997), the RBF network was first initialised using joint position and velocity data from eight 12cm-long movements spanning a range of 360° and a circle of 10cm in diameter. Both reaching movements and circular movements had duration of 300ms. This neural network was then used to simulate the learning of movements.

Results of learning with 100 reaching movements in the eight directions are shown in Figure (6.3.1B). During the before effect trials i.e. initial exposure to the force field (shown in black), movements diverge to the left. After adaptation to the external dynamics (blue lines) movements become similar to those in free-mode. After-effects trials (in red) slightly deviate opposite to the before effects trials, which confirms the development of a learned internal model for the VF (Shadmehr and Mussa-Ivaldi 1994).

Figure (6.3.1C-H) shows similar results performed in simulations as to experimental results by Conditt et al. (1997), which are also depicted in Figure (6.3.2). Figure (6.3.1C,F,G) shows the circular movement in NF (C), in the initial exposure to the VF (F) and after learning (G). Figure (6.3.1D) shows the effect of removing the VF after this learning. The flat circle resulting from the after effects illustrates the learned internal model. Interestingly, similar results are obtained when the VF is learned in

reaching movements, corresponding to the first subjects group in the human experiment (Figure 6.3.1H after learning and Figure 6.3.1E for the after effects). In particular the ratios between the horizontal and vertical axes changes are {1.02, 1.38, 1.21, 0.76, 1.00, 1.05} for figures C-H respectively. The ratios show that NF and VF after learning have a ratio ~ 1 , which characterises a circle, while during initial trials in the VF the ratio is < 0.8 , and all after-effects have similar ratio > 1.2 whether learned along the circle or in reaching movements. This demonstrates a transfer of learning from the reaching movements to the circle, and in turn illustrates that the state space model of the VF learned in the reaching movements is valid for other movements, i.e. the generalisation property of the model.

6.3.2 *Resolution of Internal Model (Thoroughman and Taylor 2005)*

Thoroughman & Taylor (2005) investigated which complexity of force fields could be learned in the CNS. Subjects made reaching movements in 16 directions from 0° to 337.5° separated by 22.5° while the robotic arm disturbed the hand in increasingly variant velocity dependent force fields VF1, VF2, VF4, described by:

$$\mathbf{F} = -15\sqrt{\dot{x}^2 + \dot{y}^2} \begin{bmatrix} -\sin(\nu\Phi) \\ +\cos(\nu\Phi) \end{bmatrix}, \quad \Phi = \arctan\left(\frac{\dot{y}}{\dot{x}}\right), \quad (6.13)$$

where $\dot{x}, \dot{y}$ are actual components of the hand velocity, and $\nu=1$ for VF1, $\nu=2$ for VF2 and $\nu=4$ for VF4 (Figure 6.3.3A).

In this simulation, 12cm long movements of duration 300ms were made to targets that were randomly presented in one of the 16 directions. First, 80 free movements were performed, and then followed by 160 movements in either of VF1, VF2 or VF4.

The neural network was created with both position and velocity input data for all 16 directions of movements. The learning rate, the number of neurons and their corresponding activation fields were kept the same during adaptation in all force fields. The force field defined in Equation (6.12) was implemented with movements randomly asserted towards each of 16 targets.

Results illustrate that the controller was able to learn the dynamics in all three force fields, but did not produce similar learning in VF4 as in the other two fields (Figure 6.3.3B). Specifically, movements performed in VF1 and VF2 show excellent compensation, while compensation to field VF4 was not as good. This observation is confirmed when looking at the trajectories made in each force field (Figure 6.3.3B). Movements diverged widely at the beginning of adaptation and were straightened after learning in all fields. However, after-effect trials that were performed after adaptation was complete show movements diverging in the opposite direction as to before adaptation in VF1 and VF2, but to a less extent in VF4. This indicates that the internal model developed in VF1 and VF2 was able to compensate for each of these force fields, but not for VF4.

To analyse this trend systematically, the correlation of the velocity time series in the last trial in NF and each movement in the $VF_{(1,2,4)}$ (in the same direction) was computed as in (Shadmehr and Brashers-Krug 1997). The evolution of correlation during learning was then smoothed using a 20-movement moving average, for each force field (Figure 6.3.3C). Results show that adaptation to fields 1 and 2 were high and closely similar, but performance of the model in learning the more complex field 4 seems to be limited in comparison. The experimental findings of Thoroughman and Taylor (2005) are illustrated in Figure (6.3.4), which show that the computer model could replicate learning seen in experiments.

While the results of Thoroughman and Taylor (2005) may suggest that the resolution of the internal model is adapted to match the force field spatial complexity, our simulations demonstrate that a single neural coding produces an internal model able to deal with the fine granularity of the external environment (Reinkensmeyer et al. 2007). However, as in the results from (Thoroughman and Taylor 2005), the approximation property of the internal model was limited, such that VF4 with its fine complexity could not be adequately approximated.

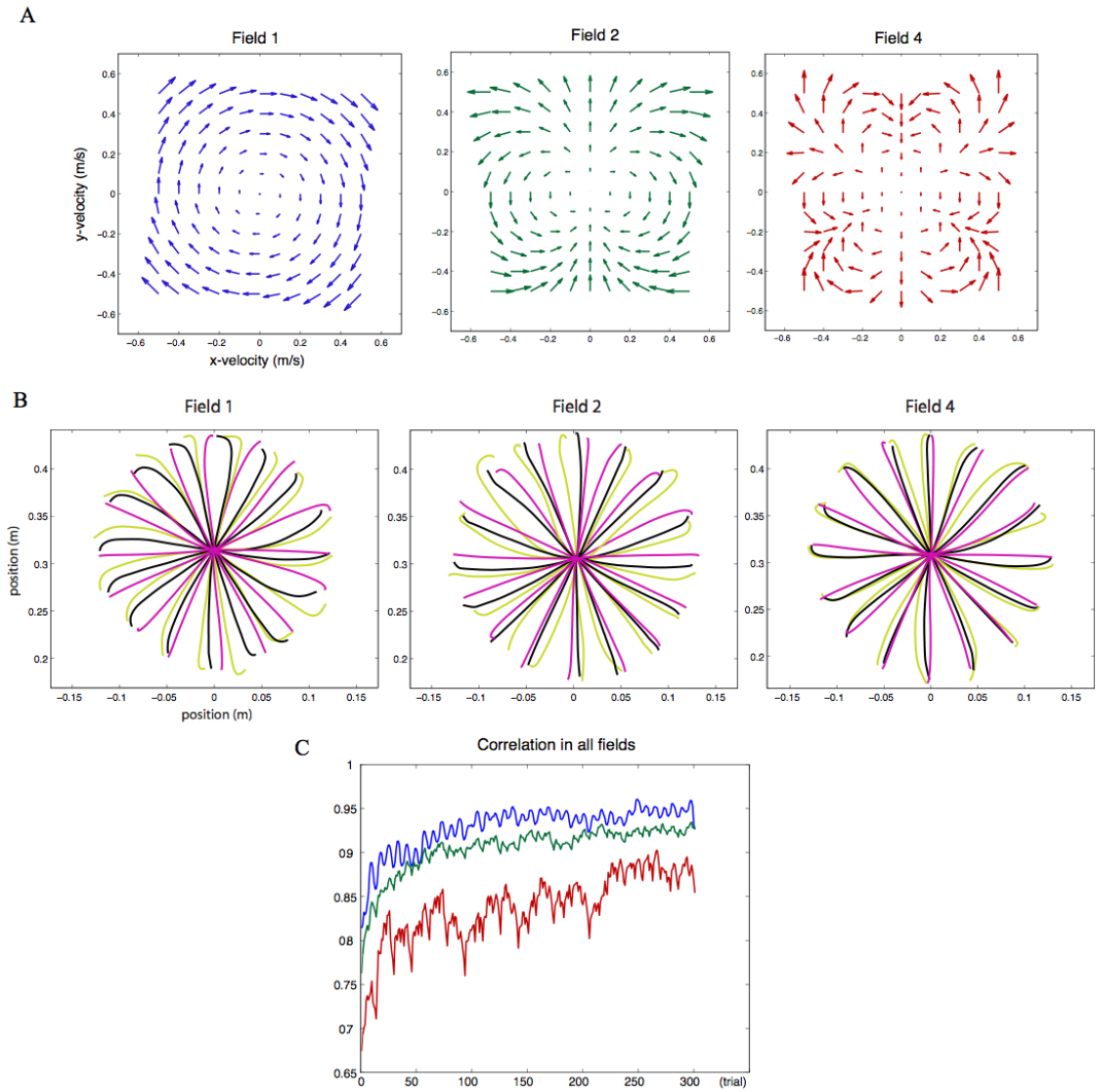


Figure 6.3.3: Simulation of reaching movements in different force fields of varied complexity as in (Thoroughman and Taylor 2005). A: velocity dependent force fields of increasing complexity. B: Effect of these force fields before learning (yellow), paths after learning (black) and after effect of learning (pink). C: Evolution of correlation between velocity profiles of movements in VF and the NF during learning. The figure shows moving average during adaptation in field 1 (blue), field 2 (green) and in field 4 (red).

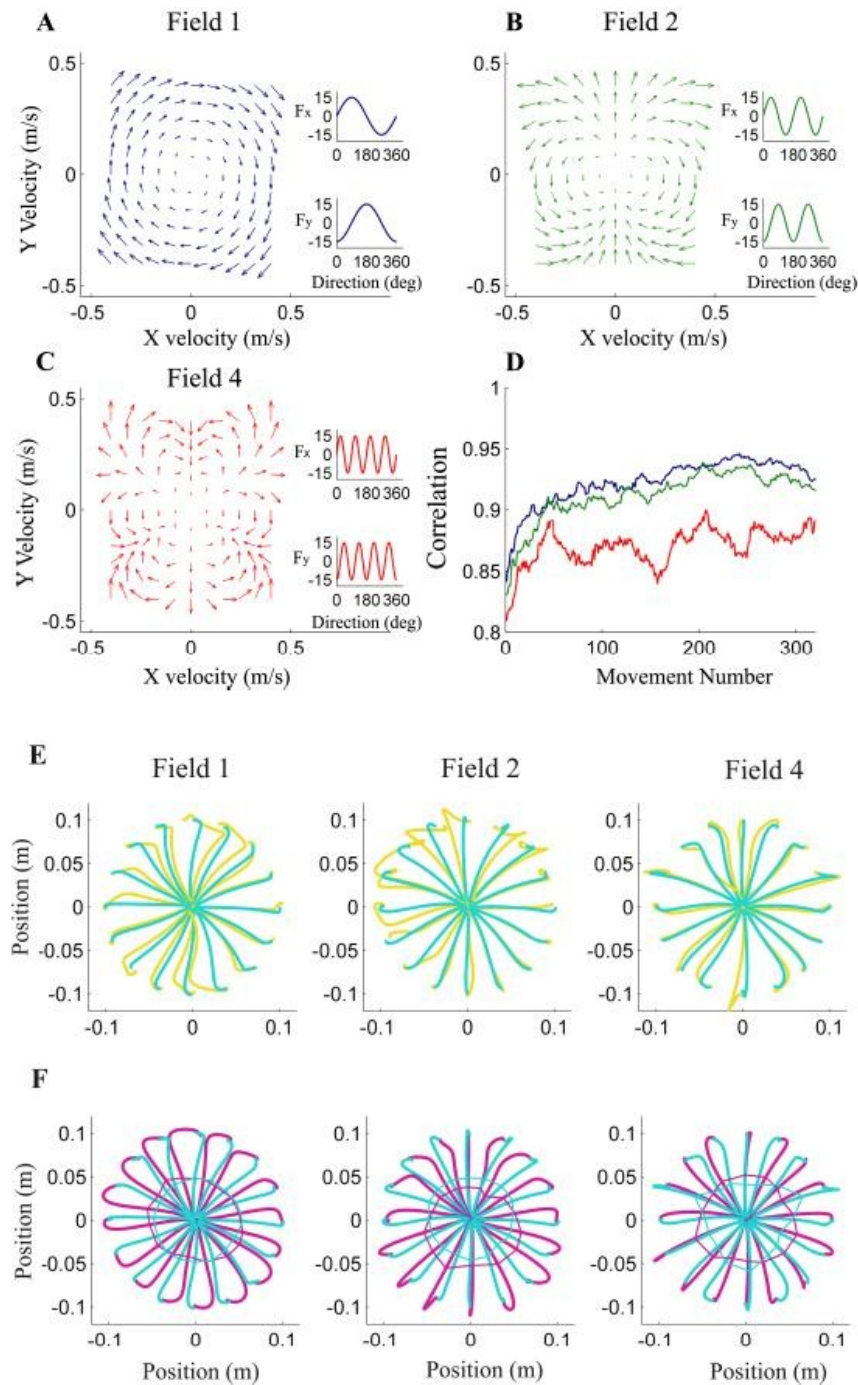


Figure 6.3.4: Results of reaching movements in different force fields of varied complexity performed from experiments by Thoroughman and Taylor (2005). Results in this figure are comparable to simulation results in Figure (6.3.3). A-C: the three velocity-dependent force fields. D: correlations of velocity times-series of movements during learning. E: hand trajectories of subjects during learning. Gold lines represent the first movement in the field in each direction, while the green lines represent the last movements immediately before catch-trials. F: blue lines are the last trials before catch trials as in E, while magenta lines represent the catch-trials.

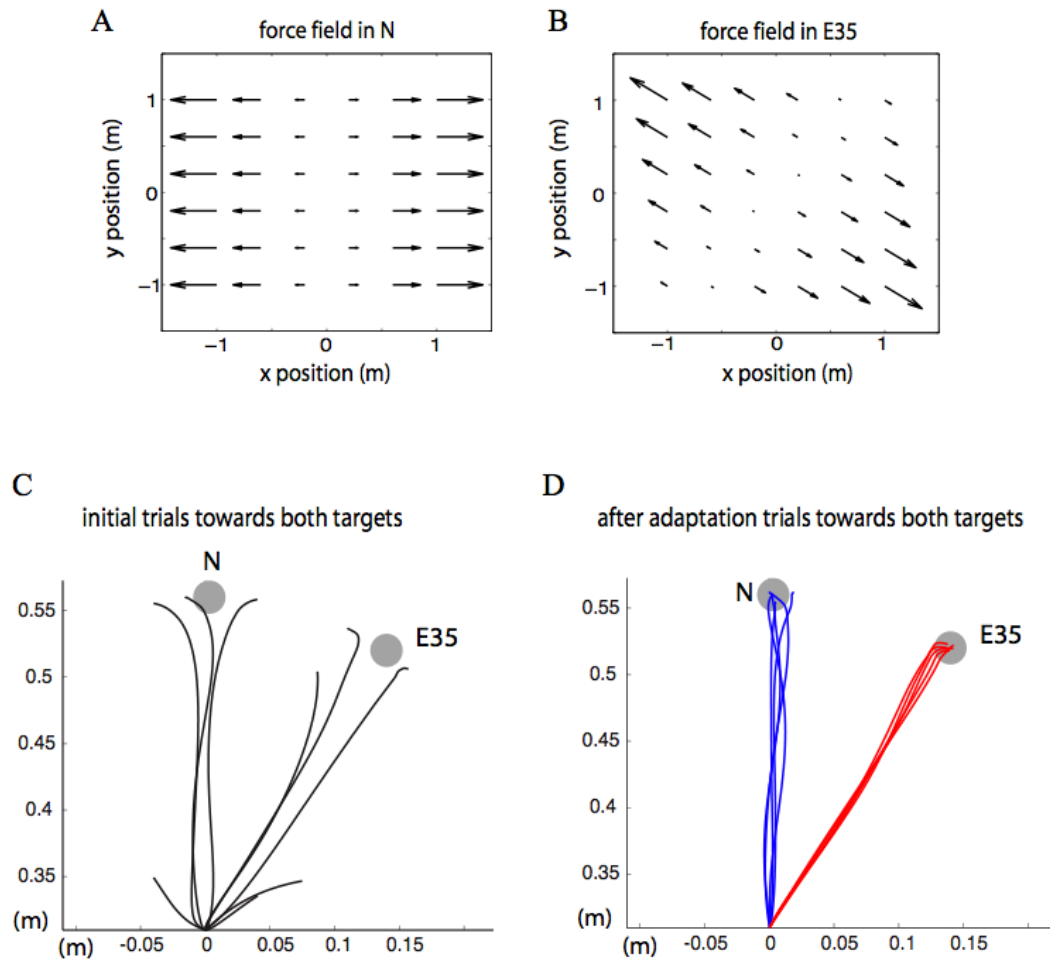


Figure 6.3.5: Simulation of learning lateral destabilisation simultaneously in directions N and E35. A-B: position-dependent force field normal to each direction of movement. C: initial movements in the divergent fields in both directions (black). D: final movements in N (blue) and E35 (red) after 300 trials.

6.3.3 Generalisation in impedance learning (Kadiallah et al. 2008)

The recent experiment of Kadiallah et al. (2008) was also simulated in order to test the capability of our model for impedance learning and unstable tasks. In that experiment, subjects performed reaching movements with lateral instability to any of two targets separated by 35°. We simulated 600ms long point-to-point movements from a start circle at (0, 31)cm relative to the shoulder towards either of two 2.5cm diameter targets, N at (0, 56)cm or E35 at (14, 52)cm. Lateral instability along the movements was produced by a position-dependent divergent force field (DF) of the form:

$$\begin{bmatrix} F_{\perp} \\ F_{\parallel} \end{bmatrix} = \begin{bmatrix} Bp_{\perp} \\ 0 \end{bmatrix} \quad (6.14)$$

where $F_{\perp}$ and $F_{\parallel}$ indicate the force components normal and parallel to the straight line from start to end points, respectively. $B=-300N/m$ and $p_{\perp}$ is the lateral deviation of the hand from this straight line (Figure 6.3.5A-B). A virtual safety barrier was implemented when the hand deviated by more than 4cm from the straight line between start and finish points, consisting of large damping replacing the negative stiffness of Equation (6.14). There was no force field inside the start and end circles.

Simulations of hand trajectories and endpoint stiffness during adaptation to DF in both N and E35 directions are similar to experimental data in (Kadiallah et al, 2008). Results in Figure (6.3.5C-D) show that the model can adapt to the instability in both directions. Initial trajectories deviated to either the right or the left of the straight-line trajectory, but with adaptation the model produced straight-line movements similar to free movements (i.e. NF movements).

Figure (6.3.6A) shows the endpoint stiffness orientation relative to the NF. After learning in DF stiffness increased in size for both N and E35 movements, and the stiffness ellipse elongated in the respective direction of instability. Figure (6.3.7) shows the how the weights associated with each neuron during learning changed for each of the six muscles separately. Weights values were initially set to zero and then updated using Equation (5.14). Weights of the network converged to different values as the controller learned feedforward force to compensate for the external dynamics. These results show that the model learnt to use shoulder and biarticular muscles more than

elbow muscles during adaptation to the fields in directions N and E35, confirming previous experiments results by Kadiallah et al. (2008).

These results show that our model is capable of learning to perform multiple movements with lateral instability, a characteristic of several human tasks using tools. As in the experiment with human subjects, the simulation used minimal force and impedance, resulting in a stiffness ellipse elongated in the direction of instability and compensating for it. Two hypotheses are compatible with the results of (Kadiallah08): either the CNS would switch between multiple internal models acquired simultaneously, or a single internal model could generalise over the multiple movements. While our simulations cannot decide between these two hypotheses, they demonstrate the plausibility of the second one.

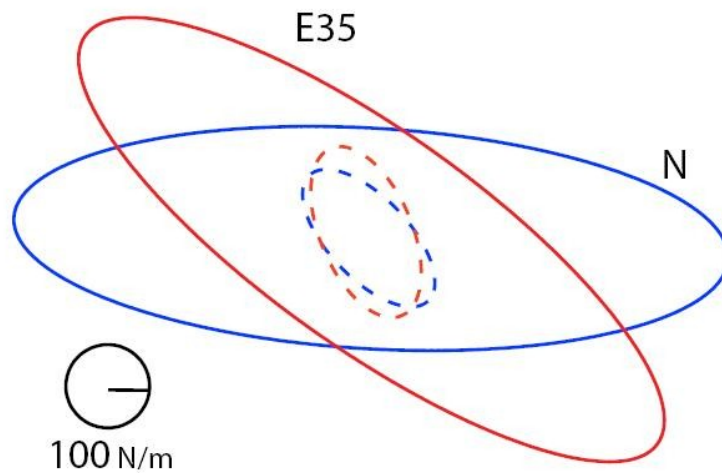


Figure 6.3.6: Simulation of stiffness ellipse before (dashed-line) and after (continuous-line) learning in directions N (blue) and E35 (red). Stiffness ellipse is shown to tune specifically in the direction of instability of each movement after adaptation to the field.

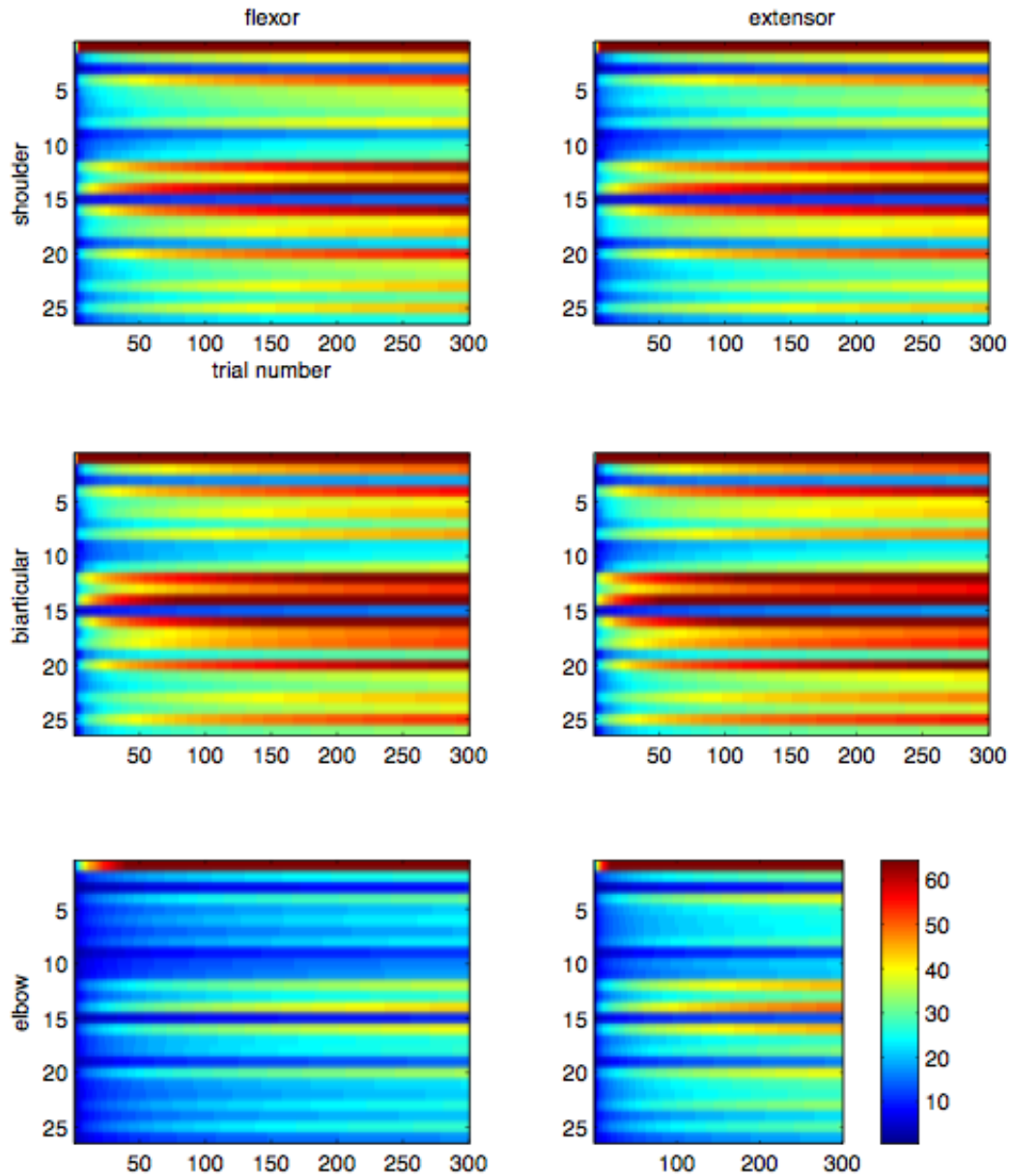


Figure 6.3.7: Evolution of the weights of the RBF neural network for each muscle during learning in both directions N and E35. The colour bar shows the level of weights values for all six panels. The figure shows how the algorithm updated weights directly related to shoulder and biarticular muscle force rather than elbow force, which conforms to previous experimental findings in Kadiallah et al. (2008).

6.4 Prediction of complex impedance learning

Before analysing any prediction of the computational model developed, it is worth presenting the graphical user interface (GUI) version of the model that was developed in the aim to provide a reliable platform for prospect easy user-interaction. This would be a useful interface for future simulations without the need to access the inner code.

The GUI was created to simulate point-to-point reaching movements where the user is able to select from different options available. It is possible to choose the location of targets, the number of trials required to make movements, the type of the force field (i.e. null field, velocity-dependent field, or position-dependent field) and the intensity of the field. The output from the GUI could be modified to illustrate various data analysis and properties of the interaction. For example, this includes the initial and final trajectories made towards a target direction, initial and final hand stiffness ellipses, hand-path error during adaptation, direction of the force field and muscular force during learning. An example of simulating an arm movement in a divergent field in a direction located at 45° anticlockwise from the north movement at 0° (Figure 6.4.1).

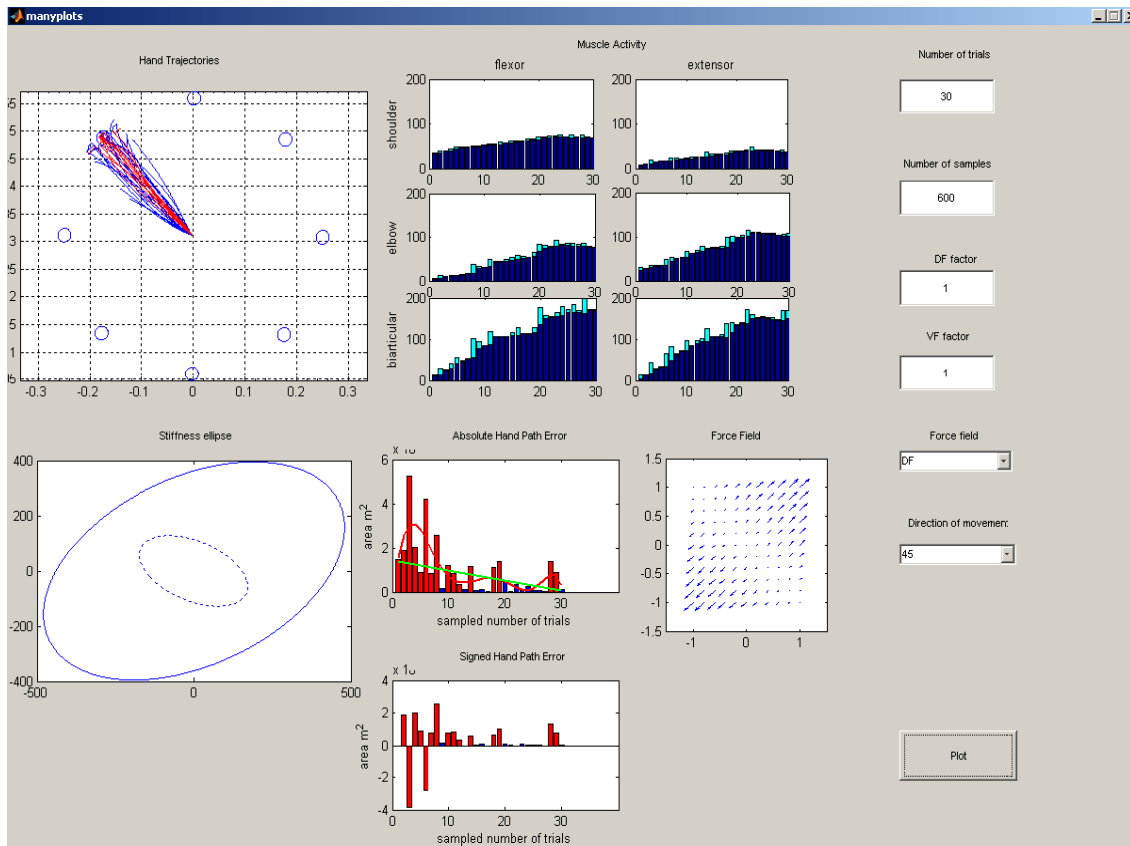


Figure 6.4.1: A graphical user interface (GUI) showing results of simulating reaching movements towards a selected target in the task-space during 30 trials. Movements are simulated in a position-dependent divergent field. Hand-path error, which is the area between the actual movement and straight-line movement joining start and finish points, is shown for the duration of training. Corresponding muscles activity is also illustrated together with initial and final endpoint stiffness ellipses.

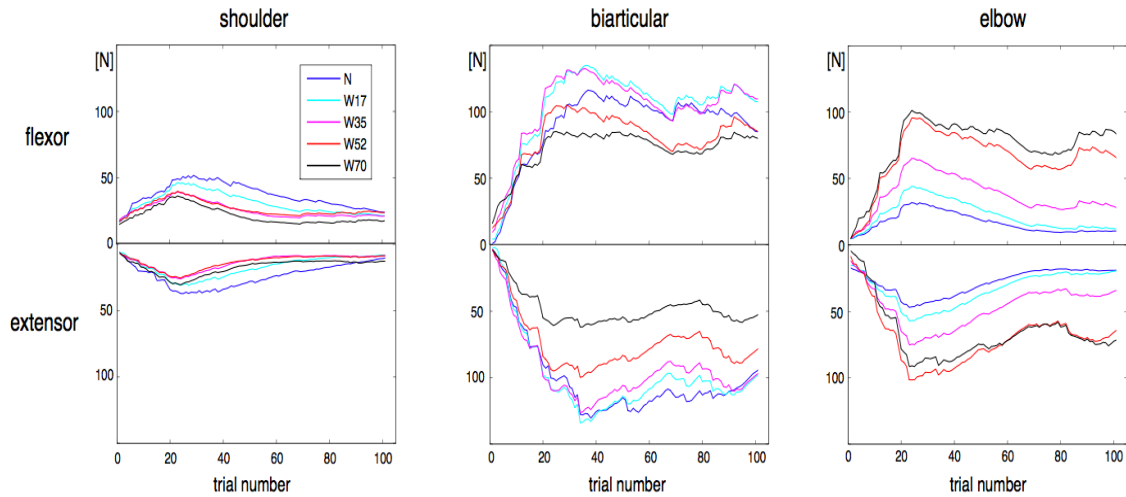


Figure 6.4.2: Predicted (integral of) activity of three flexor-extensor muscles pairs while learning for 100 trials in each of five directions. There is more co-contraction in biarticular and shoulder muscles in direction N (blue), decreasing while the movement direction is more to the left. On the other hand, elbow muscles are activated most in direction W70 (black) and less as the movement is closer to the north direction.

6.4.1 Selective tuning of muscle force in different directions

Because estimating stiffness requires a significant number of trials, it is a cumbersome task to analyse impedance learning in psychophysical experiments. However, the computer model developed could be used to perform simulations of this learning. The model is employed as a tool to predict adaptation of force and impedance in various environments and show the underlying muscle activation patterns. Here, the capability of the predictive computer model is further illustrated by simulating movements in different directions while measuring muscle activity. In this case, an experiment would be very long and difficult, because EMG recordings should normally be performed on the same day so it is possible to compare over different directions, or through an extensive calibration.

The aim of this simulation is to examine how subjects would use different pairs of agonist-antagonist muscles in an unstable environment while executing movements in different directions that have not been studied before. The utility of the computer model is illustrated by simulating movements in directions (0° , 17.5° , 35° , 52° , 70°) counter-clockwise relative to the north direction at 0° . The five directions are denoted

by (N, W17, W35, W52, W70), respectively for easier interpretation. Simulations are performed separately over 100 trials in each direction in a position-dependent divergent field, the gain of which is 400 N/m . Similar to the physical experiments, muscular activities from the six muscles of the arm, which span the shoulder and elbow joints, are recorded in each trial.

Results in Figure (6.4.2) show muscle tensions predicted in the various movements performed with lateral instability. Results show a larger dependence on shoulder and biarticular muscles in directions N and W17, and this dependence decreases as the angular separation from N increases. On the other hand, elbow muscles are used more in direction W70, and are gradually less involved in stabilising the movement as the direction becomes closer to N.

6.4.2 Angle separation effect during trial-to-trial generalisation

Another interesting simulation would be to look at the effect of kinematic mapping selection on the predicted muscle activity during generalisation of impedance learning. A previous study of Gandolfo et al. (1996) looked at subjects' interpolation and extrapolation of learning across directions. In that experiment, subjects made reaching movements in two directions of the workspace in a stable velocity-dependent force field until full adaptation was observed. Subjects were then tested during catch-trials in the training directions as well as other directions not visited before. Results indicated that the after-effects were present not only in the trained directions, but also along the directions of the test targets. Most interestingly, the magnitude of the after-effects was found to decay smoothly with increasing distance from the trained movements.

The aim of this simulation is to follow a similar approach to (Gandolfo et al. 1996), but by making reaching movements in an unstable force field while measuring muscle activity change. Furthermore, it was essential to test the effect of the intrinsic kinematic coordinates, which are position and velocity data, on the predicted forward muscle force at the output of the radial-basis-function neural network.

Optimum muscle force required for adaptation in the two directions N and W35 was collected after extensive learning in both directions concurrently in a position-dependent divergent field. This information was then included, as a batch, in the model together with position and velocity data. The test consisted of predicting the muscle

activity in all six muscles in a novel direction, which would be either W17, W52 or W70. Predicted muscle force is collected in one trial and in order to check the extent of good prediction of the model, trends of muscle activity were compared from each test to activity measured after iterative and extensive adaptation in the same direction.

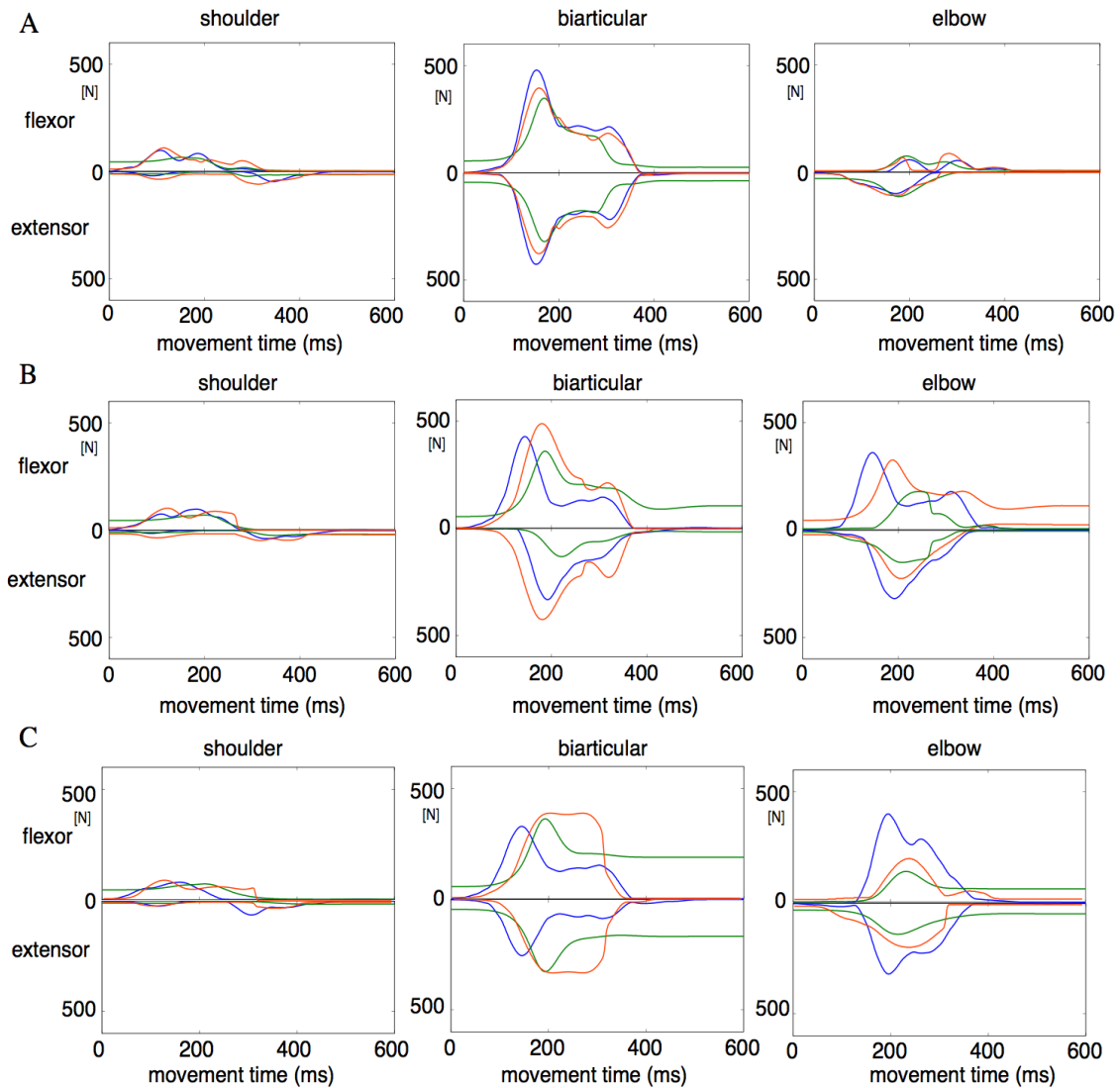


Figure 6.4.3: A: muscle activity from six muscles after one trial, after adaptation in W17 only (blue), and then predicted in W17 after learning in N and W35 simultaneously using an RBF mapping joint position only (green) and both position and velocity (red). B-C: same as in A, but muscle activity prediction was in directions W52 (B) and W70 (C) respectively after training in N and W35 simultaneously.

Results in Figure (6.4.3A) show the predicted muscle force in direction W17 after learning in directions N and W35 simultaneously, which compares well to muscle activity after extensive learning in W17 only. The difference between predicted and learnt muscle force shows that prediction is better when the network is built with both joint position and velocity input data rather than joint position only. After that, the capacity of the network model was tested to extrapolate muscle force outside the learning space. After adaptation in both directions N and W35, the model was used to predict the force in direction W52 (Figure 6.4.3B) and in another simulation in direction W70 (Figure 6.4.3C). It seems that predicting outside the learning field is harder for the network model, particularly when the input data to the RBF includes joint position only.

This set of simulations shows that when the information fed to the neural network model comprises both position and velocity coordinates about directions of movements, then prediction of muscle activity slightly improves. However, the further the direction is away from the learning space, the less accurate the prediction of muscle activity is achieved.

6.5 Discussion

This chapter presented a computer model of motor learning in humans able to learn multiple movements and generalise over movements and workspaces. This model extends the single movement formulation of Franklin et al. (2008) and Burdet et al. (2008). Adaptation arose from the gradient descent minimisation of a cost function corresponding to feedback and feedforward muscle activation. A mapping from a state space to muscle tension coded in a radial basis function network was gradually identified during movements, yielding a model of feedforward valid in this state space.

The simulations of this chapter, together with the results from (Burdet et al. 2008), first demonstrate the efficiency of this nonlinear adaptive controller. The algorithm derived and used in this paper was able to learn various movements in all directions in stable and unstable dynamics, to generalise across movements, and converge to suitable force and minimal impedance behaviour. The model could be used to learn to coordinate optimal motor commands without requiring any inversion or any model of the redundant actuators, and could easily be implemented on a robot in order

to automatically learn stable behaviours with appropriate force and impedance in interaction with stable and unstable environments while performing movements. To the author best knowledge, no previous robotics algorithm is able to control force and impedance and acquire stability. Therefore, the model could be used to realise skilful robotic control in tasks such as bimanual coordination and manipulation with a fingered hand.

The simulation results further demonstrated that this model is able to predict the generalisation patterns observed during learning of multiple movements (Shadmehr and Mussa-Ivaldi 1994, Thoroughman and Taylor 2005, Kadiallah et al. 2008), and across movements (Conditt et al. 1997). It was able to predict correct patterns of force, impedance and change of muscle activation in multiple directions (Kadiallah et al. 2008) and various dynamic environments (Franklin et al. 2007). Also, similar limitations in the granularity of dynamic environments possible to compensate well were observed as in results by (Thoroughman and Taylor 2005). The model can also predict learning and control in tasks that are difficult to experiment with human subjects, such as learning multiple movements in unstable dynamics and measuring impedance requiring many movements. Such method would be tiring for the subjects and may have to be performed over several days, while additional complications can apply when wanting to calibrate EMG measurements for instance.

Previous models based on optimisation such as (Burdet and Milner 1998, Harris et al. 1998, Stroeve 1999, Todorov and Jordan 2002, Trainin et al. 2007, Guigon et al. 2007, Izawa et al. 2008) could compute the coordination of processes, muscles and limbs in one step, yielding the post-learning optimal behaviour. In contrast, the algorithm presented in this work is able to predict the trial-by-trial changes of muscle activation, which may be critical to developing efficient rehabilitation protocols and neural prostheses and may predict distinct behaviours resulting from convergence to local minima, or to bifurcations.

Previous models based on iterative control or adaptive control such as (Kawato et al. 1987, Thoroughman et al. 2000, Slotine and Weiping 1991, Burdet and Milner 1998, Sanner and Kosha 1999, Gribble et al. 2000, Donchin et al. 2003, Emken et al. 2007) could predict the evolution of force, but did not have a mechanism to adapt impedance, and so they could not succeed in unstable dynamics. These models also produced transients of learning not conforming to the EMG patterns observed for

example in Franklin et al. (2003A), which are provided automatically in our simple algorithm.

Appropriate force and impedance in multiple directions may result from learning multiple models and switching appropriately between them (Kawato and Wolpert 1998), or from learning a global model valid in multiple movements. While our model cannot decide between these alternatives, it demonstrates the possibility of using a global model, and suggests that such a model should use a state space including the kinematic velocity.

Chapter 7

CONCLUSIONS & FUTURE WORK

7.1 Summary of contributions and main results

This thesis investigated the ability of the CNS to learn impedance control in movements in multiple directions and the generalisation across different movements while compensating for various stable and unstable dynamics, as is typically required for tool use. This investigation involved performing psychophysical experiments with healthy human subjects as well as the development of mathematical algorithms and implementation of computer models of motor learning in humans.

In the experimental part, the modification of motion patterns was studied when subjects adapted to lateral instability while performing reaching movements towards two different targets separated by a 35° angle. The corresponding force field is different from force fields previously used to study generalisation, because it is unstable and defined locally relatively to the performed trajectories. The experiment paradigm was for subjects to compensate for instability in one direction on the first day, then in the other direction on the second day, and finally they learned movements in both directions simultaneously on the final day of the experiment.

Results showed that the CNS did not employ a global strategy to compensate for the instability in both directions, but in contrast subjects compensated for the instability differently in each direction. Further, the activity in muscles was modified during learning to minimise movement error with minimal effort. Stability was provided mainly by the biarticular muscles in the forward movement, and by the shoulder muscles in the movement to the right, which was consistent with the muscles geometry. Interestingly, subjects retained different impedance adaptation learned for one direction at a time during the first two days when learning to perform simultaneously in the two directions on the third day. This demonstrates that the CNS is able to selectively tune the endpoint stiffness even when local force fields are concurrently applied to two contextually different movements.

This thesis also developed a computational model of motor learning in humans able to learn arbitrary movements of the arm. The model enabled to simulate experiments and predict their results. First, a model was developed that integrated movements at the joint-coordinates level, which was conceived as an adaptive controller concurrently learning both force and impedance to compensate for stable and unstable movements. It was enhanced with a radial-basis-function (RBF) network, which enabled investigating generalisation of force and impedance. This simple model

helped in designing the experiments investigating impedance adaptation in a multiple-directions task, by predicting the possible generalisation capacity of the human controller. It also suggested that both position and velocity are required to build a model of the necessary motor command to succeed in generalisation of learning in unstable dynamics.

A general algorithm for human motor adaptation and generalisation of learning was then derived, which considers limb interaction at the muscle coordinates with the external environment. The algorithm was developed to adapt muscle force from various pairs of agonist-antagonist pairs while learning in both stable and unstable limb interactions. Adaptation was realised as a gradient-descent algorithm to minimise motion error, instability and muscle activation. This was achieved to regulate the feedforward muscle force. Using a radial-basis-function neural network for the feedforward mapping enabled transfer of learning between trials in possibly different directions of movements. The neural network was designed to permit automatic selection of the number and locations of the neurons, as well as of the widths of the basis functions, which enabled fine coding of the input space with relatively few neurons.

In order to assess the functionality of the model, the muscles-space learning controller was implemented for a two-link and six muscles human arm and simulated during point-to-point planar reaching movements similar to the psychophysical studies. The model proved successful in simulating past experiments investigating generalisation of learning from straight-line movements to circular movements in a stable velocity-dependent force field. The model could also simulate patterns of impedance control during simultaneous trial-by-trial learning towards two different targets in a position-dependent divergent field. The simulations suggest that the CNS could develop an impedance internal model that is able to concurrently control stiffness selectively in each direction. The muscle activation patterns observed corresponded to those previous empirical findings, in addition that the model could predict patterns that otherwise are hard to implement during the experiments at the moment.

7.2 Limitations and suggestions for future work

There are a few limitations in this thesis in both the experimental and the theoretical work, which will be discussed next, while propositions for future work will also be given.

7.2.1 *Experimental work*

Would the subjects have performed similarly if they started learning in both directions concurrently on the first day of the experiment? Initial tests before performing the experiments suggested that similar results would be obtained. However, before conducting this study it was not possible to state whether endpoint stiffness could be selectively tuned toward the direction of instability in other movements requiring different arm configurations. It was only possible to speculate potential results based on strong evidence from previous modelling studies (Kadiallah et al. 2007) as well as work investigating adaptation in a single movement but a changing force field direction (Franklin et al. 2007). Because this was the first study to investigate learning of impedance in multiple directions, it was preferred to perform learning in multiple stages. Now that we have provided clear evidence that the CNS is capable of selectively controlling impedance in different directions, then implementing a new task that requires learning in two directions on the same day could be performed in a separate study.

In the experiment, two directions were chosen to study concurrent impedance control in multiple directions. However, by choosing two targets only, the study may not reflect true learning that is observed in real life in tool handling tasks (e.g. when sculpting or using a chisel). Previous studies investigating generalisation of learning, in particular, have examined movements in several directions of the workspace, using eight and sixteen directions for instance. This way, it is possible to investigate generalisation to other arm configurations or to drawing other geometrical shapes rather than simple straight-line reaching movements. On the other hand, it was not possible in this study to make movements towards more than two targets concurrently, because this would require many trials, and hence a large effort from the subjects to accomplish the task. Analysing complete adaptation in one direction requires already about 100 successful trials (e.g. Burdet et al. 2001, Franklin et al. 2003A), and any extra targets

requiring the same amount of learning would take a considerable energy. Then, subjects would most likely fail to learn the tasks. Furthermore, stiffness estimation using the algorithm of Burdet et al. (2000) requires that subjects make at least 128 trials in each direction of movement (as shown in Kadiallah et al. 2008). This method, even though is successful, it is not ideal if more than two movement directions are selected during learning. It is important to find another method requiring less number of trials such as that of Perreault et al. (2001) before attempting a broader task investigation. The latter method needs to be tested during motion, though, as it has only been tested during static arm configurations so far. Another suggestion for future work that considers following the same experimental paradigm but for movements in more than two targets, would be to make shorter movements needing less time and hence would require less effort by the subjects.

Using the current stiffness estimation methods it is not possible to observe whether the CNS is capable of switching stiffness in different directions trial-after-trial. Functional Magnetic Resonance Imaging (fMRI) and suitable robotic interfaces might enable studying impedance adaptation for movements to multiple directions, assuming that direction specific activation can be detected. Recently, Gassert et al. (2006) developed a robotic manipulandum similar to the one used in this work, but is an MRI compatible interface. The robotic arm could be programmed to stimulate external perturbations inducing position- or velocity-dependent force fields, which is usable inside the MRI machine and subjects can perform point-to-point reaching movements. Such technique would enable comparing brain activity during adaptation to multiple movements in an unstable environment. If adaptation is different across directions, because the CNS can tune stiffness differently, then maybe it will be possible to distinguish dissimilar areas of brain activity. Additionally, what would be particularly interesting is to test interpolation between the learned direction and extrapolation of impedance learning for directions outside the learning space (similar experiment paradigm to Gandolfo et al. 1995). However, it is still possible that fMRI would not show any difference in the brain areas involved during adaptation to two or more movements, because adaptation is performed in the same force field.

Most results from adaptation experiments published so far studied planar two-dimensional movements. However natural human arm movements are performed in the three-dimensional space and are for example influenced by gravity. Perreault et al. (unpublished observations) developed techniques for estimating impedance in the three-

dimensional space, which might be implemented in future similar experiments investigating impedance control. In addition, it should be interesting to investigate impedance learning in orientation, e.g. in the three dimensions of the plane (displacement in the two dimensional space and orientation of the hand), which could give insight into the control of stiffness in sports for instance.

If the CNS is capable of performing multiple directions impedance control and is able to generalise learning across directions, then what intrinsic kinematic information is facilitating such adaptation? A previous study by Shadmehr and Moussavi (2000) investigated spatial generalisation properties of the intrinsic computational elements that represent the state of motion of the arm. They found that the internal model of dynamics is formed by elements that globally encode the position of the shoulder joint but locally encode arm velocity. Other work by Karniel and Mussa-Ivaldi (2003) investigated motor adaptation in a time-dependent force field and found that subjects did not employ time representation during motor learning, but they could well develop a strategy to compensate for time-varying disturbances. A primary question is whether the CNS is able to generalise impedance learning in velocity-dependent and time-dependent orthogonal fields as well as in a position-dependent field? And if so then what information does it use?

Therefore, the next experiment involving healthy subjects I want to perform will investigate whether the CNS could encode position, velocity, or time cues in generalising impedance learning across different movements. The concept of the experiment would ideally be to test for each cue separately, using the following experimental protocol. When examining for encoding of the velocity cue, subjects would be required to compensate for a velocity-dependent divergent field while making a {25cm, 600ms} movement. Subjects are then tested for generalisation of learning in movements that are {20cm, 480ms} and {30cm, 720ms}, thus keeping the same velocity across all trials, but with different lengths and times of movements. A similar approach should be followed when testing for position encoding in a position-dependent divergent field. Experiments would consist of adapting to {20cm, 600ms} movements and subjects are then tested while making {20cm, 400ms} and {20cm, 800ms} movements, thus keeping the same position coordinates for training and test movements, but changing velocity and time cues. In the last experiment, subjects should train to make movements in a divergent time-dependent force field by making {20cm, 600ms} movements. Subjects would then be tested in {10cm, 600ms} and

{30cm, 600ms} movements for instance. This would keep the time cue constant, while changing the position and velocity information used to test the capability of the CNS to cope with such changes. Data would then be analysed for trajectory of movements, hand-path error, endpoint stiffness and most importantly muscle activity in test trials.

7.2.2 *Computational modelling*

While performing the complete study of learning in all directions may be long to perform, the computational model developed suggests possible human attributes until these experiments will be performed. The novel algorithm of motor adaptation and generalisation of learning in the muscle space is robust and shows that its design provides a compact structure to simulate various movements in different environments. However, there are some shortages that could be overcome in future versions, depending on where the model will be employed.

The mathematical algorithm was implemented by using an artificial neural network in the feedforward term of a nonlinear adaptive controller, which allowed using feedback muscle force from precedent trial to update the feedforward term of the following trial. The radial-basis-function network was designed to calculate the output force promptly without exhausting learning time required by other artificial networks (e.g. multi-layer perceptron or MLP). However, if in the future the model is required for broader tasks that require more calculations, then time is important and better optimisation would be required.

The muscle space model developed investigated different past experiments as well as predicting muscle transients for possible future experiments. However, it is not clear yet how the model would behave as the parameters employed are altered. Future work will need to examine the sensitivity and convergence of the model in broader situations while analysing its convergence. For instance, the anthropometric parameters could change the behaviour of the model during adaptation, and so could the control or the learning parameters such as the decay and learning factors, the elasticity parameters, the change in neurons number etc. Therefore, future work will need to critically investigate the limitations of the model within these bounding conditions.

The computational model is in line with the theory that the CNS develops an internal model using inverse kinematics and dynamics to calculate joint coordinates and torques necessary to move the limb. The algorithm assumes that the CNS implements a

reference-desired trajectory, and that the descending motor force is obtained using inverse dynamics transformations. While it is still not clear whether the brain follows a fixed desired trajectory, recent experiments demonstrated that the CNS is able to modify the planned trajectory during motion (Chib et al. 2006), and this is a feature that could be added to the current algorithm in the future. Further, models such as optimal control in principle do not assume a desired trajectory (Todorov and Taylor 2002), though the progressive cost function used to compute the error might be interpreted as a desired trajectory.

An important question concerning the motor learning studies is to what extent the results presented in this work (and other similar studies) could be attributed to human daily-life tool-handling tasks? The movements examined in this thesis are simple point-to-point directed movements, which do not necessarily reflect how a carpenter's arm would stiffen when chiselling for example. The work presented here has not investigated the coordination of movements for instance, despite that restricting the arm to simple two-dimensional movements helps to create a near-similar environment to real world movements and reveals important information about the mechanisms of the brain during learning. Therefore, a possible extension to the model investigating impedance control and generalisation of learning in unstable tasks would better concentrate on directly investigating movements similar to real world tool-handling tasks, such as chiselling and carving. For example, one task would be to combine several movements together, probably using via-points, to perform a complex movement amid instability.

Generally, only horizontal planar arm movements, where the wrist is fixed to the robot handle, are considered during motor learning experiments. This was mainly performed to facilitate movement control and analysis of learning properties, while still preserving the nonlinear and redundant aspects of the human arm. However, in terms of stiffness measurement, this set-up also meant that endpoint stiffness would be measured in a two-dimensional space only, even though in reality it is three-dimensional. Furthermore, restricting the arm to non-natural free movements means that less muscles and degrees of freedom are considered, which might impair the arm from using its full dynamic and physiological capacity for adaptation. That is, endpoint stiffness could be realised through changing arm posture instead of choosing what muscles are co-contracted in each direction of movement. Therefore, the computational model could be further developed and used to investigate a more natural movement of the arm by

allowing more flexibility. The learning algorithm developed should be valid to implement in many limb configurations, which renders it ideal to examine three-dimensional learning and stiffness estimation.

Finally, the values of the physiologically derived parameters result in learning and control patterns that are quantitatively consistent with previous experimental results. The computational model developed should be used to further examine the neural control of posture and movement. It could be used to simulate the effect of neuro-muscular disorders on learning of both force and impedance, to develop better control strategies for rehabilitation patients (e.g. post-stroke) who require intensive training for a particular set of muscles to restore the neural connections, and to the development of better controllers for neuronal-prostheses.

REFERENCES

- Acosta AM, Kirsch RF, Perreault EJ (2000) A robotic manipulator for the characterization of two-dimensional dynamic stiffness using stochastic displacement perturbations. *J Neurosci Methods* 102:177-186.
- Akazawa K, Milner TE, Stein RB (1983) Modulation of reflex EMG and stiffness in response to stretch of human finger muscle. *Journal of neurophysiology* 49:16.
- Albus JS (1975) A new approach to manipulator control: The cerebellar model articulation controller (CMAC). *Journal of dynamic systems, measurement, and control* 97:220.
- Ariff G, Donchin O, Nanayakkara T, Shadmehr R (2002) A real-time state predictor in motor control: study of saccadic eye movements during unseen reaching movements. *J Neurosci* 22:7721-7729.
- Barnett CH, Harding D (1955) The activity of antagonist muscles during voluntary movement. *ANNALS OF PHYSICAL MEDICINE* 2:290.
- Bayard D, Wen JT (1998) A New Class of Stabilizing Control Laws for Robotic Manipulators. Part II: Adaptive Case. *International journal of control* 47(5):1387-1406.
- Bennett DJ, Hollerbach JM, Xu Y, Hunter IW (1992) Time-varying stiffness of human elbow joint during cyclic voluntary movement. *Exp Brain Res* 88(2):433-442.
- Bennett DJ (1993) Torques generated at the human elbow joint in response to constant position errors imposed during voluntary movements. *Exp Brain Res* 95(3):488-498.
- Bernstein NA (1967) The coordination and regulation of movements. Oxford: Pergamon Press.
- Bhushan N, Shadmehr R (1999) Computational nature of human adaptive control during learning of reaching movements in force fields. *Biol Cybern* 81:39-60.
- Bien Z, Xu J-X (1998) Iterative learning control: analysis, design, integration and applications: Springer.
- Billings SA, Chen S (1998) The determination of multivariable nonlinear models for dynamic systems using neural networks. *Int J Control* 49(6):2157-2189.
- Billings SA, Wei HL, Balikhin MA (2007) Generalized multiscale radial basis function networks. *Neural Networks* 20:1081-1094.
- Bizzi E, Accornero N, Chapple W, Hogan N (1984) Posture control and trajectory formation during arm movement. *The journal of neuroscience* 4:2738-2744.
- Bizzi E, Mussa-Ivaldi FA, Hogan N (1986) Regulation of multi-joint arm posture and movement. *Prog Brain Res* 64:345-351.
- Bock O, Schneider S, Bloomberg J (2001) Conditions for interference versus facilitation during sequential sensorimotor adaptation. *Exp Brain Res* 138(3):359-365.
- Brashers-Krug TT, Shadmehr EE, R BB (1996) Consolidation in human motor memory. *Nature* 382:252-255.
- Burdet E (1996) Improving the tracking of objects by a robot during the movements. *Studies in informatics and control* 5:247-268.

- Burdet E, Milner TE (1998) Quantization of human motions and learning of accurate movements. *Biol Cybern* 78:307-318.
- Burdet E, Osu R, Franklin DW, Yoshioka T, Milner TE, Kawato M (2000) A method for measuring endpoint stiffness during multi-joint arm movements. *J Biomech* 33:1705-1709.
- Burdet E, Osu R, Franklin DW, Milner TE, Kawato M (2001) The central nervous system stabilizes unstable dynamics by learning optimal impedance. *Nature* 414:446-449.
- Burdet E, Tee KP, Chew CM, Franklin DW, Osu R, Kawato M, Milner TE (2001b) Stability and learning in human arm movements. In: *International Conference on Computational Intelligence, Robotics and Autonomous Systems*, Singapore.
- Burdet E, Franklin DW, Osu R, Tee KP, Kawato M, Milner TE (2004) How are Internal Models of Unstable Tasks Formed? *IEEE Conference on Engineering in Medicine and Biology*.
- Burdet E, Tee KP, Mareels I, Milner TE, Chew CM, Franklin DW, Osu R, Kawato M (2006) Stability and motor adaptation in human arm movements. *Biol Cybern*:1-13.
- Burdet E, Tee KP, Franklin DW, Milner TE, Kawato M (2008) Concurrent Adaptation of Force and Impedance in the Redundant Muscle System. Submitted.
- Caithness G, Osu R, Bays P, Klassen J, Kawato M, Wolpert DW, Flanagan JR (2004) Failure to consolidate the consolidation theory of learning for sensorimotor adaptation tasks. *The journal of neuroscience* 24:8662-8671.
- Capaday C, Cooke JD (1983) Vibration-induced changes in movement-related EMG activity in humans. *Experimental brain research* 52:139-146.
- Carter RR, Crago PE, Keith MW (1990) Stiffness regulation by reflex action in the normal human hand. *Journal of neurophysiology* 64:105.
- Chen-Harris H, Joiner WM, Ethier V, Zee DS, Shadmehr R (2008) Adaptive control of saccades via internal feedback. *The journal of neuroscience* 28:2804-2813.
- Chib VS, Patton JL, Lynch KM, Mussa-Ivaldi FA (2006) Haptic identification of surfaces as fields of force. *J Neurophysiol* 95:1068-1077.
- Clancy EA, Hogan N (1995) Multiple site electromyograph amplitude estimation. *IEEE Trans Biomed Eng* 42(2):203-211.
- Colgate JE, Hogan N (1988) Robust Control of Dynamically Interacting Systems. *International journal of control* 48:65-88.
- Coltz JD, Johnson MT, Ebner TJ (1999) Cerebellar Purkinje cell simple spike discharge encodes movement velocity in primates during visuomotor arm tracking. *J Neurosci* 19:1782-1803.
- Conditt MA, Gandolfo F, Mussa-Ivaldi FA (1997) The motor system does not learn the dynamics of the arm by rote memorization of past experience. *J Neurophysiol* 78:554-560.
- Conditt MA, Mussa-Ivaldi FA (1999) Central representation of time during motor learning. *Proc Natl Acad Sci U S A* 96:11625-11630.
- Cooke JD (1980) The role of stretch reflexes during active movements. *Brain Research* 181:493-497.
- Craig J (1989) *Introduction to robotics mechanics and control*. New York: Pearson Education.

- Criscimagna-Hemminger SE, Donchin O, Gazzaniga MS, Shadmehr R (2003) Learned dynamics of reaching movements generalize from dominant to nondominant arm. *J Neurophysiol* 89:168-176.
- Criscimagna-Hemminger SE, Shadmehr R (2008) Consolidation patterns of human motor memory. *J Neurosci* 28(39):9610-9618.
- Cunningham HA, Welch RB (1994) Multiple concurrent visual-motor mappings: implications for models of adaptation. *Journal of experimental psychology Human perception and performance* 20:987-999.
- d'Avella A, Bizzi E (1998) Low dimensionality of supraspinally induced force fields. *Proc Natl Acad Sci U S A* 95:7711-7714.
- d'Avella A, Saltiel P, Bizzi E (2003) Combinations of muscle synergies in the construction of a natural motor behavior. *Nat Neurosci* 6:300-308.
- Darainy M, Malfait N, Gribble PL, Towhidkhah F, Ostry DJ (2004) Learning to control arm stiffness under static conditions. *J Neurophysiol* 92(6):3344-3350.
- De Serres SJ, Milner TE (1991) Wrist muscle activation patterns and stiffness associated with stable and unstable mechanical loads. *Exp Brain Res* 86:451-458.
- Diffrient N, Tillery AR, Bardagjy JC (1978) *Humanscale*. Cambridge MA: MIT press.
- Dingwell JB, Mah CD, Mussa-Ivaldi FA (2002) Manipulating objects with internal degrees of freedom: evidence for model-based control. *J Neurophysiol* 88:222-235.
- Dingwell JB, Mah CD, Mussa-Ivaldi FA (2004) Experimentally confirmed mathematical model for human control of a non-rigid object. *J Neurophysiol* 91:1158-1170.
- Donchin O, Francis JT, Shadmehr R (2003) Quantifying generalization from trial-by-trial behavior of adaptive systems that learn with basis functions: theory and experiments in human motor control. *J Neurosci* 23:9032-9045.
- Duda R, Hart P, Stork D (2001) *Pattern classification*, Second Edition Edition: John Wiley and Sons Inc.
- Dudai Y (2004) The neurobiology of consolidations, or, how stable is the engram? *Annu Rev Psychol* 55:51-86.
- Emken JL, Reinkensmeyer DJ (2005) Robot-enhanced motor learning: accelerating internal model formation during locomotion by transient dynamic amplification. *IEEE Trans Neural Syst Rehabil Eng* 13:33-39.
- Emken JL, Benitez R, Sidris A, Bobrow JE, Reinkensmeyer DJ (2007) Motor adaptation as a greedy optimization of error and effort. *Journal of neurophysiology* 97:3997.
- Eng JJ, Hoffer JA (1997) Regional variability of stretch reflex amplitude in the cat medial gastrocnemius muscle during a postural task. *Journal of neurophysiology* 78:1150.
- Feldman AG (1966) Functional tuning of the nervous system with control of movement or maintenance of a steady posture — II. Controllable parameters of the muscles. *Biophysics* 11:565-578.
- Flanagan JR (2003) Prediction precedes control in motor learning. *Current biology* 13:146-150.
- Flanders M, Soechting JF (1990) Arm muscle activation for static forces in three-dimensional space. *J Neurophysiol* 64:1818-1837.

- Flanders M (1991) Temporal patterns of muscle activation for arm movements in three-dimensional space. *J Neurosci* 11:2680-2693.
- Flash T, Hogan N (1985) The coordination of arm movements: an experimentally confirmed mathematical model. *J Neurosci* 5:1688-1703.
- Flash T (1987) The control of hand equilibrium trajectories in multi-joint arm movements. *Biol Cybern* 57:257-274.
- Flash T, Mussa-Ivaldi F (1990) Human arm stiffness characteristics during the maintenance of posture. *Exp Brain Res* 82:315-326.
- Franklin DW, Burdet E, Tee KP, Osu R, Kawato M, Milner TE (2002) A computational model of adaptation to novel stable and unstable dynamics. In: *Ann Conf of the Neuroscience Society*. Orlando, Florida.
- Franklin DW, Burdet E, Osu R, Kawato M, Milner TE (2003a) Functional significance of stiffness in adaptation of multijoint arm movements to stable and unstable dynamics. *Exp Brain Res* 151:145-157.
- Franklin DW, Osu R, Burdet E, Kawato M, Milner TE (2003b) Adaptation to stable and unstable dynamics achieved by combined impedance control and inverse dynamics model. *J Neurophysiol* 90:3270-3282.
- Franklin DW, Milner TE (2003c) Adaptive control of stiffness to stabilize hand position with large loads. *Experimental brain research* 152:211-220.
- Franklin DW, So U, Kawato M, Milner TE (2004) Impedance Control Balances Stability with Metabolically Costly Muscle Activation. *J Neurophysiol* 92:3097-3105.
- Franklin DW, Liaw G, Milner TE, Osu R, Burdet E, Kawato M (2007) Endpoint stiffness of the arm is directionally tuned to instability in the environment. *The journal of neuroscience* 27:7705-7716.
- Franklin DW, Burdet E, Tee KP, Osu R, Chew C-M, Milner TE, Kawato M (2008) CNS learns stable, accurate, and efficient movements using a simple algorithm. *The journal of neuroscience* 28:11165.
- Gais S, Plihal W, Wagner U, Born J (2000) Early sleep triggers memory for early visual discrimination skills. *Nature neuroscience* 3:1335-1339.
- Gandolfo F, Mussa-Ivaldi FA, Bizzi E (1996) Motor learning by field approximation. *Proc Natl Acad Sci U S A* 93:3843-3846.
- Gassert R, Yamamoto A, Chapuis D, Dovat L, Bleuler H, Burdet E (2006) Actuation Methods for Applications in MR Environments. *Concepts in Magnetic Resonance Part B* 28B(4):191-209.
- Gazzaniga MS (2000) *The new cognitive neurosciences*, MIT Press, 2nd Edition.
- Ghahramani Z, Wolpert DM, Jordan M (1996) Generalization to local remappings of the visuomotor coordinate transformation. *J Neurosci* 16(21):7085-7096.
- Ghahramani Z, Wolpert DM (1997) Modular decomposition in visuomotor learning. *Nature* 386:392-395.
- Goedert KM, Willingham DB (2002) Patterns of interference in sequence learning and prism adaptation inconsistent with the consolidation hypothesis. *Learning & memory* 9(5):279-292.
- Gomi H, Kawato M (1996) Equilibrium-point control hypothesis examined by measured arm stiffness during multijoint movement. *Science* 272(5258):117-120.

- Gomi H, Kawato M (1997) Human arm stiffness and equilibrium-point trajectory during multi-joint movement. *Biol Cybern* 76:163-171.
- Gomi H, Osu R (1998) Task-dependent viscoelasticity of human multijoint arm and its spatial characteristics for interaction with environments. *J Neurosci* 18:8965-8978.
- Goodbody SJ, Wolpert DM (1998) Temporal and amplitude generalization in motor learning. *J Neurophysiol* 79:1825-1838.
- Gribble PL, Ostry DJ (1998) Independent coactivation of shoulder and elbow muscles. *Experimental brain research* 123:355-360.
- Gribble PL, Ostry DJ (2000) Compensation for loads during arm movements using equilibrium-point control. *Experimental brain research* 135:474.
- Guigon E, Baraduc P, Desmurget M (2007) Coding of movement- and force-related information in primate primary motor cortex: a computational approach. *The European journal of neuroscience* 26:250.
- Hallett M, Shahani BT, Young RR (1975) EMG analysis of stereotyped voluntary movements in man. *J Neurosurg Psychiatry* 38:1154-1162.
- Hamilton AF, Jones KE, Wolpert DM (2004) The scaling of motor noise with muscle strength and motor unit number in humans. *Exp Brain Res* 157(4):417-430.
- Harris CM, Wolpert DM (1998) Signal-dependent noise determines motor planning. *Nature* 394:780-784.
- Haruno M, Wolpert DM, Kawato M (2001) Mosaic model for sensorimotor learning and control. *Neural Comput* 13:2201-2220.
- Hebert LJ, De Serres SJ, Arsenault AB (1991) Cocontraction of the elbow muscles during combined tasks of pronation-flexion and supination-flexion. *Electromyogr Clin Neurophysiol* 31:483-488.
- Hogan N (1984a) An organizing principle for a class of voluntary movements. *J Neurosci* 4:2745-2754.
- Hogan N (1984b) Adaptive control of mechanical impedance by coactivation of antagonist muscles. *IEEE transactions on automatic control* AC-29:681-690.
- Hogan N (1985) The mechanics of multi-joint posture and movement control. *Biological cybernetics* 52:315-331.
- Hogan N, Bizzi E, Mussa-Ivaldi FA, Flash T (1987) Controlling multijoint motor behavior. *Exerc Sport Sci Rev* 15:153-190.
- Houk JC, Rymer PE (1981) Dependence of dynamic response of spindle receptors on muscle length and velocity. *Journal of neurophysiology* 46:143-166.
- Huber R, Ghilardi MF, Massimini M, Tononi G (2004) Local sleep and learning. *Nature* 430:78-81.
- Huxley AF, Simmons RM (1971) Mechanical properties of the cross-bridges of frog striated muscle. *The Journal of physiology* 218:59P.
- Hwang EJ, Donchin O, Smith MA, Shadmehr R (2003) A gain-field encoding of limb position and velocity in the internal model of arm dynamics. *PLoS Biol* 1:E25.
- Hwang EJ, Shadmehr R (2005) Internal models of limb dynamics and the encoding of limb state. *J Neural Eng* 2:S266-278.

- Imamizu H, Miyauchi S, Tamada T, Sasaki Y, Takino R, Putz B, Yoshioka T, Kawato M (2000) Human cerebellar activity reflecting an acquired internal model of a new tool. *Nature* 403:192-195.
- Ito M (1970) Neurophysiological aspects of the cerebellar motor control system. *Int J Neurol* 7(2):162-176.
- Izawa J, Rane T, Donchin O, Shadmehr R (2008) Motor adaptation as a process of reoptimization. *The journal of neuroscience* 28:2883.
- Jeremy L E, Raul B, Athanasios S, James E B, David J R (2007) Motor adaptation as a greedy optimization of error and effort. *Journal of neurophysiology* 97:3997.
- Jones KE, Hamilton AF, Wolpert DM (2002) Sources of signal-dependent noise during isometric force production. *Journal of neurophysiology* 88:1533-1544.
- Jordan M, Rumelhart D (1992) Forward models: supervised learning with a distal teacher. *Cognitive Science* 16:307-354.
- Jordan M (1996) Computational aspects of motor control and motor learning In: *Handbook of Perception and Action: Motor Skills* (H. Heuer & S. Keele E, ed). New York: Academic Press.
- Kadiallah A, Burdet E, Franklin DW (2007) A 2 dof arm simulator with an ANN to model human motor learning. In: 1st international meeting on control, instrumentation and mechatronics. Johor Bahru, Malaysia.
- Kadiallah A, Liaw G, Burdet E, Kawato M, Franklin DW (2008) Impedance Control is Tuned to Multiple Directions of Movements. In: 30th Annual Meeting of the Engineering in Medicine and Biology Society, pp 5358-5361. Vancouver, Canada.
- Kalaska JF, Scott SH, Cisek P, Sergio LE (1997) Cortical control of reaching movements. *Curr Opin Neurobiol* 7:849-859.
- Kalman RE (1960) A new approach to linear filtering and prediction problems. *Journal of Basic Engineering* 82(1):35-45.
- Karni A, Sagi D (1993) The time course of learning a visual skill. *Nature* 365:250-252.
- Karni A, Tanne D, Rubenstein BS, Askenasy JJM, Sagi D (1994) Dependence on REM sleep of overnight improvement of a perceptual skill. *Science* 265:679-682.
- Karni A, Meyer G, Rey-Hipolito C, Jezard P, Adams MM, Turner R, Ungerleider LG (1998) The acquisition of skilled motor performance: Fast and slow experience-driven changes in primary motor cortex. *Proceedings of the National Academy of Sciences of the United States of America* 95:861-868.
- Karniel A, Mussa-Ivaldi FA (2002) Does the motor control system use multiple models and context switching to cope with a variable environment? *Exp Brain Res* 143:520-524.
- Karniel A, Mussa-Ivaldi FA (2003) Sequence, time, or state representation: how does the motor control system adapt to variable environments? *Biol Cybern* 89:10-21.
- Kawato M, Furukawa K, Suzuki R (1987) A hierarchical neural-network model for control and learning of voluntary movement. *Biol Cybern* 57:169-185.
- Kawato M, Isobe M, Maeda Y, Suzuki R (1988) Coordinates transformation and learning control for visually-guided voluntary movement with iteration: a Newton-like method in a function space. *Biol Cybern* 59(3):161-177.

- Kawato M (1990) Feedback-error-learning neural network for supervised learning. In: Advanced neural computers ((Ed) RE, ed), pp 365-372. Amsterdam: North-Holland.
- Kawato M, Wolpert DM (1998) Internal models for motor control. Novartis Foundation symposium 218:291-297.
- Kearney RE, Hunter IW (1982) Dynamics of human ankle stiffness: variation with displacement amplitude. *Journal of Biomechanics* 15:753.
- Kearney RE, Hunter IW (1990) System identification of human joint dynamics. *Critical reviews in biomedical engineering* 18:55.
- Krakauer JW, Ghilardi C, Ghez C (1999) Independent learning of internal models for kinematic and dynamic control of reaching. *Nature neuroscience* 2:1026-1031.
- Krakauer JW, Ghilardi M, Ghez C, Silvestri G (2003) Interference or consolidation? It depends on how much you learn initially. In: Abstract Society of Neuroscience.
- Krakauer JW, Shadmehr R (2005) Consolidation of motor memory. *Trends Neurosci* 29(1):58-64.
- Krakauer JW, Ghez C, Ghilardi C (2005) Adaptation to visuomotor transformations: consolidation, interference, and forgetting. *J Neurosci* 25(2):473-478.
- Krakauer JW, Mazzoni P, Ghazizadeh A, Ravindran R, Shadmehr R (2006) Generalization of motor learning depends on the history of prior action. *PLoS Biol* 4:e316.
- Kuo AD (1995) An optimal control model for analyzing human postural balance. *IEEE transactions on bio-medical engineering* 42:87-101.
- Kudo K, Ohtsuki T (1998) Functional modification of agonist-antagonist electromyographic activity for rapid movement inhibition. *Exp Brain Res* 122:23-30.
- Kuperstein M (1988) An adaptive neural model for mapping invariant target position. *Behav Neuroscience* 102(1):148-162.
- Lacquaniti F, Carrozzo M, Borghese NA (1993) Time-varying mechanical behavior of multijointed arm in man. *J Neurophysiol* 69(5):1443-1464.
- Lackner JR, DiZio P (1994) Rapid adaptation to Coriolis force perturbations of arm trajectory. *J Neurophysiol* 72:299-313.
- Lackner JR, DiZio P (1998) Adaptation in a rotating artificial gravity environment. *Brain Research Reviews* 28:194-202.
- Latash ML, Gottlieb GL (1991) Reconstruction of shifting elbow joint compliant characteristics during fast and slow movements. *Neuroscience research* 43(2-3):697-712.
- Mah CD, Mussa-Ivaldi FA (2003a) Generalization of object manipulation skills learned without limb motion. *J Neurosci* 23:4821-4825.
- Mah CD, Mussa-Ivaldi FA (2003b) Evidence for a specific internal representation of motion-force relationships during object manipulation. *Biol Cybern* 88:60-72.
- Malfait N, Shiller DM, Ostry DJ (2002) Transfer of motor learning across arm configurations. *The journal of neuroscience* 22:9656.
- Malfait N, Gribble PL, Ostry DJ (2005) Generalization of motor learning based on multiple field exposures and local adaptation. *Journal of neurophysiology* 93:3327.

- Matsuoka Y (1998) Models of Generalization in Motor Control. PhD thesis, MIT.
- Mattar AAG, Ostry DJ (2007) Neural averaging in motor learning. *Journal of neurophysiology* 97:220-228.
- McIntyre J, Mussa-Ivaldi FA, Bizzi E (1996) The control of stable postures in the multijoint arm. *Exp Brain Res* 110:248-264.
- Mcqueen J (1967) Some methods for classification and analysis of multivariate observations. In: 5th Berkeley symposium on mathematics, statistics and probability, pp 281-298.
- Merfeld DM, Zupan L, Peterka RJ (1999) Humans use internal models to estimate gravity and linear acceleration. *Nature* 398:615-618.
- Miall RC, Weir DJ, Wolpert DM, Stein JF (1993) Is the Cerebellum a Smith Predictor? *Journal of motor behavior* 25:203.
- Miall RC, Jenkinson K, Ned K (2004) Adaptation to rotated visual feedback: a re-examination of motor interference. *Experimental brain research* 154:201-210.
- Miller WT (1987) Sensor-based control of robotic manipulators using a general learning algorithm. *IEEE J Robotics and Automation* 3:157-165.
- Milner TE, Cloutier C (1993) Compensation for mechanically unstable loading in voluntary wrist movement. *Exp Brain Res* 94:522-532.
- Milner TE, Cloutier C, Leger AB, Franklin DW (1995) Inability to activate muscles maximally during cocontraction and the effect on joint stiffness. *Exp Brain Res* 107(2):293-305.
- Milner TE (2002) Contribution of geometry and joint stiffness to mechanical stability of the human arm. *Exp Brain Res* 143(4):515-519.
- Milner TE, Franklin DW (2005) Impedance control and internal model use during the initial stage of adaptation to novel dynamics in humans. *J Physiol* 567:651-664.
- Milner TE, Franklin DW, Imamizu H, Kawato M (2005) Central Representation of Dynamics when Manipulating Handheld Objects. *J Neurophysiol*.
- Moise A (2001) Cartesian space neural network control of robot manipulators. *Systems science* 27:35-45.
- Moody J, Darken C (1989) Fast learning in networks of locally-tuned processing units. *Neural Comput* 1:289-303.
- Moran DW, Schwartz AB (1999a) Motor cortical activity during drawing movements: population representation during spiral tracing. *J Neurophysiol* 82:2693-2704.
- Moran DW, Schwartz AB (1999b) Motor cortical representation of speed and direction during reaching. *J Neurophysiol* 82:2676-2692.
- Morasso PG, Schieppati M (1999) Can muscle stiffness alone stabilize upright standing? *Journal of neurophysiology* 82:1622.
- Mussa-Ivaldi FA, Hogan N, Bizzi E (1985) Neural, mechanical, and geometric factors subserving arm posture in humans. *J Neurosci* 5:2732-2743.
- Mussa-Ivaldi FA, Giszter SF, Bizzi E (1990) Motor-space coding in the central nervous system. *Cold Spring Harb Symp Quant Biol* 55:827-835.

- Mussa-Ivaldi FA, Giszter SF (1992) Vector field approximation: a computational paradigm for motor control and learning. *Biol Cybern* 67:491-500.
- Mussa-Ivaldi FA (1999) Modular features of motor control and learning. *Curr Opin Neurobiol* 9:713-717.
- Mussa-Ivaldi FA, Bizzi E (2000) Motor learning through the combination of primitives. *Philos Trans R Soc Lond B Biol Sci* 355:1755-1769.
- Nakano E, Harris CM, Kawato M (2002) Task optimization in the presence of signal-dependent noise: impedance control. Internal report. In: Information Science Division: ATR International.
- Nakazawa K, Yamamoto SI, Ohtsuki T, Yano H, Fukunaga T (2001) Neural control: novel evaluation of stretch reflex sensitivity. *Acta physiologica Scandinavica* 172:257-268.
- Nanayakkara T, Shadmehr R (2003) Saccade adaptation in response to altered arm dynamics. *J Neurophysiol* 90:4016-4021.
- Nichols TR, Houk JC (1976) Improvement in linearity and regulation of stiffness that results from actions of stretch reflex. *Journal of neurophysiology* 39:119-142.
- Osu R, Franklin DW, Kato H, Gomi H, Domen K, Yoshioka T, Kawato M (2002) Short- and long-term changes in joint co-contraction associated with motor learning as revealed from surface EMG. *Journal of neurophysiology* 88:991.
- Osu R, Burdet E, Franklin DW, Milner TE, Kawato M (2003) Different mechanisms involved in adaptation to stable and unstable dynamics. *J Neurophysiol* 90:3255-3269.
- Osu R, Hirai S, Yoshioka T, Kawato M (2004a) Random presentation enables subjects to adapt to two opposing forces on the hand. *Nat Neurosci* 7:111-112.
- Osu R, Kamimura N, Iwasaki H, Nakano E, Harris CM, Wada Y, Kawato M (2004b) Optimal impedance control for task achievement in the presence of signal-dependent noise. *J Neurophysiol* 92(2):1199-1215.
- Overduin SA, Richardson AG, Lane CE, Bizzi E, Press DZ (2006) Intermittent practice facilitates stable motor memories. *The journal of neuroscience* 26:11888-11892.
- Park J, Sandberg IW (1991) Universal approximation using radial-basis-function networks. *Neural Comput* 3(2):246-257.
- Patton JL, Mussa-Ivaldi FA (2004) Robot-assisted adaptive training: custom force fields for teaching movement patterns. *IEEE Trans Biomed Eng* 51:636-646.
- Perreault EJ, Kirsch RF, Acosta AM (1999) Multiple-input, multiple-output system identification for characterization of limb stiffness dynamics. *Biol Cybern* 80:327-337.
- Perreault EJ, Kirsch RF, Crago PE (2001) Effects of voluntary force generation on the elastic components of endpoint stiffness. *Exp Brain Res* 141(3):312-323.
- Perreault EJ, Kirsch RF, Crago PE (2002) Voluntary control of static endpoint stiffness during force regulation tasks. *J Neurophysiol* 87(6):2808-2816.
- Perreault EJ, Kirsch RF, Crago PE (2004) Multijoint dynamics and postural stability of the human arm. *Experimental brain research* 157:507.
- Poggio T, Girosi F (1990) Regularization Algorithms for Learning That Are Equivalent to Multilayer Networks. *Science* 247:978.

- Poggio T, Fahle M, Edelman S (1992) Fast perceptual learning in visual hyperacuity. *Science* 256:1018-1021.
- Poggio T, Bizzi E (2004) Generalization in vision and motor control. *Nature* 431:768-774.
- Pollick F, Ishimura G (1996) The Three-Dimensional Curvature of Straight-Ahead Movements. *Journal of motor behavior* 28:271-279.
- Pouget A, Sejnowski T (1997) Spatial transformation in the parietal cortex using basis functions. *Journal of Cognitive Science* 9:222-237.
- Pouget A, Snyder LH (2000) Computational approaches to sensorimotor transformations. *Nat Neurosci* 3 Suppl:1192-1198.
- Rack PM, Westbury DR (1969) The effects of length and stimulus rate on tension in the isometric cat soleus muscle. *The Journal of physiology* 204:443-460.
- Rack PM, Westbury DR (1974) The short range stiffness of active mammalian muscle and its effect on mechanical properties. *The Journal of physiology* 240:331-350.
- Rancourt D, Hogan N (2001) Stability in force production tasks. *J Mot Behav* 33(2):193-204.
- Robertson EM, Pascual-Leone A, Miall RC (2004) Current concepts in procedural consolidation. *Nat Neurosci* 5(7):576-582.
- Saha A, Keeler JD (1989) Algorithms for better representation and faster learning in radial basis function networks. In: *Advances in neural information processing systems* 2, pp 482-489. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.
- Sainburg RL, Ghez C, Kalakanis D (1999) Intersegmental Dynamics Are Controlled by Sequential Anticipatory, Error Correction, and Postural Mechanisms. *J Neurophysiol* 81(3):1045-1056.
- Sanner RM, Slotine J-JE (1992) Gaussian Networks for Direct Adaptive Control. *Neural Networks, IEEE Transactions on* 3:837-863.
- Sanner RM, Kosha M (1999) A mathematical model of the adaptive control of human arm motions. *Biol Cybern* 80:369-382.
- Schaal S, Schweighofer N (2005) Computational motor control in humans and robots. *Curr Opin Neurobiol* 15:675-682.
- Scheidt RA, Dingwell JB, Mussa-Ivaldi FA (2001) Learning to move amid uncertainty. *J Neurophysiol* 86:971-985.
- Scheidt RA, Conditt MA, Secco EL, Mussa-Ivaldi FA (2005) Interaction of visual and proprioceptive feedback during adaptation of human reaching movements. *J Neurophysiol* 93:3200-3213.
- Schweighofer N, Doya K, Fukai H, Chiron JV, Furukawa T, Kawato M (2004) Chaos may enhance information transmission in the inferior olive. *Proc Natl Acad Sci U S A* 101:4655-4660.
- Scott SH, Sergio LE, Kalaska JF (1997) Reaching movements with similar hand paths but different arm orientations. II. Activity of individual cells in dorsal premotor cortex and parietal area 5. *J Neurophysiol* 78:2413-2426.
- Selen LP, Beek PJ, Van Dieën JH (2005) Can co-activation reduce kinematic variability? A simulation study. *Biol Cybern* 93(5).
- Shadmehr R, Arbib MA (1992) A mathematical analysis of the force-stiffness characteristics of muscles in control of a single joint system. *Biol Cybern* 66:463-477.

- Shadmehr R (1993) Control of Equilibrium Position and Stiffness Through Postural Modules. *J Mot Behav* 25:228-241.
- Shadmehr R, Mussa-Ivaldi FA, Bizzi E (1993) Postural force fields of the human arm and their role in generating multijoint movements. *J Neurosci* 13:45-62.
- Shadmehr R, Mussa-Ivaldi FA (1994) Adaptive representation of dynamics during learning of a motor task. *J Neurosci* 14:3208-3224.
- Shadmehr R, Brashers-Krug T (1997) Functional stages in the formation of human long-term motor memory. *J Neurosci* 17:409-419.
- Shadmehr R, Holcomb HH (1997) Neural correlates of motor memory consolidation. *Science* 277:821-825.
- Shadmehr R, Moussavi ZM (2000) Spatial generalization from learning dynamics of reaching movements. *J Neurosci* 20:7807-7815.
- Shadmehr R (2004) Generalization as a behavioral window to the neural mechanisms of learning internal models. *Hum Mov Sci* 23:543-568.
- Shidara M, Kawano K, Gomi H, Kawato M (1993) Inverse-dynamics model eye movement control by Purkinje cells in the cerebellum. *Nat Neurosci* 365(6441):50-52.
- Shuzhi SG (1997) Adaptive neural network control of robot manipulators in task space. *IEEE transactions on industrial electronics* 44:746-752.
- Sinkjaer T, Toft E, Andreassen S, Hornemann BC (1988) Muscle stiffness in human ankle dorsiflexors: intrinsic and reflex components. *Journal of neurophysiology* 60:1110-1121.
- Slotine J-JE, Weiping L (1991) *Applied nonlinear control*: Prentice-Hall.
- Stickgold R, James L, Hobson JA (2000) Visual discrimination learning requires sleep after training. *Nature neuroscience* 3:1237-1238.
- Stickgold RR (2005) Sleep-dependent memory consolidation. *Nature* 437:1272-1278.
- Stroeve S (1999a) Impedance characteristics of a neuromusculoskeletal model of the human arm II. Movement control. *Biol Cybern* 81(5-6):495-504.
- Stroeve S (1999b) Impedance characteristics of a neuromusculoskeletal model of the human arm I. Posture control. *Biol Cybern* 81(5-6):475-494.
- Sutanto EL, Mason JD, Warwick K (1997) Mean-tracking Clustering Algorithm For Radial Basis Function Centre Selection.
- Takahashi CD, Scheidt RA, Reinkensmeyer DJ (2001) Impedance control and internal model formation when reaching in a randomly varying dynamical environment. *J Neurophysiol* 86:1047-1051.
- Tamada T, Miyauchi S, Imamizu H, Yoshioka T, Kawato M (1999) Cerebro-cerebellar functional connectivity revealed by the laterality index in tool-use learning. *Neuroreport* 10:325-331.
- Tanaka H, Tai M, Qian N (2004) Different predictions by the minimum variance and minimum torque-change models on the skewness of movement velocity profiles. *Neural computation* 16:2021.
- Tee KP (2003) *Feedback Error Learning at the Muscle Level: A unified Model of Human Motor Adaptation to Stable and Unstable Dynamics*. Masters Thesis. In: Department of Mechanical Engineering. Singapore: National University of Singapore.

- Tee KP, Burdet E, Chew CM, Milner TE (2004) A model of force and impedance in human arm movements. *Biol Cybern* 90:368-375.
- Thoroughman KA, Shadmehr R (1999) Electromyographic correlates of learning an internal model of reaching movements. *J Neurosci* 19:8573-8588.
- Thoroughman KA, Shadmehr R (2000) Learning of action through adaptive combination of motor primitives. *Nature* 407:742-747.
- Thoroughman KA, Taylor JA (2005) Rapid reshaping of human motor generalization. *J Neurosci* 25:8948-8953.
- Todorov E, Shadmehr R, Bizzi E (1997) Augmented Feedback Presented in a Virtual Environment Accelerates Learning of a Difficult Motor Task. *J Mot Behav* 29:147-158.
- Todorov E (2000) Direct cortical control of muscle activation in voluntary arm movements: a model. *Nature neuroscience* 3:391.
- Todorov E, Jordan M (2002) Optimal feedback control as a theory of motor coordination. *Nature neuroscience* 5:1226.
- Tong C, Wolpert DW, Flanagan JR (2002) Kinematics and dynamics are not represented independently in motor working memory: evidence from an interference study. *The journal of neuroscience* 22:1108-1113.
- Tong C, Flanagan JR (2003) Task-specific internal models for kinematic transformations. *Journal of neurophysiology* 90:578-585.
- Trainin E, Meir R, Karniel A (2007) Explaining patterns of neural activity in the primary motor cortex using spinal cord and limb biomechanics models. *Journal of neurophysiology* 97:3736.
- Tsuji T, Morasso PG, Goto K, Ito K (1995) Human hand impedance characteristics during maintained posture. *Biol Cybern* 72:475-485.
- Tsuji T, Takeda Y, Tanaka Y (2004a) Analysis of mechanical impedance in human arm movements using a virtual tennis system. *Biol Cybern* 91:295-305.
- Tsuji T, Terauchi M, Tanaka Y (2004b) Online learning of virtual impedance parameters in non-contact impedance control using neural networks. *IEEE Trans Syst Man Cybern B Cybern* 34:2112-2118.
- Uno Y, Kawato M, Suzuki R (1989) Formation and control of optimal trajectory in human multijoint arm movement. Minimum torque-change model. *Biological cybernetics* 61:89-101.
- van Galen GP, van Huygevoort M (2000) Error, stress and the role of neuromotor noise in space oriented behaviour. *Biol Psychol* 51(2-3):151-171.
- Vertes RP, Jerome M S (2005) Time for the sleep community to take a critical look at the purported role of sleep in memory processing. *Sleep* 28:1228-1223.
- Wada Y, Shinya Y, Kitazawa M, Kawabata K, Kotosaka S, Kawato Y (2003) Acquisition and contextual switching of multiple internal models for different viscous force fields. *Neuroscience research* 46:319-331.
- Wainscott SK, Donchin O, Shadmehr R (2005) Internal models and contextual cues: encoding serial order and direction of movement. *J Neurophysiol* 93:786-800.
- Walker MP, Hobson AH, Stickgold R, Brakefield RB, Morgan TM (2002) Practice with sleep makes perfect: sleep-dependent motor skill learning. *Neuron* 35:205-211.

- Walker MP, Stickgold JAS, Brakefield RB, Hobson TH (2003a) Dissociable stages of human memory consolidation and reconsolidation. *Nature* 425:616-620.
- Walker MP, Morgan JM, Hobson R, Brakefield A, Seidman JA, Stickgold T (2003b) Sleep and the time course of motor skill learning. *Learning & memory* 10:275-284.
- Walker MP, Stickgold R (2004) Sleep-dependent learning and memory consolidation. *Neuron* 44:121-133.
- Walker MP (2008) Sleep-dependent memory processing. *Harv Rev Psychiatry* 16(5):287-298.
- Wang T, Dordevic GS, Shadmehr R (2001) Learning the dynamics of reaching movements results in the modification of arm impedance and long-latency perturbation responses. *Biol Cybern* 85:437-448.
- Weiss PL, Hunter IW, Kearney RE (1988) Human ankle joint stiffness over the full range of muscle activation levels. *Journal of Biomechanics* 21:539.
- Wigmore VV, Tong JRJR, Christine FF (2002) Visuomotor rotations of varying size and direction compete for a single internal model in motor working memory. *Journal of experimental psychology Human perception and performance* 28:447-457.
- Winter DA, Palta AE, Prince F, Ishac M, Gielo-Perczak K (1998) Stiffness control of balance in quiet standing. *J Neurophysiol* 80(3):1211-1221.
- Witney AG, Vetter P, Wolpert DM (2001) The influence of previous experience on predictive motor control. *Neuroreport* 12:649-653.
- Wolpert DM, Ghahramani Z, Jordan MI (1995) An internal model for sensorimotor integration. *Science* 269:1880-1882.
- Wolpert DM, Miall RC (1996) Forward Models for Physiological Motor Control. *Neural Networks* 9(8):1265-1279.
- Wolpert DM, Kawato M (1998) Multiple paired forward and inverse models for motor control. *Neural Networks* 11(7-8):1317-1329.
- Wolpert DM, Ghahramani Z (2000) Computational principles of movement neuroscience. *Nat Neurosci* 3 Suppl:1212-1217.
- Won J, Hogan N (1995) Stability properties of human reaching movements. *Exp Brain Res* 107(1):125-136.
- Yamamoto K, Kawato M, Kotosaka S, Kitazawa S (2007) Encoding of movement dynamics by Purkinje cell simple spike activity during fast arm movements under resistive and assistive force fields. *Journal of neurophysiology* 97:1588.