Sensory-Motor Control and Adaptation in Cooperative Action

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Abstract

The objective of this thesis is to present how implicit, nonverbal cues support coordinated action between two people. A set of five experiments shows how people utilise sensory information about a partner in order to control goal-directed action involving synchronous vertical hand movement. Chapter 1 reviews recent developments in studies of interpersonal interaction and highlights control issues that are critical in cooperative action. In Chapter 2, an experimental study addresses the importance of haptic feedback about object dynamics for learning behavioural characteristics of another person who manipulated the same object from the other side. In Chapter 3, the contributions of feedback and feedforward control are assessed as the interaction of the task partners are experimentally controlled using a humanoid robot which serves the role of task partner. Chapter 4 proposes error-based learning as a model of cooperative action wherein subsequent motor response is regressed on current error in order to improve coordination between partners. Chapter 5 shows that adaptation rate of a participant is modulated with respect to the rate of the task partner so that the net adaptation of the two partners becomes optimal using a computer simulated task partner. In Chapter 6, this joint adaptation model is applied to continuous movement to demonstrate the generalisability of the model. The last chapter discusses the contribution of the empirical chapters and reviews the theoretical and methodological contribution of the thesis as a whole to the field of cognitive neuroscience. In conclusion, the thesis provides strong evidence that movement characteristics of a partner expressed both within and across trials determine the way a person engages in a joint task.

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Lastly, I would like to thank my poor friends/colleagues, Matt and Adrian who proof-read a manuscript of this thesis. I am sure I have traumatised them with hearing the word “cooperative” or any sentence with “however” placed between a subject and a predicate. I’m really sorry…

Declarations

Chapter 1: A part of Chapter 1 was published in a following article. I declare to claim more than 80% of responsibility for this publication.

Endo, S., Bracewell, R. M., & Wing, A. M. (2009). Two hands in object oriented action. In D.A.Nowak & J. Hermsdorfer (Eds.), *Sensorimotor Control of Grasping: Physiology and Pathophysiology (pp. 204-218).* Cambridge: Cambridge University Press.

Chapter 3: The experiment was conducted in collaboration with Dr. Sylvain Miosses and Prof Abderrahmane Kheddar at National Institute of Advanced Industrial Science and Technology, Japan. I had a full responsibility for the design, testing, analyses, and write up with the support by my supervisor, Prof. Alan Wing.

Chapter 5: This experiment was conducted in collaboration with Dr. Joern Diedrichsen at University College London, UK. The chapter is co-authored with Dr Diedrichsen and I declare that I had more than 50% share of responsibility in this work, including the design, analyses and writing up with my supervisor's support.

Chapter 6: The experiment was conducted in collaboration with Drs. Angelika Peer, Zheng Wang and Professor Martin Buss at Technischen Universität München, Germany and Dr. Christos Giachritsis at University of Birmingham. I was fully responsible for design and analyses and more than 80% of responsibility for writing up of this chapter with my supervisor's support.

Contents

Table of Contents

List of Figures

Lift of Tables

Table of Appendices

Chapter 1

General Introduction:

Interpersonal Coordination in Action Manipulation

1.1. Preface

Social skills are what largely distinguish humans from other animals and they are considered to underpin the development of our civilization in the process of evolution (Danchin, Giraldeau, Valone, & Wagner, 2004; Herrmann, Call, Hernandez-Lloreda, Hare, & Tomasello, 2007). Altruistic interaction among organisms has been considered to exist in terms of kin selection or prosocial reciprocity to increase the chance of “survival” (Brosnan & Bshary, 2010). In particular, cooperation, an act of working towards and achieving a shared goal with other agents, is a useful strategy to accomplish tasks that are otherwise inefficient or impossible to complete by a single person. From a psychological perspective, there is growing research interest in so-called “joint action”, an umbrella term which covers any form of social interaction between two or more people (Sebanz, Bekkering, & Knoblich, 2006).

A series of studies on joint action has provided compelling evidence that the manner in which the central nervous system (CNS) represents the external world is constantly influenced by the presence of others and that the actions performed by the others elicit similar neural changes to when the action is performed by him/herself (Sebanz, Knoblich, & Prinz, 2003; Tsai, Kuo, Jing, Hung, & Tzeng, 2006). It has been proposed that this alteration of the neural state is evidence for emulation of others’ action using one’s own motor system, so assisting humans to appreciate action intentions of other people and to engage in altruistic or even competitive behaviours (Knoblich & Sebanz, 2006; Rizzolatti & Sinigaglia, 2010). While these studies have advanced our understanding of the cognitive architecture of the perceptual-motor systems that support joint action, the way in which the CNS regulates its own action in the presence of others can most directly be studied through the resultant movements. To date, however, only a small number of studies have directly addressed how the presence of others or involvement of a task partner might influence the planning and control of one's own purposeful action (e.g., Bosga & Meulenbroek, 2007; Newman-Norlund, Noordzij, Meulenbroek, & Bekkering, 2007; Reed et al., 2006). That is the focus of this thesis.

1.2. Human Movement Analyses

Computationally, the CNS may be viewed as an information processor which utilises sensory inputs to generate motor outputs. In planning for reaching under visual guidance, for instance, the brain controls hand movement using sensory information as an input. Aggregated sensory inputs across modalities, such as visual and somatosensory information regarding the spatial-temporal relationship between the hand movement and the target, provide a foundation for the planning and monitoring of action outcomes. Sensory information is then transformed and expressed in terms of intrinsically-defined motor commands which dictate flexion and extension by the particular muscle groups (Wolpert, Ghahramani, & Flanagan, 2001). What makes this sensory-motor transformation challenging is that relationships between sensory and motor signals are highly dynamic. For example, the spatial configuration of a static object projected onto the retina can change dramatically when the observer moves the eyes to foveate the object. Yet, the object can still be perceived as static because the visual representation of the object is updated by an anticipatory signal about the eye movement from the oculomotor system (Duhamel, Colby, & Goldberg, 1992; Snyder, Grieve, Brotchie, & Andersen, 1998). In complementary fashion, the outcome of a motor command can be evaluated by contrasting a predicted motor command with the sensory consequence of that action (Wolpert, Ghahramani, & Jordan, 1995). This type of anticipatory signal, or efference copy of the motor command, thus plays an important role in updating the sensory representation as well as monitoring the accuracy of movement.

Sensory-motor systems are subject to internal errors, including inaccurate target specification due to sensory noise and faulty movement execution due to motor noise, which manifest as fluctuation sof movement over repetitions (Faisal, Selen, & Wolpert, 2008). One approach to overcome such error is through on-line corrections wherein on-going movements are continuously monitored using sensory feedback and any difference between intended and actual movement is corrected whenever an error is detected. A weakness in this control scheme is the necessity of waiting for sensory feedback, which inevitably delays response execution and which could present an insurmountable problem when, for example, a rapid response is required. Studies have provided evidence for the presence of on-line movement correction, inferred from kinematic analyses. For example, a simple reaching movement is characterised by a bell-shaped velocity profile. The acceleration phase of the velocity profile is considered directly to reflect planned movements whereas the deceleration phase may be partially affected by online corrections. Thus, extensive involvement of on-line movement adjustments results in a longer deceleration period (Nagasaki, 1989), such that the trajectory deviates from the bell-shaped velocity profile (Plamondon, Alimi, Yergeau, & Leclerc, 1993). Another method for overcoming motor error is through learning and adaptation. A large proportion of motor adaptation theories suggest that the CNS generates predictions about the sensory consequences of a given action in order to help make that action become more accurate (Kawato, 1999). When the same movement is repeated, the CNS learns and adapts the movement to reduce the chance of making the same error by adjusting motor outputs (Wolpert & Ghahramani, 2000).

In contrast to individual action, cooperative action between two actors requires two independent sets of actions that are coordinated in time and space. Thus, the movement plans of the partner may not be known and the detailed movement characteristics of the other actor need to be predicted for efficient interaction. Furthermore, one’s task partner is also mutually interactive in a sense that he/she could also modify his/her movements with respect to one's own actions. Thus, understanding the intentions and movement characteristics of one's task partner is crucial in deriving one's own action plan for successful cooperative action. Recently, neuroscientists have started unveiling the brain mechanisms involved in how people make predictions about other people's behavioural goals and intentions through action observation (Rizzolatti, Fogassi, & Gallese, 2001). Nevertheless, motor theories of individual action and its integration into interpersonal scenarios are lacking in evidence and need to be closely investigated.

In this chapter the literature on bimanual coordination is first briefly reviewed to highlight key issues of motor coordination during two-hand manipulation and the role of prediction of motor consequences therein. This is followed by an overview of recent joint action studies which advocate that sensory prediction about others' actions plays a similarly important role in successful interpersonal interaction.

1.3. Bimanual Coordination as a Model of Two-Effector Coordination

In bimanual action, elements of movements executed by each hand are elegantly organised by the CNS. While control of the two hands is constrained by various factors, such as the physical and cognitive capacities to implement two sets of movements, complete knowledge about the motor plans of each hand enables the actor to perform a task in an optimal or near-optimal fashion (Heuer, Spijkers, Steglich, & Kleinsorge, 2002; Marteniuk, MacKenzie, & Baba, 1984; Schmidt, Shaw, & Turvey, 1993; Spijkers, Tachmatzidis, Debus, Fischer, & Kausche, 1994). This precision of two-hand coordination can be demonstrated by a person placing an object on one hand (i.e., postural hand) and then removing it using the other hand. When the object is supported by the postural hand, the weight of that object is counteracted by an equal amount of upward force produced by the postural hand in order to maintain its posture. When the unloading is performed by the other hand, the CNS predicts the outcome of the weight loss and it adjusts the counteracting postural force prior to the weight offset in order to maintain the stability of the hand posture (Gahery & Massion, 1981; Lum, Reinkensmeyer, Lehman, Li, & Stark, 1992; Dufosse, Hugon, & Massion, 1985; Hugon, Massion, & Wiesendanger, 1982). However, this predictive behaviour, termed an anticipatory postural adjustment (APA), is not observed when the unloading is produced by an external agent or when the participants only have control over the timing of unloading by pressing a button to initiate the unloading (Dufosse et al., 1985). When the object is removed by somebody else, lack of information about the removed weight results in upwards movement of the postural hand since, with the departure of the object, the counteracting upward force is now inappropriately large. Thus, anticipating the movement outcome of one effector provides a computational foundation for planning a congruent movement by the other effector.

Often, routinely used bimanual actions consist of different movements in detail yet they are functionally congruent. A number of authors have suggested that each hand’s function maps onto specific manipulative and postural sub-goals (Guiard, 1987; Johansson et al., 2006; Macneilage, Studdertkennedy, & Lindblom, 1987; Weiss, Jeannerod, Paulignan, & Freund, 2000; Wiesendanger & Serrien, 2004; Serrien & Wiesendanger, 2000). In general, the postural role refers to the hand which defines a global coordinate for a given action, and the manipulative role completes the action with finer movements within the global framework. Guiard (1987) relates these sub-goals to handedness after observing that people typically assign their dominant hand to a manipulative role, such as opening a lid of a box, whilst the non-dominant hand supports the box. His account conceptualises bimanual action as “a kinematic chain” of two hands and proposes that the action of the non-dominant hand forms a reference frame for action by the dominant hand.

A similar sub-goal perspective was taken by Wiesendanger and colleagues. In their bimanual drawer-opening task, participants were trained to reach and open a drawer to pick up an object inside the drawer. The drawer was spring-loaded so one hand had to hold the drawer open to obtain a reward with the other hand. Kinematic analyses revealed very consistent timing, with the arrival of the pull-hand (i.e., postural role) leading the pick-hand (i.e., manipulative role) by 10-50 ms, despite large temporal variability in the single limb components prior to this point (Perrig, Kazennikov, & Wiesendanger, 1999). This temporal synchronisation of the two hands was sustained when an external load was added to the pull-hand which led to a prolonged movement time (Kazennikov & Wiesendanger, 2005). In contrast, when sensory feedback from the leading arm was distorted by vibration, the movements of the hands became desynchronised, suggesting the importance of sensory feedback from the postural hand in defining the action of the manipulative hand (Wiesendanger et al., 2004). Thus, it seems that the CNS makes predictions about the two hands by utilising sensory feedback. Similar to the observation made by Guiard (1987), all the participants in the drawer-pulling experiments assigned their dominant hand to the pick-hand (manipulative role) even though they were not given any instruction to do so (Heuer, 2007; Serrien, Ivry, & Swinnen, 2006).

External factors, as well as internally driven factors such as hand dominance, can affect the functional specialization of the two hands. In a study by Johansson and his colleagues (2006), participants bimanually held a stylus and exerted longitudinal and twist forces in order to control a visual cursor and hit a target displayed on a screen. To keep the object steady in the air, the force at each hand had to match that of the other in magnitude, but in the opposite direction. During the task, participants experienced two different spatial mappings to control the vertical position of the visual cursor. In one, cursor movements were compatible with the force directions produced by the left hand; in the other, with the right hand. They hypothesized that one hand would provide a postural role for the other hand, and the directional displacement of the object should reflect the force exerted by the manipulative hand, just as in opening a jar. The results revealed that the allocation of the manipulative hand was determined by the spatial congruency between the direction of the twisting force and the movement of the cursor. Namely, the non-dominant hand played the manipulative role when this hand action was expressed in the compatible mapping. As the participants were exposed to the task repeatedly, this tendency was increased and stabilized. Thus, the functional specialization can be induced by externally driven factors and override the internal ones.

It seems reasonable to suppose that hand dominance and functional specialisation of the hands are a result of the CNS maximising the efficacy of the overall performance rather than a simple preference for using one hand over the other. In particular, it has been assumed that the dominant arm is more efficient in exploiting intersegment dynamics (i.e., torque as a consequence of the movement produced by an adjacent proximal body segment) when controlling the trajectory of the hand, due to a more accurate anticipatory knowledge (Sainburg, 2005). The non-dominant hand, operating largely under feedback control, shows superiority in counteracting unexpected perturbations thus providing a more stable spatial reference for the dominant arm (van Ulzen, Lamoth, Daffertshofer, Semin, & Beek, 2008; Zivotofsky & Hausdorff, 2007). These bimanual studies indicate that there is strong bias in the way the two hands are controlled. Such control strategies generally reflect the optimal solution, either with respect to internal factors such as the reliability of the effectors, or external factors such as the task goal, both of which can influence an assignment of sub-goals in bimanual coordination.

1.4. Sharing Intentionality and Forming Prediction in Joint Action

Just as inferred from studies of bimanual coordination, anticipating the movement plan of a task partner is likely to play a key role in joint action. When interacting with another person, the goal of action may not have been initially agreed explicitly or in detail between the task partners. Resulting erroneous beliefs about the partner's action intention could be problematic. A verbal comment could be sufficient to exchange general motor strategies such as a path the pair should take when they translate an object together. Nevertheless, cooperative action with another person does not necessarily require conversation; other sensory information can provide sources of information enabling prediction of the partner's actions. For example, after seeing somebody reach to a glass and fill it with water, people can logically deduce that this person is likely to be thirsty and their next action will be to drink that water. People are particularly attuned to detecting people's motion and observers can infer a variety of personal and psychological attributes from only a few points representing movements of joints such as the elbows and the shoulders (Blake & Shiffrar, 2007). Examples of these attributes include type of activity (Johansson, 1973), properties of an object the person is manipulating such as weight (Shim & Carlton, 1997), gender in walking (Barclay, Cutting, & Kozlowski, 1978), and emotional expression of the actor (Brownlow, Dixon, Egbert, & Radcliffe, 1997).

At the neural level, theories of understanding about another person have been strongly identified with mirror neurons, a set of neurons originally found in the premotor and parietal cortices of the macaque monkey (Rizzolatti, Fadiga, Gallese, & Fogassi, 1996). These neurons are characterised by their unique property of being active when the monkey is executing a particular action (e.g., grasping an object) as well as when it sees somebody else performing the same action (Rizzolatti et al., 2010). The human homologue of the mirror neuron region has been identified in Broca's area and precentral motor cortex in imaging studies (Buccino et al., 2001; Decety et al., 1997) as well as in single-cell recording (Mukamel, Ekstrom, Kaplan, Iacoboni, & Fried, 2010). The mirror neurons are sensitive to both the goal of action (Ferrari, Maiolini, Addessi, Fogassi, & Visalberghi, 2005) and how the action is performed (Borroni, Montagna, Cerri, & Baldissera, 2005), and familiarity with a particular type of movement may correlate with strength of the neural responses (Calvo-Merino, Glaser, Grezes, Passingham, & Haggard, 2005). In addition, it has been suggested that the mirror neurons selectively respond to biological motion (Tai, Scherfler, Brooks, Sawamoto, & Castiello, 2004); however, a subsequent single-cell recording study by Gazzola and colleagues (2007) demonstrated that the lack of responsiveness to a non-biological motion was instead a rapid habituation of the neural response due to a repeated exposure to the same movement. The overlap of action perception and execution in the mirror neuron system has led researchers to hypothesise that interpersonal interaction is supported by the CNS which utilises its own motor system to decode actions of others (Rizzolatti et al., 2010). Though a variety of interpretations exists on how exactly the mirror system is recruited, there is a general consensus that this functionality can provide a basis for predicting movements that are performed by others (Heyes, 2001; Rizzolatti et al., 2010).

1.5. Task Division in Interpersonal Coordination

Studies of mirror neurons in general suggest that there are strong associations between performing and observing an identical action. Similarly, mimicking movements are found to be processed preferentially over other hand movements in the CNS, with motor planning facilitated by the strong perceptual-motor associations (Brass, Bekkering, Wohlschlager, & Prinz, 2000). Nevertheless, purposeful interpersonal interaction often requires sets of asymmetric yet complementary actions. Similar to the functional advantage of hand asymmetry suggested by Guiard’s (1987) kinematic chain model for bimanual coordination, simulation studies have suggested that asymmetric involvement in a task can effectively reduce conflict in cooperative interaction (Quinn, Smith, Mayley, & Husbands, 2003; Vaughan, Stoy, Sukhatme, & Mataric, 2000). Furthermore, a role assignment has been associated with more flexible adaptation to environmental changes (Stone & Veloco, 1999). Behaviourally, functional specialisation between two ostensibly symmetric effectors has been demonstrated in a situation where two people each apply force to achieve a shared goal. Reed and colleagues (2006) used a device that allowed recording of forces created by two partners, which was a rotating table with two handles attached at each end. Using this device, paired participants grasped and moved one handle each to meet the visual target as quickly as possible. Even though the participants were instructed to refrain from verbal communication, they rapidly developed a strategy such that one was more involved in accelerating the device and the other in deceleration. The study by Reed et al (2006), therefore, indicates that functional specialisation can be observed at an interpersonal level of action coordination. Hence orchestrating two effectors by functionally specialising the effectors in subtasks rather than producing identical movements may be an effective strategy, comparable to bimanual coordination (Guiard, 1987; Johansson et al., 2006).

More directly, Newman-Norlund and colleagues (2007) have asked their participants to make a hand posture which would either imitate the hand posture in a presented picture or which would complement the action in the picture. Despite the strong perceptual-response compatibility for the imitation posture, when they were asked to think of a complementary action, the reaction time of the complementary action was faster than that of the imitative posture. Thus, the perceptual-motor linkage may be cognitively set to facilitate complementary action over imitative action. Consistently, recent imaging studies have shown that the mirror system can be strongly activated during the planning of complementary action in comparison to imitation (Newman-Norlund, van Schie, van Zuijlen, & Bekkering, 2007;

Shibata, Suzuki, & Gyoba, 2007). In addition, the involvement of a parallel secondary process was hypothesised as a way of enabling flexibility in the selection of an appropriate motor plan for the complementary action (Kokal, Gazzola, & Keysers, 2009).

1.6. Mutuality in Joint Action

An important aspect of joint action is that the movement coordination of two people is inter-dependent, wherein two actors each seek a “compromise” to their own preferred course of action to find a common solution (Di Paolo, Rohde, & Iizuka, 2008; Thompson & Varela, 2001; Tognoli, Lagarde, deGuzman, & Kelso, 2007). Either intentionally or unintentionally the presence of others influences our behaviour, and the behavioural synchronicity of people, termed entrainment, has been reported in various forms and sizes of interaction such as dyadic walking rhythm (van Ulzen et al., 2008; Zivotofsky et al., 2007), body gestures (Chartrand & Bargh, 1999) and conversational pattern (Wilson & Wilson, 2005). In a study by Richardson et al (2007), for example, paired participants sat on a rocking chair side-by-side and rocked the chair at a preferred frequency. Without instruction to do so, the participants started synchronising their movements to each other. On a much larger scale, spontaneous interpersonal movement synchronisation was reported in the hand clapping pattern of thousands of members of the audience at a concert hall (Neda, Ravasz, Brechet, Vicsek, & Barabasi, 2000).

Entrainment affects not only temporal but also spatial aspects of movements. In Kilner’s study (2003), participants made lateral or vertical arm movements while attempting to synchronise their movements with a video of another person also making lateral or vertical movements. When the participants performed movements that were incongruent with those of an avatar in the video, the movement trajectory became more variable than when they performed congruent movements, suggesting that the presence of a person can interfere with execution of action. It has further been shown that emergent entrainment is often so strong that, despite an explicit instruction to move incongruently, the participants commonly failed to break the synchrony (Issartel, Marin, & Cadopi, 2007), although the strength of the coupling can be lessened when using a non-interactive pre-recorded stimulus (Oullier, de Guzman, Jantzen, Lagarde, & Kelso, 2008) or when a person believes that they are synchronising with movements that originate from a mechanical system (Stanley, Gowen, & Miall, 2007). In the study by Stanley and colleagues, their participants performed the same task as Kilner's study (2003). A critical difference in Stanley's study was that the researchers used a single dot movement to represent the avatar. Thus, participants believed they were synchronising their movement with another person or a robot by instruction despite the fact that these two movements were in fact identical. When the participants performed the task believing the observed movements originated from a robot, the interference effect due to the incongruent movements disappeared. Thus, it seems that cooperative action is not just a mere low-level coordination of movements by two actors, but it is also strongly related to high-level expectancy and executive function.

Fascinatingly, entrainment also occurs with physiological states between people as in respiration pattern and heart rate (Watanabe & Okubo, 1997) as well as in electroencephalographic (EEG) signals (Tognoli et al., 2007) although causality of physiological entrainment could be secondary to behavioural synchrony and shared attributes in the sensory-motor environment between people. Frequently, behavioural interactions of two people have been modelled in terms of a dynamical system. Namely, it has been proposed that two different sets of movements interact and mutually influence each other's state in order to find a stable solution (Oullier et al., 2008; Schmidt, Bienvenu, Fitzpatrick, & Amazeen, 1998) or reduce their differences (Felmlee & Greenberg, 1999; Kon & Miyake, 2005) in temporal motor coordination tasks. These studies provide specific predictions about how people may coordinate their movements with each other. However, the interaction process has never been studied in terms of cooperative goal-directed action such that the mutual interaction should relate to the optimal performance of cooperative outcome rather than a mere coordination of two sets of movements. This thesis therefore investigates how people modify their cooperative behaviour with movement characteristics within and across trials when working with a task partner.

1.7. Conclusions

The coordination between two people in space and time, and of the relative forces they employ, is an essential part of cooperative action. Controlling movements for interpersonal interaction imposes many unique functional requirements on the CNS. Through a series of studies, this thesis highlights a strategic solution for the performance of cooperative motor tasks that can emerge implicitly (i.e., in the absence of verbal negotiation) based on mutually interacting partners' behaviour and gathered through sensory feedback of task performance. To achieve this, the studies involve two approaches. Firstly, behavioural characteristics of human-human interaction and the importance of sensory feedback in a cooperative object lifting paradigm are addressed. Secondly, human behaviour is modelled and tested using a robot (computer simulation) as a task partner to systematically investigate how the behaviour of a modelled partner influences the behaviour of the human; this second approach enables the study of motor control of cooperative action by means of on-line correction and adaptation between partners.

In order to make the comparisons of observations made in each study tangible, this thesis primarily deals with the translation of an object in synchrony by two people as a task scenario. The advantage of this task is that, unlike direct effector-to-effector interaction such as handshaking, there is a degree of freedom in the coordination via the object and the interaction of the two partners is partially independent. Thus, their respective movement plans are kinematically observable. Another advantage of cooperative lifting is that it is a realistic object-oriented action, as it is also within the scope of this thesis to investigate the link between an object and a person in a cooperative scenario.

In **Chapter 2**, an experiment derives movement principles from the observation of the kinematics of paired participants who coordinated their actions using haptic information in a cooperative object lifting task. The results highlight that properties of the object such as its rotation and its mass distribution affect how an actor successfully recognises and responds to the movements of a task partner. In **Chapter 3**, on-line feedback movement correction processes are examined by using a humanoid robot to create an unpredictable movement during a cooperative task. In **Chapter 4**, cooperative action is realised in terms of a time-series model wherein an actor estimates joint outcome in a subsequent trial based on how the two partners perform in the current trial. The model is tested for both kinematic and kinetic parameters to identify the movement parameters that are most relevant to this error-based learning. The study demonstrates that some kinematic parameters such as the peak velocity and peak acceleration during vertical lifting movement are highly correlated with the adaptive structure of the model and further, that a linear first order correction model is sufficient to estimate the adaptation rates of the partners. **Chapter 5** addresses the effect of the adaptation by one partner on another partner using the model developed in Chapter 4. By simulating the behaviour of the task partner at a different adaptation rate in a computerised version of the cooperative lifting task, active and flexible change in the adaptation rate of the participants is revealed. The study provides direct evidence for optimisation of the behavioural performance at a cooperative level. In **Chapter 6**, the adaptive model is applied to a continuous movement task to demonstrate that this discrete time series model can be applied to different types of movements. **Chapter 7** summarises the contributions of each chapter to the current understanding of “joint action” literature, and suggests future directions for research.

Chapter 2

Interpersonal Movement Correction using Haptic Feedback in Cooperative Object Lifting

2.1. Abstract

This chapter addresses the role of haptic feedback on motor learning about a task partner when two people jointly lift an object without the aid of vision. The haptic impression of a cooperative partner was altered by reducing the rotational information and/or changing the dynamics of the object. The rotational information about the object derived from torque was varied using an object whose grasp surfaces were either rigidly fixed or free to rotate around the grasping axis; the dynamics of the object were altered by modifying its mass distribution of the object. The results showed that motor performance was less successful when the rotational information was reduced or when the dynamics of the object were changed. In the presence of the rotational information, nevertheless, the participants quickly learned new dynamics of the object with practice and improved performance, indexed as reduced jerkiness in the movements. This study suggests that partners learn each other's movement characteristics through the dynamics of the object.

2.2. Introduction

There are a variety of ways in which people engage and interact with each other for cooperative purposes. While many interpersonal interactions are primarily mediated visually or acoustically, haptic information may become a principal component of interaction when two people jointly manipulate an object. An everyday example is where two people jointly lift a large object: proper delegation of the load across partners enables heavier and larger objects to be transported. Haptic feedback is known to be a central source of information for learning dynamics of objects such as weight (Kawai, 2002) and mass distribution (Wing & Lederman, 1998), and dexterity is critically compromised when the haptic inputs are interfered with by local anaesthesia of the hand (Nowak et al., 2001) or peripheral nerve injury (Schenker, Burstedt, Wiberg, & Johansson, 2006). In one-person lifting of an object using precision grip with opposed index finger and thumb, the grip force is normal to each contact surface and allows the development of frictional resistance against the vertical load force (tangential to the surface) due to the weight of the object. In order to prevent the object from slipping, the product of the grip force and the coefficient of friction between the digits and the object must exceed the load force. It has been shown that, when manipulating a familiar object, grip force increases in parallel with load force and the rate of increase scales with object attributes including the weight and coefficient of friction (Johansson & Westling, 1984; Westling & Johansson, 1984). The precise coordination of grip and load suggests that the central nervous system (CNS) acquires an internal model about the object dynamics and inverses this model to control the movement in an anticipatory manner (Flanagan & Wing, 1997). When the object properties are unexpectedly changed, a reactive correction is made to reduce the error in the latency of 80-100 ms (Cole & Abbs, 1988; Johansson & Westling, 1988). If the error is consistent and reliable in origin, the CNS adapts the internal model to appropriately scale the motor commands for this object within one or two trials of repetition (Flanagan, Bowman, & Johansson, 2006).

When manipulating a single object with another person, the motor commands need to be scaled not only with respect to the dynamics of the object, but also to the movement of the partner. Previously, the coordination of two effectors directed to a single object were addressed in terms of bimanual coordination (Bracewell, Wing, Soper, & Clark, 2003; Johansson et al., 2006; Scholz & Latash, 1998), which highlights control issues that are unique to multi-effector movements. During bimanual object manipulation, grip force exerted by one hand or the other does not fully reflect the load of the object. Instead, the net force exerted by both hands would determine the state of the object. In the study by Bracewell et al. (2003), for example, participants bimanually lifted a tray with an external loading. When the tray was lifted, the increase of grip force was temporally coupled with the load force change at each hand. However, the respective sizes of the grip forces executed by each hand were different such that the size of the grip force of the hand with the external mass closer to it was the higher. Importantly, the sum of the bilateral grip forces was scaled to the total weight of the tray, possibly as a result of minimising the torque required by the two hands to balance the tray. Thus, it seems that the CNS incorporates information about object dynamics when delegating motor commands to two hands during bimanual object manipulation.

Unlike bimanual coordination, the lifting of an object by two partners is achieved by each partner controlling an independent set of movements. Therefore, without the aid of vision, the detailed movement of the partner on the other side of the object needs to be realised through the dynamics of the object in order to set appropriate temporal-spatial parameters of one’s own movement and so achieve successful cooperation. This study therefore investigates the extent to which the learning and control of cooperative object manipulation is governed by haptic perception of the object dynamics. The task involved paired participants cooperatively lifting a bar to a target height. Performance was considered successful when the orientation of the bar remained horizontal throughout the lifting. If the two partners lift the bar at different speeds, for instance, the bar tilts and a rotational torque develops against the direction of the tilt at the two grasping points. In addition, movement of the bar while in the participant's hand may also induce force lateral to the skin, or shear force, which causes stretch of the skin.

To assess the implication of such haptic information about the bar for learning to coordinate movement with a partner, the rotational information and dynamics of the lifting bar were independently varied. The rotational sensation of the bar was reduced using a bearing that allowed the bar to rotate with minimum friction at the grip point so the participants experienced much less rotational information. The size of the torque experienced at the participants' grips was independently manipulated by placing an external mass on the bar at different points across the bar to shift the location of the centre of mass (CoM). It has been suggested that shear force is a reliable source of information for detecting movement of an object across the skin and that it plays a central role in perceiving the dynamics of an object (Essick, 1998). Thus, it was predicted that the lack of rotational information would severely hinder motor coordination between the two partners. Furthermore, a series of studies on so-called "dynamic touch" (Turvey, 1996) has shown that people make inferences about object properties such as the length and orientation of a non-visible object by sensing inertial variables as it is actively wielded (Fitzpatrick, Carello, & Turvey, 1994; van de Langenberg, Kingma, & Beek, 2006). Thus, the change in the CoM of a bar was also predicted to impair motor coordination between the two people since the haptic impression of the object, and, by extension, of the partner's movement, would be different. Nevertheless, it was expected that the change in the CoM would impair the performance only immediately following that change, and that with practice the performance would improve by learning new object dynamics.

2.3. Method

2.3.1. Participants

Twenty participants took part in this experiment. The participants were randomly assigned in pairs to perform the task. All participants were right-handed and the average age was 26.6 ± 4.68 years old. There were 6 male-female pairs and 4 female-female pairs. All participants gave informed consent prior to the study and received £6 or course credit for their time in completing the experiment.

2.3.2. Apparatus

The participants sat at a table and lifted a wooden bar, 54 cm in length, 2 cm in width and 4 cm in height, weighing 325 g (Figure 2.1a). A separate mass of 150 g was placed in one of three compartments (7.5 cm in length, 3.5 cm in width, and 4.5 cm in height) located on top of the bar. The middle compartment was located at the centre of the bar, and the remaining two were 15 cm on either side of the centre. The location of the mass was concealed from the participants using a paper cover over all three compartments.

There were two sets of grasp surfaces located 2 cm from the longitudinal end of the bar and 2 cm from the bottom of the bar. Each pair of grasp surfaces comprised two discs (1 cm in diameter) that were attached to a bar resulting in a grip span of 4 cm. In one of the two types of bars, the grasping surfaces were rigidly embedded in the bar (Rigid object). In the other bar, the grasp surfaces were attached via bearings allowing the bar to rotate around the grasping point with little friction (Rotatable object).

On the table, there was a stand (40 cm in height) located between the participants which was used as a target for the height of the lifting motion. During the experiment, all participants wore a pair of headphones. Three auditory beeps (inter-stimulus intervals = 500 ms) were played through the headphones to provide a starting signal at the beginning of each trial. In addition, white noise was played to mask sounds that might relate to the task performance.

A 12-camera ProReflex motion tracking system (Qualisys, Sweden) tracked 2 retroreflective (at 200 Hz) markers attached above the grasping point on the bar.

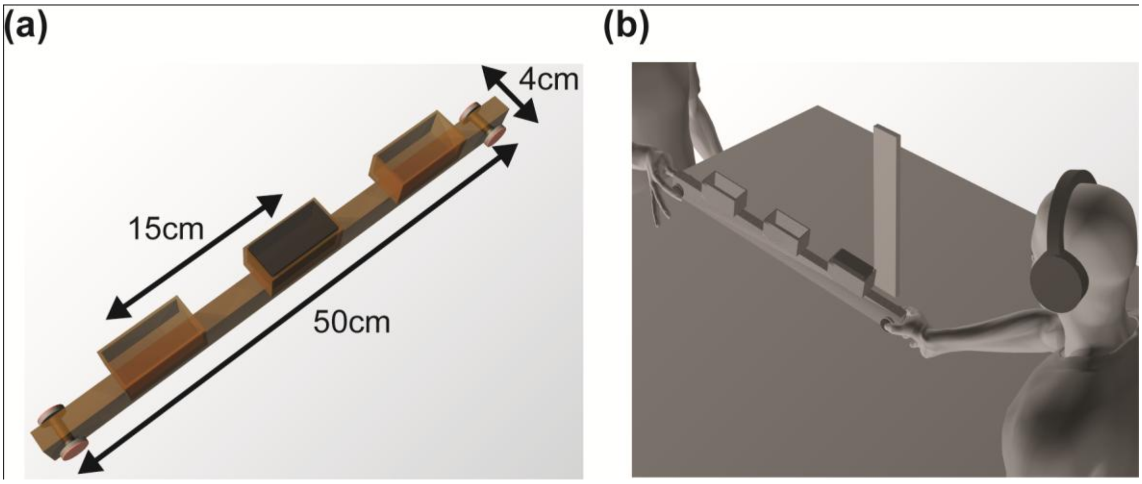

Figure 2.1. Schematic illustrations of the bar and workspace. **(a)** The bar consisted of three compartments, into one of which a mass was placed. In the experiment the mass was not visible to the participants. The two participants grasped the disks located on the edge of the bar using precision grip to lift the bar. **(b)** The participants faced each other with their eyes closed and lifted the bar. On the side of the workspace, there was a stand that indicated the target lifting height.

2.3.3. Procedure

Paired participants used arm and shoulder movement to lift the bar to a target height together as fast and as synchronously as possible. Two participants sat on adjustable chairs and faced each other (Figure 2.1b). A bar was placed on the table in front of them, aligned sagittally to the shoulder of their dominant right hands. The height of the chair was also adjusted to align the bar vertically with the position of the elbow when the arm pointed downwards. The distance of the bar in the coronal plane was equal to the length of the forearm so that the elbow angle was approximately 90 degrees as the upper arm points to ground when the bar was held. At the beginning of each trial, the participants grasped the bar using precision grip. When they were ready, they closed their eyes and waited for the auditory beeps. At the third beep, the participants started the lifting movement. At the end of the trial, the participants kept the bar on the end point for 1 second and opened their eyes to determine the position of the target and see how they had performed. The participants were told which person would be the Leader or Follower (see Design) at the beginning of each block. The mass location and object type were hidden from the participants.

2.3.4. Design

This was a 2 (Role) x 2 (Object) x 3 (Mass) within-subject block design. The first independent variable was Role, where participants were randomly assigned as a Leader or a Follower. At the start of each trial, the Leader received the auditory beeps through the headphones, with the third beep used as a timing cue to start the lift. Effectively, the Leader always initiated the lift and the Follower reacted to the Leader. The reason for defining these roles was that cooperative interaction often involves cycles of reactive responses by two partners (Bosga & Meulenbroek, 2007). Hence, this study addresses how behavioural responses would differ when one person is leading or following the other partner. Another independent variable was the type of bar, which was either Rigid or Rotatable, as previously defined. The third independent variable was Mass referring to the location of the movable mass in either the middle compartment (Centre CoM), the compartment closest to the Leader (Near CoM) or the one furthest from the Leader (Far CoM).

In the first three blocks, the pair lifted the Rigid object in the order of the Centre, Near and Far CoM. On completion of the three blocks, the roles of Leader and Follower were reversed and another three blocks were performed. Subsequently, the same procedure was repeated with the Rotatable object. The order of the experimental blocks was fixed since the main purpose of the study was to investigate how the learning of the bar dynamics and the task partner was affected by a change in the object properties. This procedure was exercised as opposed to a randomised design to allow study of kinematic change over the course of the experiment. Specifically, the experiment started with the Rigid object and then progressed to the Rotatable object since the latter object was predicted to be more difficult. Using the more difficult Rotatable object before the Rigid object might have masked some of the observed effects such that impaired performance with this condition may also be explained parsimoniously in terms of lack of practice. With the ordered design, it was hypothesised that impairment in the performance in Rotatable object or the change of the CoM would validate a claim that haptic feedback of an object plays an important role when translating an object with a task partner. The participants performed 5 trials in each block, giving a total of 60 trials.

2.3.5. Analyses

A bi-directional second-order Butterworth filter with cut-off frequency of 12Hz was applied to smooth the motion data prior to analysis. In order to calculate the reaction time and the movement duration, the start of the lift was defined as the first sample point at which velocity exceeded 5 cm/s and continuously incremented to a level of at least 10 cm/s. The end of the lift was defined as the first time the velocity fell below 5 cm/s after passing the height of 30 cm.

2.4. *Results*

2.4.1. *Reaction Time*

The reaction time of the Follower at the start of the lift was faster with the Rigid object than with the Rotatable object. The reaction times with the Rigid object were 227.4 ± 119.3 ms for Near, 307.8 ± 139.1 ms for Centre and 342.2 ± 138.3 ms for Far CoM. With the Rotatable object, the reaction times were 471.8 ± 224.2 ms for Near, 521.2 ± 346.1 ms for Centre and 676.8 ± 333.8 ms for the Far object. A 2 (Object) x 3 (Mass) ANOVA confirmed a main effect of Object, F (1, 19) = 25.530, $p < .0005$. Furthermore, a main effect of Mass was found, F (2, 38) = 6.396, $p < .005$, such that the reaction time steadily increased as the CoM moved further from the Leader. No interaction effect was observed ($p = .196$).

2.4.2. *Movement Duration*

Movement durations for the Rigid object were 1546.5 ± 343.5 ms for Near, 1560.5 ± 381.1 ms for Centre and 1584.7 ± 355.6 ms for Far CoMs. For the Rotatable object, the movement durations were 1490.0 ± 349.8 ms for Near, 1443.4 ± 467.0 ms for Centre and 1424.3 ± 525.3 ms for Far CoMs. Since the movement durations were a cooperative variable which were defined by the shared performance of the two actors and the same pairings were repeated with only a change in role allocation (Leader vs. Follower), covariance between the same pairs was partialled out from the statistical analyses. Hence, a 2 (Object) x 3 (Mass) ANCOVA was used to compare the mean differences. The analysis indicated there were no main effects of Object ($p = .129$), or Mass ($p = .168$), nor was their interaction significant ($p = .808$).

2.4.3. Position and Velocity Errors

Figure 2.2 illustrates three typical kinematic patterns in this cooperative object-lifting task. In all three types, a large difference between the partners developed as the Leader initiated the lift. This was closely followed by a compensatory burst in velocity by the Follower in an attempt to catch up. In order to analyse the time lines of the position and velocity errors between the partners, the movements were divided into four phases defined in terms of the height of the object's midpoint (i.e., average height of the two markers attached to the object). The averaged position and velocity errors of the four phases were separately analysed using a three-way (Object vs. Mass vs. Phase) repeated-measures ANOVA.

Position Error: Figure 2.3 illustrates changes in the position and velocity errors over the four phases. The results showed that there was a main effect of position error for Mass, F (2, 38) = 5.012, $p < .02$. The size of the error was largest with Far CoM (7.04 ± 6.74 cm), followed by Near CoM (5.84 ± 5.45 cm) and smallest with Centre CoM (5.26 ± 5.12 cm). A pair-wise comparison confirmed the difference between Centre and Far CoMs, $p < .05$. Furthermore, a main effect was reported for Object, F (1,19) = 60.188, $p < .0005$, such that the position error was larger with the Rotatable object (9.19 ± 4.47 cm) than with the Rigid object (2.91 ± 4.47 cm). A main effect was also observed for Phase (3, 57) = 7.628, $p < .0005$. The error was largest in Phase 2 (7.22 ± 7.48 cm), followed by Phase 3 (6.92 ± 7.47 cm), Phase 4, (6.87 ± 6.18 cm) and smallest in Phase 1 (3.17 ± 2.35 cm). Post-hoc pair-wise comparisons revealed a statistically reliable difference for Phase 1 against Phase 2 ($p < .03$) and Phase 4 ($p < .03$). Furthermore, there was a reliable Phase vs. Object interaction effect, F (3, 57) = 22.605, $p < .0005$. Although the increased difference over Phase 2 was reduced in Phase 3 with the Rigid object, as Figure 2.3 indicates, such a difference was maintained in Phase 3 with the Rotatable object. The remaining interaction terms were not significant.

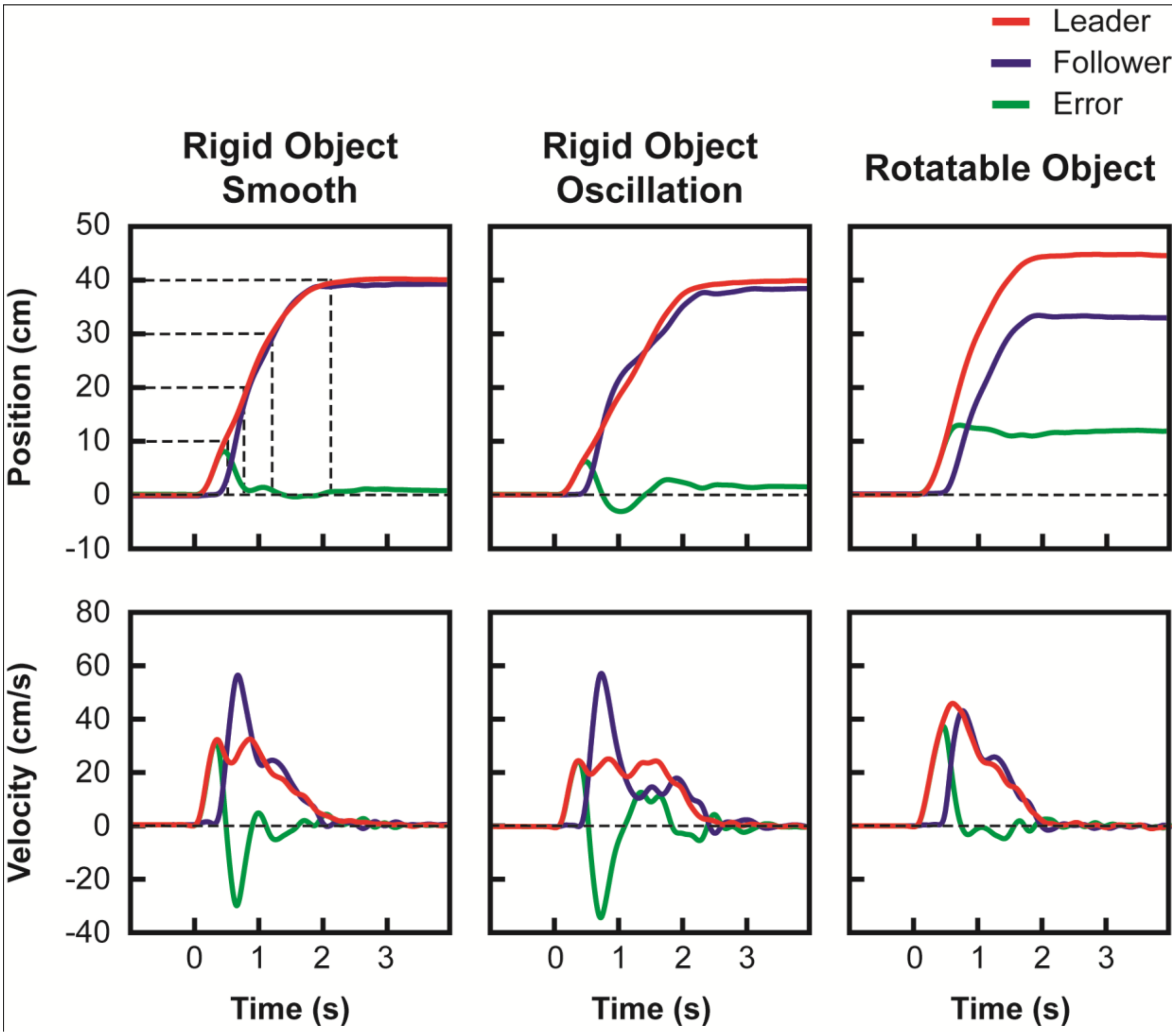

Figure 2.2. Examples of typical kinematic profiles. Figures illustrate position and velocity profiles of successful ('smooth') and less successful ('oscillation') trials with the Rigid object and another example of a stereotypical trial with the Rotatable object. The smooth and oscillation trajectories for the Rigid object were defined here by high (-10.24 cm/s^2) and low (pair average of -11.05 cm/s^2) jerk metrics, respectively (see the Jerk Metric section for detail). To assess within-trial performance, the lifting motion was separated into four phases based on the mid-position of the trajectory for the Leader (red line) and Follower (blue line). The position and velocity of the Follower were subtracted from those of the Leader to quantify the performance errors (green line).

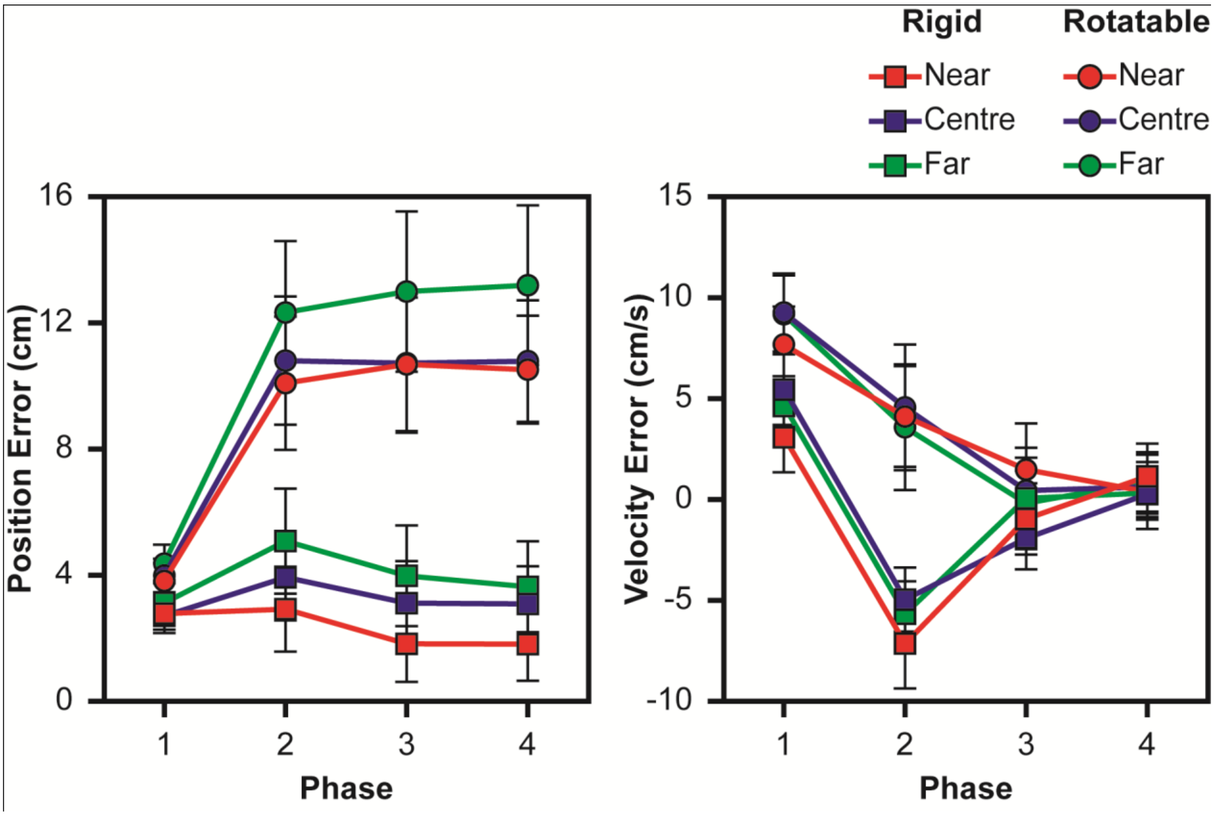

Figure 2.3. Within-trial evolution of position and velocity errors. The position and velocity of the Follower were subtracted from those of Leader and then separated into four phases in terms of the height of the bar. Small, but consistent differences between the objects are visible at Phase 1, but the most noticeable change was observed at Phase 2 in both position and velocity profiles. Error bars represent one standard error.

2.4.4. Jerk Metric

In the initial phases of the experiment, kinematic oscillations were commonly observed such that the Follower overshot the Leader and required further corrections to keep the bar horizontal (Figure 2.2; Centre). However, the oscillation was reduced as the trials were repeated (Figure 2.2; Left). When the Rotatable object was used, the Follower often failed to catch up with the Leader (Figure 2.2; Right). To demonstrate the change in smoothness of the trajectory statistically, the handle positions of the Leader and Follower were quantified using a jerk metric (Rohrer et al., 2002). The jerk metric was calculated by taking the root mean square of the jerk (rate of change of acceleration) normalised by the peak velocity and multiplied by minus one, meaning that the higher the value, the smoother was the trajectory. An advantage of this jerk metric is that the measure is normalised by the second power of the movement duration. Thus, the longer the movement duration, the lower is the resulting jerk value. To access a change of jerk matrices over the course of the experiment, the averages of the first (T1) and last two trials (T2) in each condition were analysed with a four-way (Role vs. Time vs. Object vs. Mass) mixed ANOVA.

Figure 2.4 illustrates the changes in jerk with experimental order. The jerk metrics of the two partners were initially similar for the Rigid object. This was followed by an increased smoothness over the time course of the experiment for both partners, despite the change in location of the CoM leading to a reduction in the smoothness of Follower's trajectory. Furthermore, an improvement in smoothness in the Follower's trajectory was consistently evident over the time course of each block. In contrast, the jerk metrics with the Rotatable object were inconsistent across Time. Initially, a very jerky movement was observed. Subsequently, however, much smoother movement was observed regardless of the trials; no improvement from T1 to T2.

Statistical analyses showed that there is no difference in smoothness in terms of Role, F (1, 19) = 0.059, $p < .81$, and Object F (1, 19) = 0.209, $p = .65$. A main effect was found for Time, F (1, 19) = 7.394, $p < .02$, such that the movement was smoother during T2 (-14.19 ± 5.98 cm/s^2) than T1 (-15.2 ± 6.11 cm/s^2). Furthermore, there was a main effect of Mass, F (2, 38) = 4.201, $p < .03$. The trajectory was the smoothest when the mass was Near to the Leader (-14.27 ± 5.85 cm/s^2), followed by Far (-14.44 ± 6.16 cm/s^2) and the least smooth for Centre (-15.45 ± 6.23 cm/s^2). An interaction effect was found for Time x Mass, F (2, 38) = 6.019, $p < .01$, and for Time x Mass x Object, F (2, 38) = 3.333, $p < .05$.

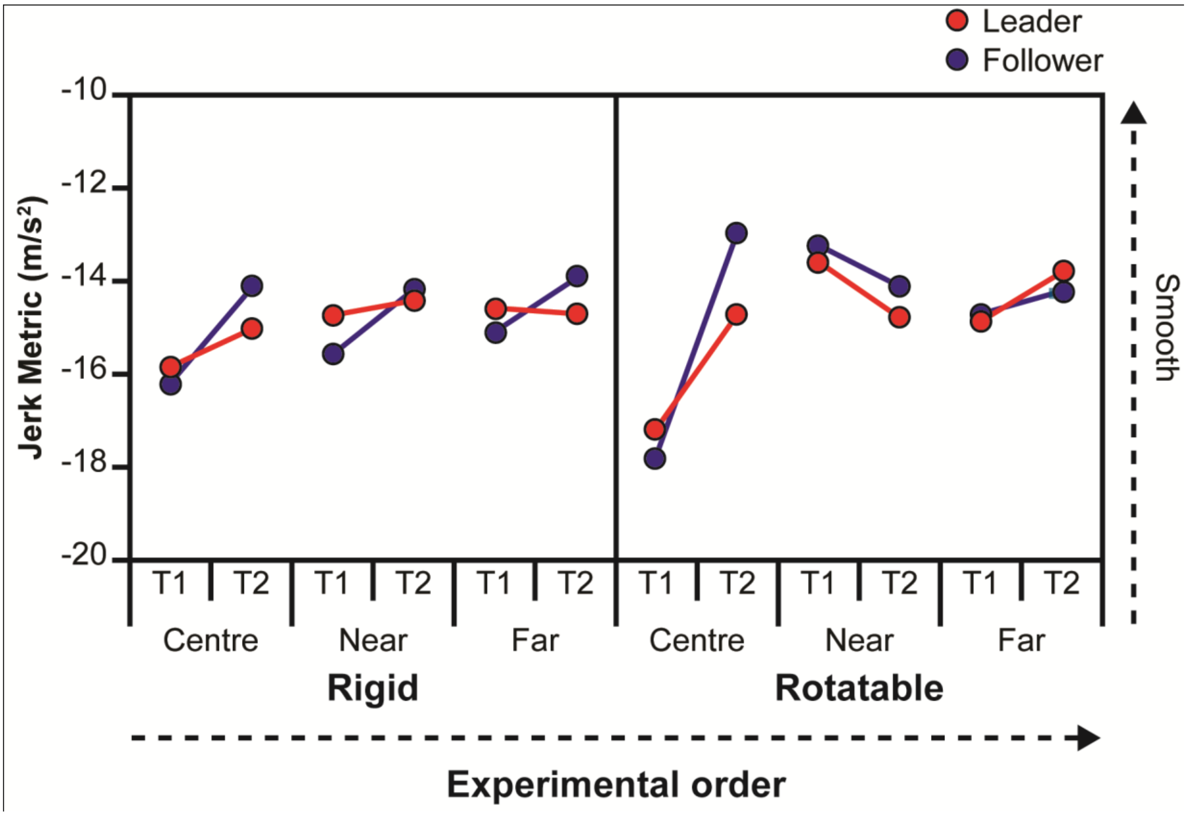

Figure 2.4. Jerk metric of the Follower and Leader. Jerk values were estimated for each member of the dyad's grasping point. A higher jerk metric indicates smoother movement. The jerk metric of the first and last two trials (T1 and T2, respectively) were averaged to show a change in the trajectory smoothness over the course of the experiment. Note that the jerk metric is the mean jerk normalised by the peak velocity and hence the unit becomes m/s^2.

2.5. Discussion

Many forms of interpersonal interaction in everyday life involve some degree of haptic information processing. This study investigated the effect of haptic rotational information about an object for vertically translating it with a task partner. It was hypothesised that interfering with the rotational information would disrupt the learning of a partner's movements. As predicted, the elimination of the object's rotational information, through the use of ball bearings at the grasping points, had a detrimental effect on the motor coordination between the partners. A lack of rotational information resulted in a longer reaction time, large position errors during lifting and less within-trial recovery in comparison with the performance using a rigid object wherein rotational information was fully available. The analyses of within-trial movement trajectory revealed that between Phase 2 and 3, there was a small reduction in position error with the Rigid object, whereas the error was sustained with the Rotatable object. In contrast, the velocity error reduced to a similar level by Phase 3 with both types of objects. When using the Rotatable object, it seems that the Follower perceived the speed at which the Leader lifted the object, but failed to realise when the object was horizontally aligned. Although the use of the ball bearing reduced the torque, it may have also eliminated other sources of rotational information such as vibrotactile flow (i.e., intentional slide of the object) (Bark, Wheeler, Premakumar, & Cutkosky, 2008). The results of the present study are consistent with findings from a single-person object manipulation (e.g., Fitzpatrick et al., 1994; van de Langenberg et al., 2006); the rotational information of the object defined by the distance between its CoM and the grasping position affects the haptic impression of the object and, by extension, the impression of the partner's movement on the other side of the object.

Another motivation for this study was to examine learning in cooperative interaction. An improvement in the smoothness of the movement trajectory, as indexed by the jerk matrix, was observed when rotational information about the object was available. In contrast, despite a large reduction in the jerk metric in the initial block, the change of the jerk in the following blocks was inconsistent when the rotational information was absent. This increased smoothness of the trajectory with the Rigid object was particularly evident in the movement of the Follower. Although the smoothness was reduced when the mass distribution of the object was changed, the smoothness at the earlier stage of the block (T1) still gradually increased as the experiment progressed. This suggests that the Follower's trajectory was affected by the change of the object's mass distribution, but he/she may have acquired task-relevant information from sources other than the dynamics of the object, such as the temporal characteristics of the Leader's movement. In contrast, the smoothness of the movement by the Leader remained relatively intact despite changes in the mass distribution of the object.

The reduction of jerk in a task has previously been reported after practice of a movement (Schneider & Zernicke, 1989) as well as in the process of recovery after stroke (Rohrer et al., 2002). It is considered that the jerk reflects on-line correction of the movements and that improvement is gradually realised as the CNS learns the dynamics of the task and as the movements become predictively controlled (von Hofsten, 2004; Thomas, Yan, & Stelmach, 2000). Thus, the improvement in the smoothness observed in this study may underlie the shift from a postdictive to a predictive model of motor control.

When an object is supported at two positions and one of them moves, it functions like a lever with a pivot point at the static side. Hence, the smaller the distance of the added mass from the grasp point, the stronger the torque, and hence the greater the grip force required to manipulate the object. The results showed that the position error between the pairs was the smallest when the external mass was located near the Leader. Considering that the trajectory refinement was largely initiated by the Follower as the reduction of the jerk metric suggests, it is likely that the Follower was more involved in adjusting his/her movement to that of his/her partner. In conjunction with this, less torque was required by the Follower to control the movement when the mass was near the Leader. Thus, the highest accuracy in this condition may be explained by a smaller force output required for motor control which is associated with smaller motor noise (Harris & Wolpert, 1998). Force and torque measurements would provide more concrete evidence to support this claim.

Alternatively, the prolonged reaction time of the Follower when the CoM was far from the Leader may have led to a larger kinematic error from the start. Since this condition required a stronger grip force for the Follower to balance the object, it is possible that the participants spent longer developing a grip force sufficient to support the object in reaction to the movement onset of the partner. This initial delay may have persisted throughout the trial.

Haptic perception is known to be inhibited during one's own action, and this may cause a further potential source of error in interpreting the force feedback. As we interact in the environment, we can readily distinguish sensations caused by external stimuli from those due to our own action. According to Blakemore and colleagues (2000), the prediction of one's own action attenuates the expected sensations, thus reducing the sensations caused by one's own action and enhancing those derived from external locations. Shergill and colleagues (2003) further demonstrated this sensory attenuation in a force matching task. In their "tit-for-tat" study, paired participants took turns to apply force on each other's index finger for 3 seconds while ensuring that the force applied on their partner's finger was matched to the force experienced by their own finger in the previous turn. The force exchange was achieved via a force transducer attached onto the finger tip to allow force measurements. The trial started with a mechanical motor producing a 0.25 N force on one of the partner's finger. Importantly, the participants were unaware of the instructions given to the other person. The results showed that forces escalated in all pairs as the pair continued to take turns, with a mean increase of 38% on each turn, suggesting that there may be systematic error in perceiving the exerted force and replicating it. As the participants to coordinate their hand positions, the positions of partners' hands were perceived through haptic interaction. Thus, it is interesting to investigate how the integrity of haptic perception about a task partner is maintained while a person performs an action simultaneously in cooperation.

In conclusion, this study emphasises the importance of haptic information of an object during cooperative object lifting and that people can improve the motor coordination with a partner though the use of this haptic feedback. This study indicates the existence of a relatively fast learning process about another person as perceived through physical interaction. In the next chapter, the learning processes during cooperative action are directly addressed in terms of feedforward and feedback control by restricting the predictability of the task partner by replacing one of the participants with a humanoid robot. In Chapters 4-6, this interpersonal learning will be modelled in terms of error-based learning wherein paired participants adapt to each other's movements at a pre-set rate.

Chapter 3

Feedforward and Feedback Motor Control during Human-Robot Interaction

3.1. Abstract

This study examined predictive and reactive control mechanisms when a participant jointly lifted an object together with a humanoid robot. The movements of the robot were controlled across three experimental blocks so that the movement was either consistent, predictably changed or erratic, depending on the block. The results revealed that when the robot moved consistently or predictably, then with practice: 1) the internal force exchange (i.e., push/pull) between the participants and the robot via the object reduced and 2) the participants became better able to coordinate movement with the robot. In contrast, the internal force increased when the robot moved, or was expected to move, erratically. This increase of the internal force was actively induced by the participants, in anticipation of erratic movement by the robot. When an unpredictable robot movement was detected during lifting, the participants still managed to follow closely the robot's trajectory after an initial delay of approximately 150 ms. In conclusion, motor control during cooperative action involves both predictive and postdictive elements that are flexibly executed in response to the behavioural characteristics of the partner.

3.2. Introduction

Chapter 2 presented evidence of a person's ability to learn the motor characteristics of a task partner as they repetitively lifted an object together. Specifically, the improvement of performance was observed as reduction of the movement jerk over the course of the experiment. When the dynamics of the object were modified by shifting its centre of mass, the jerk of the task performance reverted to previous values. In addition, motor coordination between the partners was largely disrupted when the rotational information about the object was interfered with using ball bearings attached onto the grasping points. Taken together, the results of the previous study suggested that the participants learned to coordinate movements with the task partner using cues perceived through the dynamics of the object. While this study suggests that people can learn and predict the movement of another person, a task partner may not always behave consistently and/or predictably. Therefore, control mechanisms that minimise the consequences of unexpected movements of a partner can be an important feature of motor control. By contrasting the different behaviours of the participants when their task partner behaved in a constant, predictable or erratic manner, this chapter describes how in a cooperative object-lifting task, predictive and reactive controls are executed in order to minimise interpersonal movement errors due to incompatible motor plans.

Studies of individual upper limb movements have shown that sensorimotor control is supported by two types of control schemes in order to maintain the accuracy of action: feedforward and feedback control (Desmurget & Grafton, 2000). In feedforward control scheme, the CNS implements action using a model containing information regarding the expression of the motor commands in the environment and their action consequences, information learned from previous interactions in the same or similar environments (Wolpert & Ghahramani, 2000). Thus, an executed action is uninfluenced by incoming sensory feedback. An appropriate motor prediction can then be generated by inverting this internal model. Take the example of baseball batting. As a ball is released, the future time course of its trajectory is dictated by a relatively simple law of physics involving ball inertia and gravity. Knowledge about ball dynamics allows the player to bring the bat to where and when the ball is predicted to be for a successful hit. Accuracy of the internal models, therefore, defines the accuracy of the performance in feedforward movement (Kawato, 1999). Since this motor strategy entirely relies on prediction, it is sensitive to unexpected error. For example, neural noise elicited during the transformation of sensory inputs into motor outputs or sudden changes in trajectory due to external factors, such as a strong gust of wind, may interfere with feedforward control. Only if there is a consistent error in the prediction can the CNS refine the internal model to improve the motor performance.

Another control scheme, feedback control, uses sensory feedback about the performance outcome to continuously monitor and correct on-going movements with regard to the originally intended movement. Unlike the feedforward model, performance is continuously evaluated in the CNS, and it does not require a specific motor plan. A weakness in this control scheme is that it requires sensory feedback, which inevitably delays execution of the response. The motor response is subject to a significant time delay caused by the relay of the sensory signals from the sensors to the cerebral cortex and the subsequent implementation of an appropriate response. In the case of object-lifting with precision grip (opposed thumb and index finger) by a single actor, somatosensory feedback about slippage on the digits due to an unexpected change in object weight induces a correction of the grasping force to prevent further slippage, a correction which lags at least 80-100 ms behind the onset of the perturbation (Johansson & Westling, 1988). Given that the spinal reflex takes about 30-60 ms to trigger a reflexive response (Darton et al., 1985), this type of motor correction is considered to require the supraspinal structures.

Motor planning can further be delayed when appropriate response selection requires complex cognitive processing (Klapp, 2010). In a typical computerised choice reaction-time study wherein a participant responds to a visual stimulus presented on either the left or right side of the visual field, a response to the right stimulus registered by the right hand tends to be faster in reaction time than one to the left stimulus. This is caused by the automatic activation of associated response codes in the CNS following perception of the stimulus. Conversely, when a response to the left stimulus is required by the right hand, the activated right hand code needs to be suppressed in order to make a correct response with the left hand, manifested as a prolonged reaction time. This phenomenon, termed stimulus-response compatibility effect has been widely exploited to study complexity of cognitive processes. In general, the relevant literature suggests that the simplest form of stimulus-response compatibility, as shown in example above, could involve a reaction time of as long as 180 - 200 ms (Klapp, 2010). Further delays may be incurred such as when the suppression of a wrong response code becomes difficult, as demonstrated in the Stroop effect (Macleod, 1991).

Given feedback delays, a motor system operating under a purely feedback scheme may result in erroneous responses, especially when a rapid response is required, such as in our case of baseball batting. In terms of cooperative lifting, a performance error can be seen when a person lags behind a task partner because that person initiated a slower lifting speed. Increasing the speed to catch up with the partner may not however guarantee successful coordination since that partner may concurrently lower his/her speed of lifting using feedback control. As a result, the pair may oscillate their movements around each other’s trajectory, visible as the jerky movements reported in Chapter 2.

When a single actor is handling an object, feedforward and feedback control schemes are thought to be flexibly integrated depending on the nature of the task and its familiarity.

Previously, reach-to-grasp perturbation studies of single subjects have suggested that a sudden change in the object's size or location at the onset of the movement only affects a later stage of the trajectory. Studies of individuals' reaching movements have revealed that the velocity of such a movement usually describes a simple bell-shaped profile as the hand accelerates and then decelerates to terminate the movement at a target. Competing models have been proposed to explain how such a velocity profile is preferentially produced, models which differentially highlight the efforts to minimise the joint torque of the arm (Uno et al., 1989), the jerk of the end-point trajectory as defined by the third derivative of position (Flash & Hogan, 1985) or energy expenditure (Alexander, 1997). The acceleration phase of the velocity profile is commonly considered to reflect planned movements whereas the deceleration phase may be partially affected by online corrections (Meyer, 1988). Thus, it has been suggested that the extensive involvement of on-line movement adjustments results in a longer deceleration period, so causing deviation from the bell-shaped velocity profile (Nagasaki, 1989; Plamondon et al., 1993). The CNS initially implements a control policy that is more reliant on feedback control and it gradually shifts towards feedforward control as the actor learns the dynamics of the task (Thomas et al., 2000a).

During interpersonal interaction, the movements of a task partner can be unpredictable, since his or her movement may be influenced by a variety of internal factors such as sensory and motor noises in the CNS (Faisal et al., 2008), exhaustion (Murian et al., 2008)**,** or individual preference as well as external factors such as the presence of an obstacle in the movement path (Griffiths & Tipper, 2009). In addition to learning and anticipating the task partner's movement for smooth coordination, therefore, feedback control may be required to efficiently reduce the interpersonal error with a task partner who behaves erratically.

The present study assesses predictive and reactive control of movements in a cooperative object-lifting task. In Chapter 2, human-human interaction in the object- lifting task was studied, and the examination of the behaviours of paired participants made possible an ecologically valid statement about interpersonal interaction. However, a dynamically defined relationship between the task partners introduces methodological challenges when drawing causal conclusions about the process of their interaction and their motor strategies. Therefore in this study the trajectory of one partner was explicitly defined using a humanoid robot, so enabling a systematic investigation into the motor responses of participants. In addition, this chapter introduces force measures to provide a kinetic description of human-robot cooperative lifting. In Chapter 2, the importance of the rotational information about an object was emphasised for interpersonal object manipulation. Thus, force/torque measurements are now introduced to characterise kinetic cues that may underlie learning about a partner's movement.

This study consisted of four parts. In the first part (Part 1), the learning of the cooperative lifting was examined wherein the robot consistently produced the same ('Standard') movement. It was hypothesised that the participants would quickly learn the kinematics of the robot when its lifting trajectory was consistent. This motor learning was predicted to result in the progressive reduction of differences in interpersonal kinematic errors. Furthermore, given that participants extract their knowledge of the movement of the robot from the dynamics of the object, learning about a task partner may also be expected to reduce the stiffness of the interaction (i.e., internal force in the sagittal plane) as the participants acquire an accurate predictive model about the task partner. In the second part (Part 2), the robot alternated between two movements ('Standard' and 'Fast') to enable investigation into the participants' ability to differentiate and learn two different movement trajectories of a task partner. The progress of learning in these two trajectories was contrasted with that of associated kinematic and kinetic changes during performance with the robot with the consistent ('Standard' only) movement. In the third part (Part 3) a robot produced three different movements ('Standard', ‘Retardation’ and ‘Advance’) in random order, enabling us to investigate the form in which people control their movements so as to minimise the induced motor error, with key focus on reaction time to understand the moment at which the error detection/correction is made. In the final part, the study addressed whether the participant’s detailed movement parameters might change in relation to a given speed of robot movement (‘Standard’) according to whether that movement is expected (Part 1 and Part 2) or unexpected (Part 3). When the participants expected erratic behaviour, for instance, the participants may have increased the stiffness of the haptic link with the robot through the object in order to minimise the effect of the robot’s erratic behaviour despite that the apparent motions of the partner are identical.

3.3. Methods

3.3.1. Participants

Nine right-handed participants took part in the study. One of the participants was female and the average age was 27.8 ± 7.3 years old. All participants were members of the Joint Robotics Laboratory at the National Institute of Advanced Industrial Science and Technology (AIST, Japan) and were familiar with the robot used in this study although naive as to the purpose of the experiment. The participants gave informed consent prior to participation and received 1,000 Japanese yen for their time in completing the experiment. The study was conducted at AIST, and experimental procedures complied with the ethical and safety guidelines set at AIST and with the Declaration of Helsinki.

3.3.2. Apparatus

The participant jointly lifted a bar to a fixed height with a humanoid robot, HRP-2 (Kawada Industries, Japan, Figure 3.1a). The bar was designed so that its shape and mass distribution was symmetric between the participant and the robot in the sagittal and frontal axes as he/she sat and faced the robot (Figure 3.1b). Two aluminium handles in the form of cylinders, radius 10 mm, 60 cm apart, were mounted on top of the bar so that their tops were 18 cm above the bottom of the bar. At the bottom of each handle a 6 degrees of freedom (DoF) Force/Torque sensor (Mini-45, ATI) was attached to measure the force and torque at 1,000 Hz. The total weight of the bar, handles and transducer was 1kg.

A two-sensor mini-bird motion tracking system (Ascension Technology Corporation) was attached onto the bar to record the position and orientation of the bar at 100 Hz. Although the locations of these markers were arbitrarily defined, their distances from the two handles were measured in order to allow extrapolation of the positions of the handles using the data set off-line (see Design for detail).

The robot was a full-sized humanoid robot with 30 DoF, of which 6 DoF of the right arm were position-controlled to follow a specified trajectory. A soft cushion inserted between the handle and the gripper (i.e., hand) allowed the bar to rotate as far as 30 degrees around the frontal axis even though the joints of the robot were not compliant. To prevent any auditory feedback such as noise from the actuators of the robot, white noise (80 dB) was presented to the participants via a pair of headphones (MDR-Z700DJ, Sony) throughout the experiment. Furthermore, an auditory metronome played four equi-spaced auditory beeps (0.5 second inter-stimulus interval) on top of the white noise to help the participant prepare and start the lifting motion in synchrony with the robot.

3.3.3. Procedures

The participants sat at a table across which they faced the robot. They were instructed to lift the bar with the robot and keep it level as they moved it up. For safety reasons, the participants were also told that the robot might behave differently in some trials although they did not know exactly when the different trajectories would be introduced or how they would differ. At the beginning of each trial, the participants held the handle (the one closer to them) using the whole hand (i.e., power grip) and waited with eyes closed for the auditory beeps to start. On the fourth beep, the participants lifted the bar. When the movement of the robot fully stopped, they were asked to open their eyes. On a computer screen placed next to the participant, the maximum angle of the bar (in degrees from the horizontal) during lifting was displayed as performance feedback. The participants were encouraged to reduce the maximum angle as much as they could. Three seconds after the robot arrived at the target position, it returned the bar to the starting position for the next trial to commence. There was a short break between the three blocks, and the entire experiment took approximately 1 hour to complete.

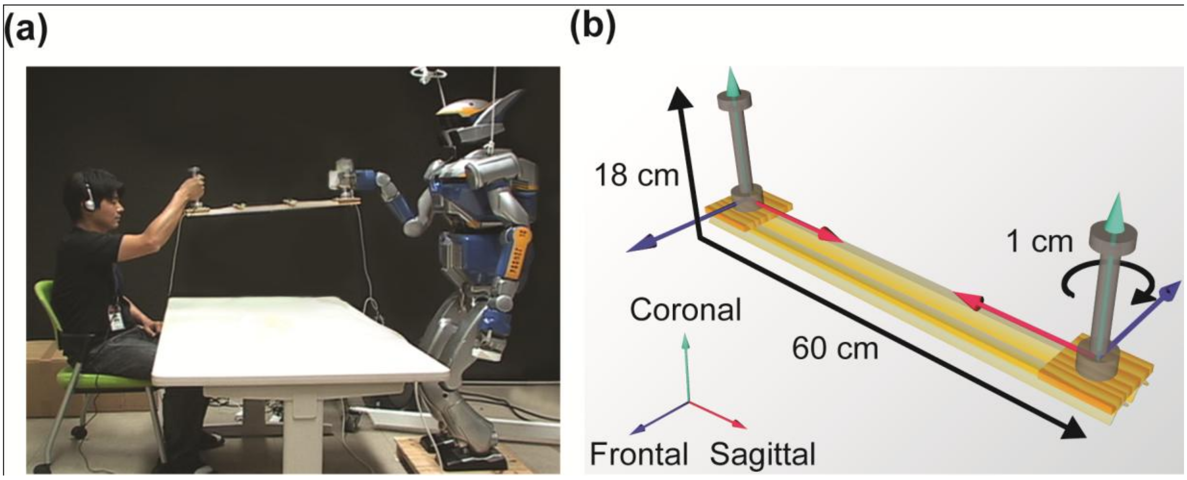

Figure 3.1. (a) Experimental setup. A participant sat in front of the robot and jointly lifted a bar. **(b)** A schematic illustration of the bar. The bar consisted of two handles with force transducers attached onto their bases. The orientation of the transducers was expressed in ego-centric coordinates with respect to each partner.

3.3.4. Design

The robot produced four different types of movement trajectories, all of which were based on a minimum-jerk trajectory (Flash & Hogan, 1985) in the coronal axis with a fixed target altitude of 40 cm (Figure 3.2 and Figure 3.3). In all cases the robot made no movement in the frontal or sagittal axes. The primary difference between the trajectories was whether the current movement was advanced or retarded relative to the standard movement.

Standard trajectory. This trajectory served as a control for the rest of the trajectories. The gripper of the robot tracked a minimum-jerk trajectory of 3 seconds movement duration. The peak velocity of this trajectory was 25.01 cm/s, occurring at 50.0 % of the movement duration. ***Perturbed trajectory: Retardation.*** The movement duration of this trajectory was 3 seconds. One second after movement onset, there was a sudden linear retardation in the velocity profile such that 70 ms after the perturbation onset, the coronal position of the gripper was 1.0 cm lower than at the equivalent time in the Standard trajectory. The choice of these values was determined by the mechanical limitations of the robot’s actuators. After the perturbation phase of 70ms the trajectory was determined by the minimum-jerk model, given the current velocity and acceleration. This resulted in a positional deviation peak of 7.56 cm from the Standard trajectory at 710 ms from the perturbation onset (57.0 % of the movement duration). The velocity peaked at 27.78 cm/s, 985 ms from the perturbation onset (66.2 % of the movement duration). ***Perturbed trajectory: Advance.*** The Advance trajectory was analogous to the Retardation trajectory except that this perturbation caused an advance of the time of peak velocity. This resulted in a maximum positional deviation from the Standard trajectory of 5 cm, 630 ms after perturbation onset (54.3 % of the movement duration). The maximum velocity deviation from the Standard trajectory was 7.45cm/s, 70 ms after the perturbation onset (35.67 % of the movement duration). The peak velocity was 34.77 cm/s. ***Fast trajectory.*** The gripper tracked a minimum-jerk trajectory with movement duration of 2.2 seconds and a peak velocity of 34.17 cm/s. This movement duration was chosen so that the peak velocity would be equivalent to that of the Advance trajectory, which had produced the highest peak velocity among the other trajectories (Figure 3.2).

This experiment consisted of three blocks. In the Repeat block, the robot always produced the Standard trajectory for a period of 15 trials. This block was used as training for the participants, with the goal of investigating learning across trials. In the Interleave block, the Standard and Fast trajectories were alternately interleaved. These trajectories were repeated 15 times each, with the starting order of the two trajectories counterbalanced across participants. This block was introduced to study whether people could distinguish and execute two different types of trajectory while the robot’s movement remained predictable. In the Perturbation block, the robot produced the Standard, Advance and Retardation trajectories in a pseudo-random order. The perturbation trials were randomly inserted between the Standard trials but they never occurred in adjacent trials. There were 15 Advance and 15 Retardation trials and 90 Standard trials.

For participants' comfort, the order of the blocks was fixed, starting with a simpler trajectory and then moving to the erratic perturbation trajectories. Thus, the experiment was conducted in the order of the Repeat, Interleave, and Perturbation blocks.

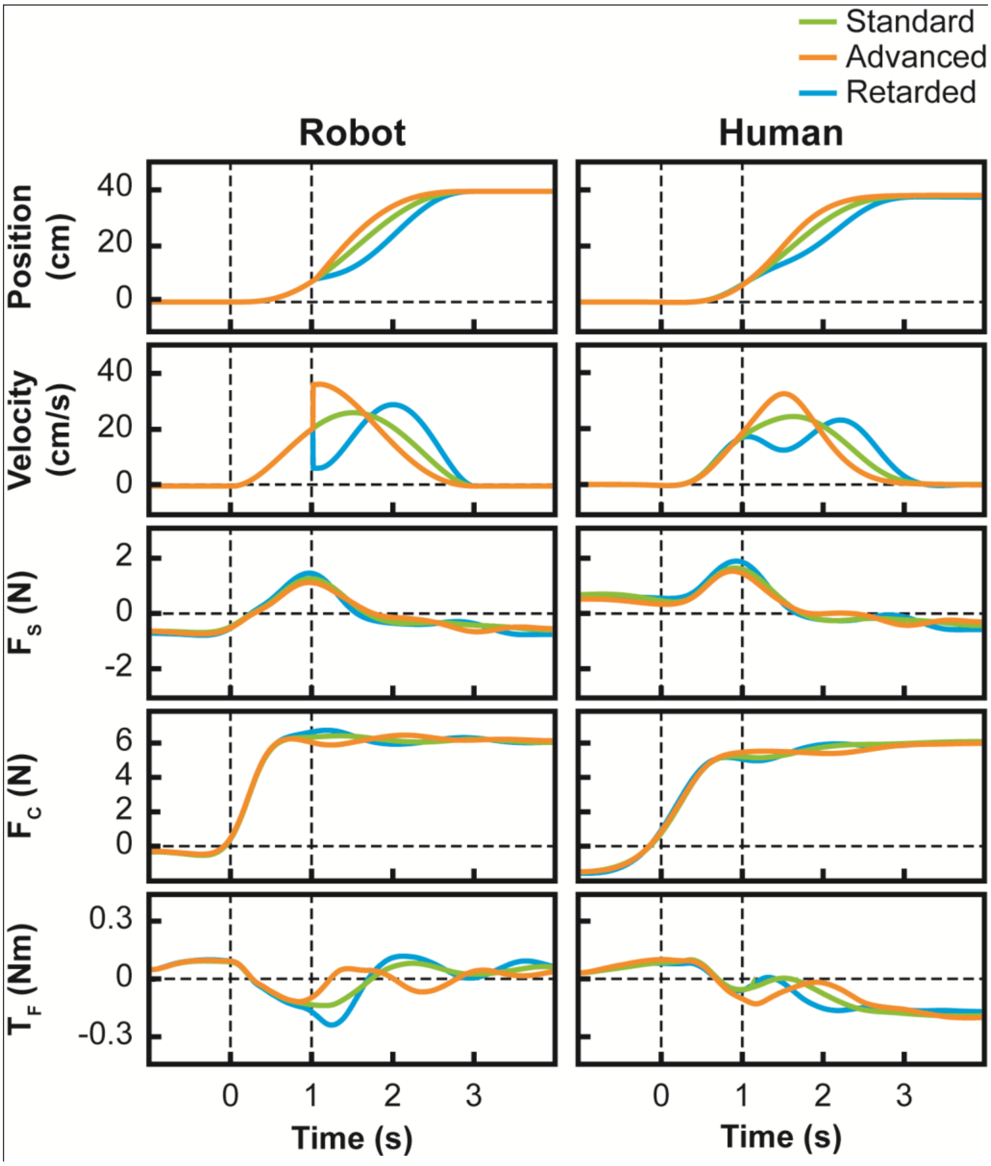

Figure 3.2. An example of movement trajectories and associated forces/torques by the robot and participant. For an illustration purpose, the robot's control signals (position and velocity) instead of the recorded motion data are depicted here. Averaged Standard, Advance, and Retardation trajectories from a single participant are presented. From the movement onset (Time = 0), the trajectories were identical for the three conditions until 1 second into the movement. Since this study focused on a one-dimensional (coronal) kinematic interaction of two agents via a sagittal linkage, only the coronal lifting force (F_C), sagittal force (F_S) and the torque at the frontal axis (T_F) are presented here.

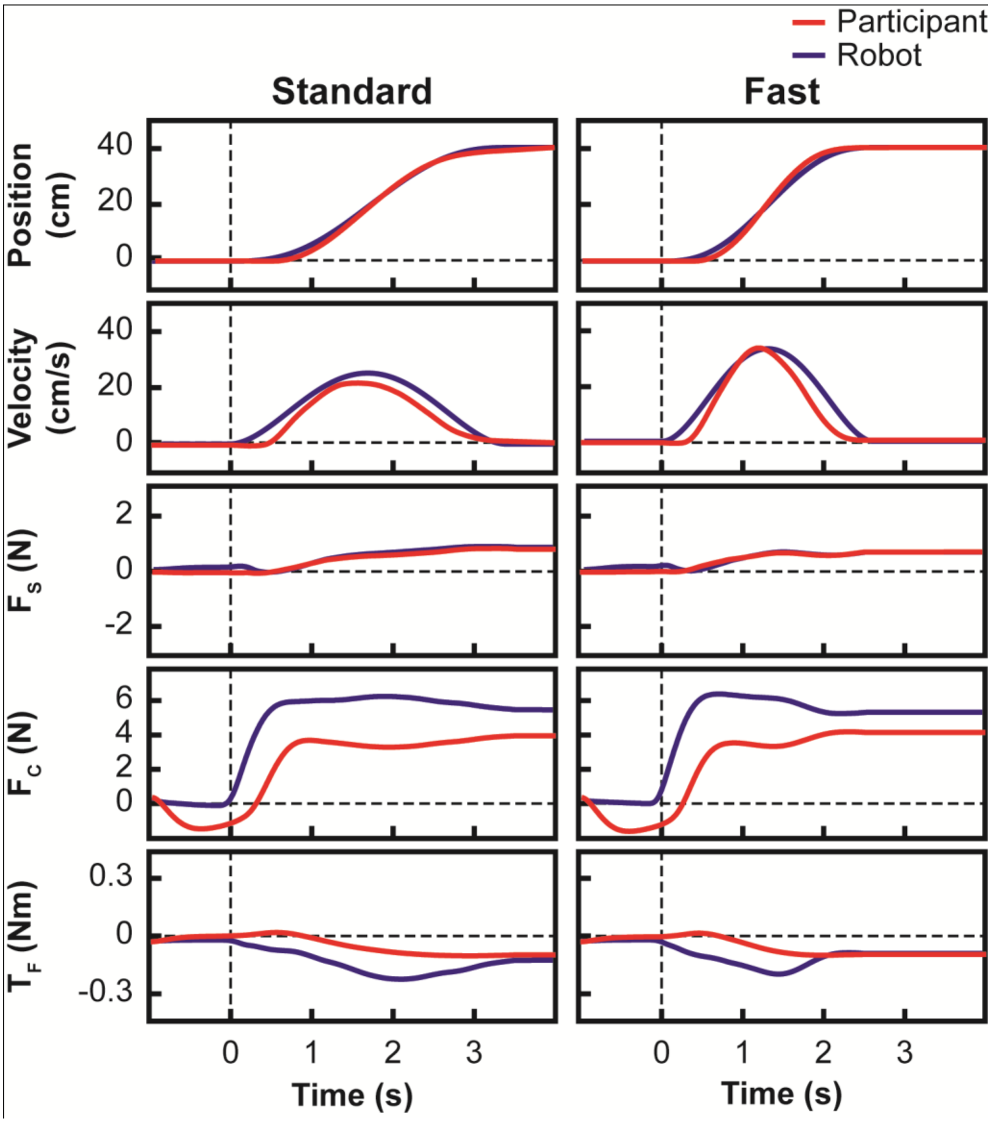

Figure 3.3. Movement profiles in the Interleaved block. Averaged Standard, and Fast trajectories from a single participant in the Interleaved block are presented (N = 15 trials). The time is locked to the start of the lift.

3.3.5. Analyses

A bi-directional second-order Butterworth filter with cut-off frequency of 9 Hz was applied to smooth the motion data prior to analysis. Given possible systematic errors inherent in the motion tracking system, the recorded force/torque and movement data rather than the control signal of the robot were used for analyses when a direct comparison between the participants and the robot was made. Using the two active markers placed on the bar, the positions and orientations of the two handles were calculated in Cartesian coordinates using Visual 3D (C-Motion, USA) and Matlab (MathWorks, USA). This procedure was necessary to determine the kinematics of the handles while they were being grasped. The kinetic measures at the handles were then transformed into fixed ego-centric (body-centred) coordinates of each participant (frontal, sagittal, and frontal axes of the torso) using information about bar rotation and participant seating position.

Chapter 2 showed that rotational information regarding the bar at the frontal axis was important for learning the lifting movement of a task partner. Consistently, the descriptions of the kinetic profiles (see Results of this section) confirmed that the key information was concentrated in the rotational torque around the frontal axis and in the sagittal and coronal linear force. Therefore, the sagittal force and frontal torque were selected for detailed analyses in addition to the velocity and position in the coronal axis. The position and the velocity error were calculated to quantify the overall cooperative performance. The position error was defined as the absolute maximum height difference between the two handles. The velocity error was obtained by subtracting peak velocity of the robot from that of the participant. The start of the lift was defined as the first sampling point where velocity exceeded 5 cm/s before continuously increasing to at least 20 cm/s. The end of the lift was defined as the first point after movement onset when the velocity descended below 5 cm/s.

To investigate the learning of the partner’s movement when the robot 1) moved consistently and 2) alternated predictably between two different movements, the kinematic and kinetic variables of the Repeated (Standard trajectory) and Interleaved (Standard and Fast trajectory) blocks were organised into 3 epochs of five trials each. Two-way repeated measures ANOVA (3 Trajectory x 3 Epochs) were performed to evaluate movement changes across Epochs. Huynh-Feldt correction was applied when the assumption of the sphericity was violated.

To investigate the feedback control and its temporal structure, reaction times to the perturbation in the Retardation and Advance trajectories of the Perturbation block were compared using a paired t-test. An alpha level of 0.05 was considered statistically significant in all analyses.

3.4. Results

The results section is organised into four parts. In the first part, descriptive statistics of the Repeat and Interleaved blocks are presented to describe typical movement profiles in this cooperative lifting task. In the second part, kinematic and kinetic changes due to practice in the Repeat and Interleaved blocks are contrasted. In the third section, corrective responses to unpredictable movements in the Perturbation block are reported. The last section addresses changes in the movement of the Standard trajectory across the three blocks to assess whether participants behaved differently when they expected their partner to repeat the same trajectory (Repeat block) or differently (i.e., Interleaved and Perturbation blocks).

3.4.1. Descriptions of the kinematic and kinetic profiles: Repeat and Interleaved blocks

Repeated block. The average lifting movement duration was 2585 ± 121 ms with a peak velocity of 25.25 ± 1.78 cm/s. The velocity trace was smooth and bell-shaped, which is commonly observed during well-practised single-person movement in reaching tasks (Plamondon et al., 1993). The peak velocity was timed at 44.8 ± 6.9 % of the movement duration. In terms of kinetics, the largest linear force component was concentrated on the coronal axis (F_C), as this was a critical component to accelerate the bar upwards and support it in the air. The peak force observed in this axis over the period of lifting was 6.08 ± 0.86 N. Although not directly linked to the task goal (i.e., coronal movement), a strong sagittal force component was also observed (2.19 ± 0.60 N in absolute value). The direction of the force in this axis (i.e., push or pull) was variable across individuals. Five out of nine participants applied a sagittal force towards the robot (i.e., positive F_S) in more than half the trials (89.3 ± 10.1 % on average for those five participants), and four participants applied the force away from the robot (81.7 ± 15.8 %). The lowest force component was observed along the frontal axis (absolute, 1.15 ± 0.36 N). The largest torque was observed around the frontal axis (absolute, 0.41 ± 0.19Nm). Three participants applied the torque inward (in terms of the resulting direction of hand motion had it not been restrained by the bar handle) towards the robot around the frontal axis (93.3 ± 6.7 %). Six participants applied the torque outward from the robot (78.9 ± 7.8 %). The torque was smaller around the sagittal axis (0.22 ± 0.08 Nm) and almost no torque was observed around the coronal axis (0.05 ± 0.02 Nm).

Interleaved block. The robot produced the Fast and Standard trajectories in an alternating order. Consistent with the reference trajectories of the robot, as Figure 3.4 shows, the peak velocity of the participant's movement was higher for the Fast trajectory (34.04 ± 3.30 cm/s) than for the Standard trajectory (24.61 ±1.33 cm/s). This mean difference was supported by a paired-sample t-test, t (8) = -11.247, $p < .0005$. The time of peak velocity was observed at around the midpoint of the movement duration for both trajectories (49.7 ± 4.3 %). No statistical difference was detected between them ($p = .581$), suggesting that the shapes of the velocity profiles for the Standard and the Fast trajectories were similar. The size of the maximum F_S was larger with the Fast (2.51 ± 0.96 N) than with the Standard (1.83 ± 0.87 N) trajectory, t (8) = -3.593, $p < .01$. The maximum T_F was no different when comparing the two trajectories (0.51 ± 0.30 Nm), and no statistical difference was observed ($p =.667$). The velocity error was larger with the Fast (3.63 ± 1.07 cm/s) than with the Standard trajectory (2.67 ± 1.51 cm/s), t (8) = -2.472, $p < .04$. In contrast, the position error was similar between the two trajectories (4.42 ± 1.74 cm, $p = .910$).

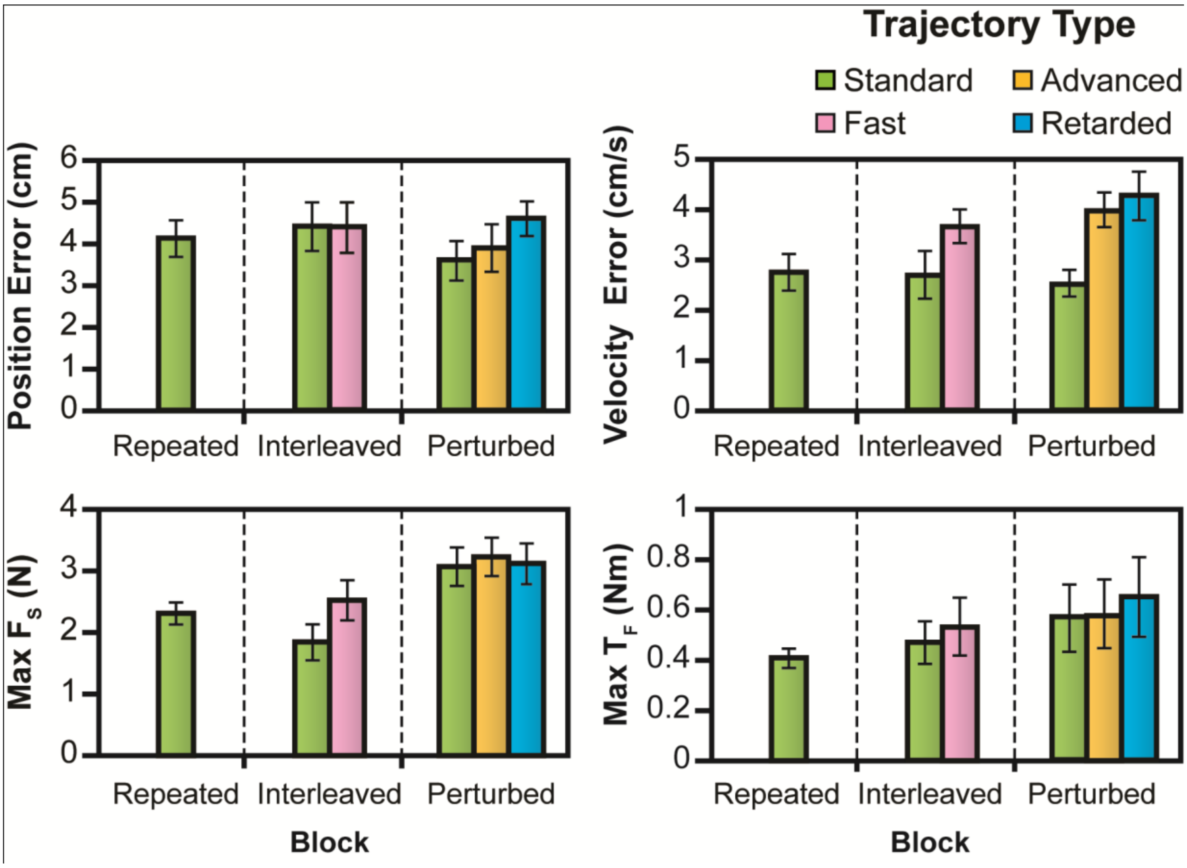

Figure 3.4. Summary statistics. The position error, velocity error, maximum F_S, and maximum T_F of participants when interacting with each trajectory type presented in the different conditions/blocks of trials. Error bars denote one standard error.

3.4.2. Learning about a task partner

In this section, the effect of the trajectory prescribed by the robot on changes in the participants' movement parameters, or the 'learning effect', was studied. In particular, evolution of the position error, velocity error, maximum F_S and maximum T_F across trials in the Repeated (Standard trajectory) and Interleaved (Standard and Fast trajectory) blocks were studied using 2-way (3 Trajectory vs. 3 Epochs) ANOVAs (Figure 3.5).

There was a reduction of the position error from Epoch 1 (4.78 ± 1.86 cm), through Epoch 2 (4.29 ± 1.96 cm) to Epoch 3 (3.93 ± 1.26 cm). The ANOVA supported a significant main effect for Epoch, F (2, 16) = 3.524, p = .05. No significant effect for Trajectory (p = .911) or interaction effect (p = .583) was observed. Similarly, there was a steady reduction of the velocity error from Epoch 1 (3.57 ± 2.03 cm/s) through Epoch 2 (2.60 ± 1.43 cm/s) to Epoch 3 (2.47 ± 1.16 cm/s). The ANOVA revealed a main effect for Epoch, F (2, 16) = 4.897, $p < .03$. There was a trend for Trajectory (p = .083), such that the velocity errors in the Repeated block (2.70 ± 1.15 cm/s) and in the Standard trajectory in the Interleaved block (2.52 ± 1.71 cm/s) were slightly smaller than those in the Fast (3.42 ± 1.53 cm/s) trajectory. No interaction effect was observed (p = .181).

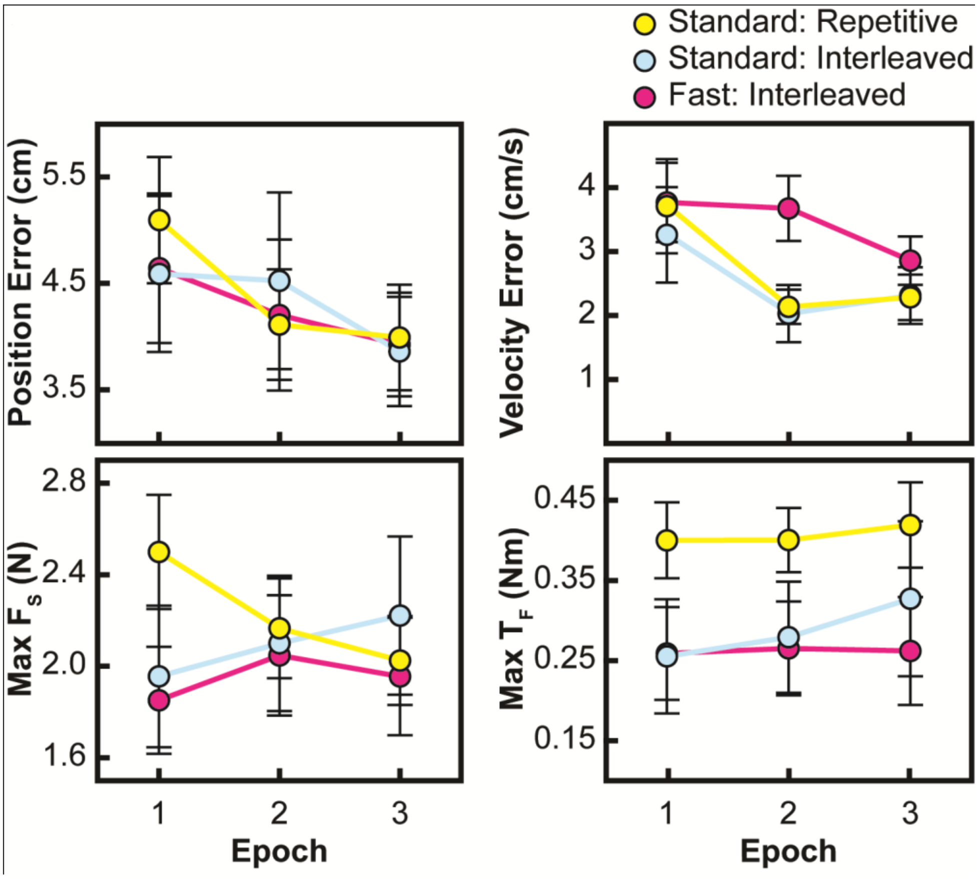

Figure 3.5. Practice effect. The graphs depict the absolute means of the maximum position error, velocity error, F_S and T_F across participants. Each of these movement parameters of 15 trials were grouped into three epochs, Error bars represent one standard error.

Concerning F_S, no main effect for Trajectory ($p = .122$) or Epoch ($p = .915$) was observed. However, there was an interaction effect $F(4, 32) = 4.729$, $p < .005$. Across Epochs, the F_S in the Repetitive block was reduced from Epoch 1 (2.50 ± 0.75 N), through Epoch 2 (2.16 ± 0.65 N) to Epoch 3 (2.02 ± 0.58 N). In contrast, the F_S was low at Epoch 1 in both the Standard (1.96 ± 0.93 N) and the Fast Trajectories (1.85 ± 0.70 N) in the Interleaved block. This level of force was sustained for Epoch 2 (Standard; 2.10 ± 0.88 N, Fast; 2.05 ± 0.79 N) and Epoch 3 (Standard; 2.22 ± 1.03 N, Fast; 1.95 ± 0.79 N).

T_F was much smaller in the Repeat block (0.41 ± 0.12 Nm) than Fast (0.54 ± 0.18 Nm) or Standard trajectories (0.58 ± 0.34 Nm) in the Interleaved block. A main effect for Trajectory was supported by the ANOVA, $F(1.19, 9.53) = 6.405$, $p < .03$. Neither a main effect for Epoch ($p = .499$), nor their interaction, ($p = .550$) was found to be significant.

3.4.3. Perturbed Trajectories

Overall description. Figure 3.2 shows the averaged kinematic and kinetic profiles from the Perturbation Block of the robot and a single participant. When the robot executed the Standard trajectory, the participants generally produced a bell-shaped velocity profile similar to that of the minimum-jerk trajectory with the time of the peak velocity at 51.3 ± 3.8 % of the movement duration. With the Perturbation trajectories, the time of the peak velocity was at 49.4 ± 1.0 % and 62.3 ± 8.8 % for Advance and Retardation trajectories, respectively. The time of the peak velocity was *delayed* by an average of 413.2 ± 30.5 ms in the Advance perturbation whereas the peak velocity occurred *earlier* by 115.9 ± 263.7 ms with the Retardation perturbation. A *delay* of 39.3 ± 112.6 ms was observed for the Standard trajectory. One-way repeated ANOVA showed that there was a significant main effect for Trajectory, $F(1.37, 10.97) = 32.457$, $p < .0005$. Pair-wise comparisons revealed that the delay was larger with the Advanced trajectory than with the Retardation ($p < .005$) or the Standard ($p < .0005$) trajectories.

As Figure 3.4 shows, the Retardation trajectory produced the largest position error (4.64 ± 1.25 cm), followed by the Advance trajectory (3.92 ± 1.67 cm). The position error was the smallest for the performance with the Standard trajectory (3.62 ± 1.42 cm). A statistical difference was confirmed by a repeated-measures ANOVA, $F(2, 16) = 11.973$, $p < .005$, with pair-wise comparisons revealing the difference as being between the Standard and Retardation trials ($p < .002$). The velocity error also differed in size across the three trajectories, $F(2, 16) = 7.965$, $p< .01$. The peak velocity in the Retardation trajectory was significantly larger (4.24 ± 1.54 cm/s) than in the Advanced trajectory (3.96± 1.07 cm/s, $p < .02$) or the Standard trajectory (2.51 ± 0.85 cm/s, $p < .04$). Thus, perturbation influenced the size of the velocity error.

At the kinetic level, a repeated-measures ANOVA showed no difference in the maximum F_S across three types of trajectories in the Perturbation block (3.12 ± 0.31 N, $p = .153$). Detailed inspection of the data from the Perturbation block revealed a consistent increase of F_S nearly 1 second in (just before perturbation onset time) in all three types of trajectories, regardless of the presence of the perturbation. Thus, the time of the peak F_S rate was further studied. In general, the participants exerted a strong internal force to cope with the unpredictable perturbation. The peak F_S rate occurred at an average of 263.15 ± 59.43 ms prior to the potential perturbation time across the three trajectories. A one-way ANOVA indicated that there was no time difference across the trajectory types ($p = .447$).

On-line correction to perturbation. Reaction time to the perturbation was defined as the time at which the participant’s trajectory during the Perturbation trajectories deviated from their Standard trajectory. To calculate the reaction time, each trajectory type was averaged for each participant. The averaged Advance trajectory and averaged Retardation trajectory were each then subtracted by the averaged Standard trajectory (Figure 3.6). The reaction time to the perturbation was then defined as the time the perturbed trajectory deviated from the averaged standard trajectory by more than 0.02m/s and continued to exceed it for more than 200 ms. Recovery time was defined as the time when the velocity of human participants and the robot were closer than 0.02 m/s and continued within this range until the end of the trial.

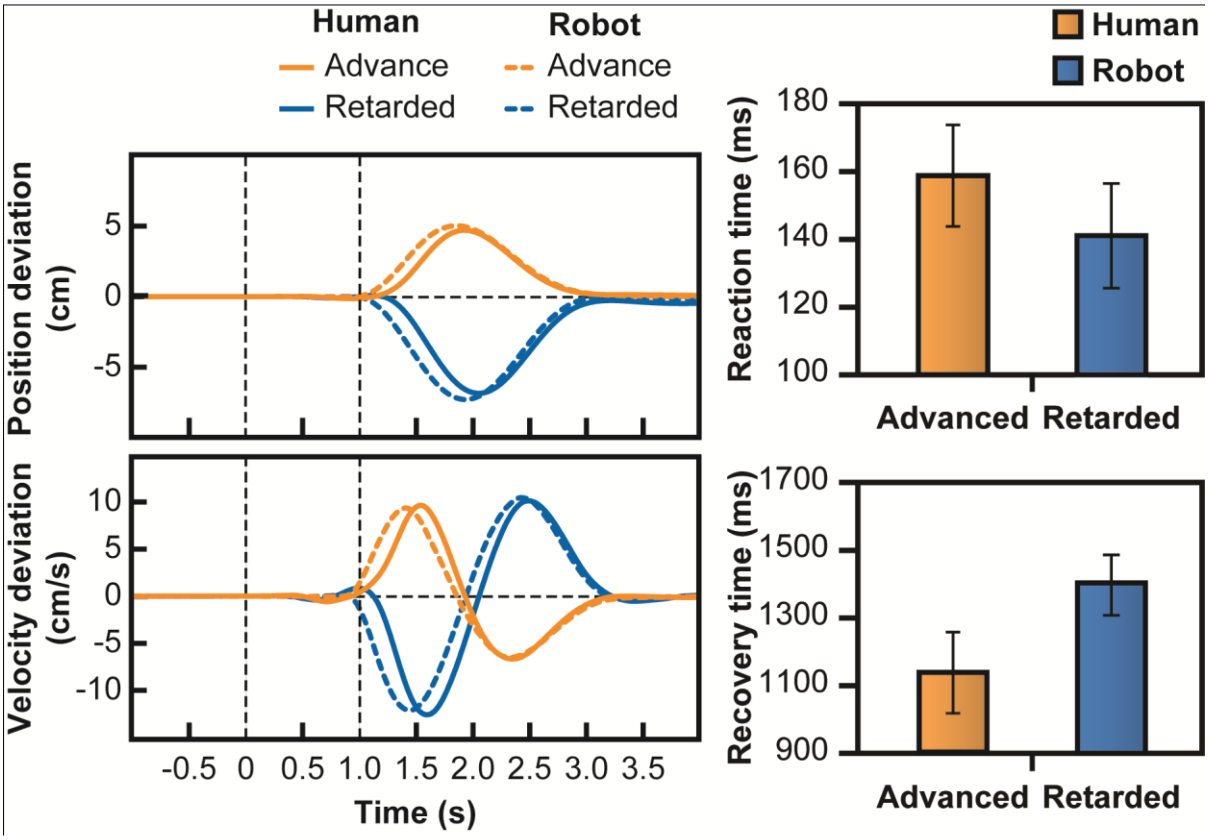

Figure 3.6. (a) Kinematic divergences of averaged Perturbation trajectories from the Standard trajectory of a single participant. The position and velocity profiles of the Standard trajectory were subtracted from the Perturbation trajectories. Note that a deviation from the Standard trials, which occurred in relation to a perturbation in the robot's trajectory, was observed in the participant after a small delay. Towards the end of the trial, both position and velocity were synchronised with the robot. **(b)** The reaction time to, and recovery time from, the Advance and Retardation perturbations. The error bars represent one standard error.

The reaction times were 158.9 ± 44.9 ms and 141.1 ± 46.5 ms to the Advance and to the Retardation perturbations, respectively. A one-sample t-test comparing the observed values against zero confirmed the delay in response to the perturbation produced by the robot for the Advanced, $t(8) = 10.629$, $p < .0005$, and for the Retardation, $t(8) = 9.106$, $p < .0005$, trajectories. A paired-sample t-test indicated there was no significant difference between the reaction times in the Advance and Retardation trials, $t(8) = .919$, $p = .385$. The recovery times following perturbation onset were 1132 ± 365 ms and 1396 ± 272 ms for the Advanced and Retardation perturbations, respectively. A paired-sample t-test indicated a significant difference in the mean recovery times such that the recovery was quicker for the Advanced trials than for the Retardation trials, $t(8) = -2.287$, $p = .05$.

3.4.4. Standard trajectories in the presence of other trajectories

To examine how the kinematic and kinetic parameters in the Standard trajectory differed when the participants were/were not expecting different trajectories, the maximum F_S, T_F, position error and velocity error of the Standard trajectory in the Repeat, Interleaved, and Perturbation blocks were analysed using a repeated-measures ANOVA (Figure 3.4). The position error of the Standard trajectory was 2.76 ± 1.16 cm during the Repeat block. During the Interleaved block, the position error was slightly larger with 3.12 ± 1.58 cm. During the Perturbation block, the error was 2.60 ± 0.84 cm. The analyses showed no difference in the position error size ($p = .485$). The velocity error was 4.40 ± 1.32 cm/s for the Repeat block, 4.90 ± 2.24 cm/s for the Interleaved block, and 3.63 ± 1.42 cm/s for the Perturbation block. Again, no difference for velocity error was observed ($p = .105$). Furthermore, no difference across Blocks was observed in T_F ($p = .976$) or F_C ($p = .08$). The only statistical difference was observed in the F_S, $F(2, 16) = 14.371$, $p < .002$, such that the maximum F_S in the

Standard trajectory was larger in the Perturbation block (3.05 ± 0.31 N) than in the Repeat (2.30 ± 0.18 N, $p < .043$) or the Interleaved blocks (1.83 ± 0.29 N, $p < .006$).

Discussion

Since cooperative action involves two sets of actions that are generated by separate CNSs, the movement of a partner may not always be predictable. This study examined how the participants' movements responded to cope with different types of movement trajectory prescribed by a task partner – the robot - as they jointly lifted an bar. The robot either repeated the same trajectory, repeated two different trajectories in an alternating order, or produced a perturbing movement randomly embedded in trials of a routine trajectory.

The study demonstrated that cooperative actions are supported using two schemes: an anticipatory control of movement adjustment to a task partner (which develops over the course of interaction) in addition to an online correction within a single movement when the robot suddenly deviates the trajectory from a routine trajector. These schemes are eployed in order to minimise the error induced by the partner. The results revealed that the participants very quickly learnt the movement trajectory of the robot, as shown by the reduction of the position and velocity errors when the robot only produced the same movements. The practice effect of the performance was also in evidence when two different trajectories were alternately prescribed. Thus, the results indicate that there was a learning of the task partner, which resulted in a quick reduction of the error, and that this learning could be achieved for different movement trajectories in parallel.

The sagittal force was gradually reduced over the course of the interaction and, unlike positional and velocity errors, the course of its reduction was not affected by the introduction of predictable speed change of the partner (Interleaved block). Thus, the smaller sagittal force is unlikely to be a simple by-product of reduced coordination error. Importantly, the sagittal force exchange between the partners is redundant (i.e., task irrelevant) to the primary goal of the task. Thus, the reduction of the sagittal force may be linked to minimising redundant interaction in cooperative action (Ito et al., 1999). In support of this hypothesis, a localised increase of the sagittal force was observed in anticipation of possible erratic behaviour by the robot, possibly due to an effort to increase the stiffness of the interaction between the partners in order to secure the mechanical linkage and minimise movement disturbance by the perturbation. Therefore, it seems that the participants evolve their behaviours in terms of reducing performance error with the partner as well as in response to the expectation of erratic behaviour by the partner. The remaining chapters in this thesis focus on patterns of error correction in response to the behavioural statistic of a task partner in an effort to validate this account.

The position errors were not strongly affected by expectation about the erratic movements by the task partner such that the errors during the Standard trajectory when expecting different/perturbing movements were statistically no different to those made when the participants performed the task with the robot which repeated the same movement throught the block. On the other hand, the size of the velocity error was influenced by the speed and erratic behaviour of the robot. In particular, a notably large velocity error was evident during the perturbation trajectories. These results may reflect that the participants engaged in feedback control during the perturbation try to maintain the position error by modulating the velocity. When the robot's movement was unpredictably perturbed, the participants followed the robot's movement with a lag of about 150 ms. This is much longer than the 80 or so ms taken, according to the literature, by the supraspinal reflex for movement correction via the somatosensory system (Johansson & Westling, 1988). The lag between the participants and the robot was smoothly recovered at around the deceleration phase of the lifting movement. While the type of the perturbation did not influence the reaction time, the recovery time was slightly longer when the robot unpredictably advanced its trajectory.

The coordination of reaching movements with a moving target has been studied in terms of a single actor intercepting a moving object (Smeets & Brenner, 1995). Such interceptive movement is performed by utilising knowledge of the velocity of the moving object, or how it behaved previously (Brouwer et al., 2000). Importantly, these studies indicated that the interceptive movements are invariant across the spatial point of the interception, regardless of the velocities of the movements. Thus, it was suggested that the interceptive movement is implemented by estimating the time when the object arrives at a particular position rather than predicting the position of the object given the velocity (Rushton & Wann, 1999). In our study, the position error as well as the recovery time was found to be smaller with the Advance trajectory. This may be explained by the fact that the spatial position of the Advance trajectory was ahead of the Retardation trajectory in time during a large proportion of the movement (Figure 3.2). Hence, any given “catch-up” position was reached earlier in time with the Advance trajectory than with the Retardation trajectory.

In order to implement a specific reference trajectory for one of the pair, the present study used a humanoid robot as a task partner. There is a large debate as to how people may interact differently to movements of another person in comparison to non-biological agents (Tai et al., 2004). It is well known that people are tuned to detect biological motion and can extract a range of social attributes from movements of small points (Blake & Shiffrar, 2007). Previously, it has been shown that believing one is coordinating an action with a human or a robotic partner can result in different behavioural responses of the perceiver regardless of whether the action was of human or robotic simulation (Stanley et al., 2007). In addition, differences in neural responses have been demonstrated during observations of biological compared with non-biological movements, especially when the latter lacked the natural variability of human movements (Gazzola et al., 2007) or the former followed a non-Gaussian velocity profile (Kilner et al., 2007). In our study, although the robot executed minimum-jerk movements, which are known to closely approximate simple human arm movements, nonetheless the observer was presented with visual information that clearly signalled a robot. Thus, caution should be exercised in generalising the conclusions regarding the results of this experiment to include natural social interaction between people. On the other hand, the present study has demonstrated that the CNS can support cooperative object-lifting by flexibly implementing feedforward and feedback controls. Furthermore, a different motor strategy was evident when the task partner's behaviour was unreliable and so needed compensation. In order to further elucidate the adaptive mechanisms underlying cooperative interaction, the next chapter sees interpersonal interaction realised in terms of error-based learning wherein two people cooperatively lift the object used in the present study.

When a pair performs a shared motor task, the difference in the movements exerted by each partner should be corrected as a pair and not as an individual. Thus, lack of knowledge about what the partner might do can lead to an unstable outcome. One of the problems involved in understanding behaviour of two persons is that they are responsive to each other and their task solutions can be highly interactive. Such mutual responsiveness can create difficulties in the interpretation of the behavioural data.

Chapter 4

Error-Based Learning in Cooperative Action

4.1. Abstract

The central nervous system (CNS) maintains the accuracy of motor outputs by learning from motor errors. This study investigated whether motor learning by practices in a cooperative task varies according to the information available to each partner about previous trial outcome, with specific regard to the effect of failure to coordinate movement with another person. In the study, paired participants lifted an object to targets of varying heights whilst keeping the object orientation as level as possible, and the evolution of their kinematic and kinetic parameters was analyzed. These movement parameters were fitted to a simple first-order time series model to describe cooperative action as a dynamic process of two partners mutually reducing the movement difference between them. Just as in single-person motor task repetition, the study suggests that error-based learning is evident in a cooperative task.

4.2. Introduction

The central nervous system (CNS) maintains accuracy of motor commands through adaptation. In individual action, voluntary movements, such as moving the hand between two points in space, are subject to errors. The noises inherent in the sensory and motor processes (Faisal et al., 2008), and a lack of information about the associations between motor commands and the changes they bring to the environment (Shadmehr & Mussaivaldi, 1994), deviate movement from accomplishing a desired effect. When the motor outcome reliably deviates from the intended movement, the CNS adapts and refines the output signal to minimise the risk of making the same error again (Wolpert & Ghahramani, 2000). Such adaptive behaviour can be accounted for by simple linear models (Thoroughman & Shadmehr, 2000; Vorberg & Wing, 1996). In these models, motor output is realised in a time-dependant fashion such that the motor output in a subsequent response is adjusted by some proportion of the observed error from the desired state in the previous movement. In principle, various adaptive models conform to this structure (Behrens et al., 2008; Kon & Miyake, 2005; Repp & Keller, 2008; Thoroughman & Shadmehr, 2000). This “error-based learning” plays a key role in optimising anticipatory movements in individual action (Thoroughman & Shadmehr, 2000).

Recently, studies on joint action have shown that people are sensitive to errors produced by others, errors that may be processed in a similar fashion to our own. Evidence for this is provided by feedback-related negativity (FRN), a neural event observed using electroencephalography (EEG). This neural component is elicited as a negative deflection of the event-related potential following presentation of a negative stimulus such as when a person perceives his/her own mistake during a cognitive task; it peaks at 200 – 350 ms following the stimulus presentation (Holroyd & Coles, 2002). However, the FRN is not only observed after a person detects an error in his/her own behaviour. An observational FRN also manifests after observing another person making an error, suggesting that the detection of one's own and others' observed errors involve similar neural mechanisms (Yu & Zhou, 2006; van Schie et al., 2004; Bates et al., 2005). A behavioural study by Schuch and Tipper (2007) also demonstrated that observation of another person's error invokes similar effects to those invoked by one's own errors. In their study, participants either performed a speeded choice-reaction-time task or observed another person performing the same task. When a participant performed the task and made a mistake, the reaction time in the subsequent trial was slowed, a phenomenon termed as post-error slowing (Rabbitt, 1966). Interestingly, the results of the Schuch and Tipper study showed that the reaction time was also slowed after observing somebody else making the error. Their study demonstrated that observing another person's error influences that observer's subsequent behaviour, strengthening the argument for the existence of common mechanisms for processing one's own errors and the errors of others (Notebaert et al., 2009).

Despite evidence that people can predict the actions of others and are aware of others' errors, little is known about how error signals are utilised in making predictions about the actions of others. For example, it would be interesting to know if one's own error correction is reduced when one's task partner's error correction increases. This study, therefore, investigates whether error-based learning is present during a cooperative task. In the study, the participants performed a task which required explicit coordination with their partner, wherein good performance depended on responding to the task partner's movement characteristics. The task involved paired participants grasping an object by its longitudinal ends and vertically lifting it to a target height while relying only on haptic feedback. In order to manipulate knowledge about the task, the target was provided to either just one or to both participants.

This study serves three purposes for furthering our understanding of cooperative object lifting. Chapters 2 and 3 analysed the role of haptic feedback in cooperative action using kinematic information. However, systematic interpersonal error-related response may be evident at the kinetic level and this is included in the following study. Secondly, the study investigates whether error-based learning by a task partner takes place with the error being defined by the interpersonal difference in a movement parameter, and if so, which movement parameter best characterises the learning in a cooperative task. It was hypothesised that the interpersonal movement error would be reflected in changes in participants' movement parameter values in the subsequent trials, such that a strong correlation between a movement error and a subsequent change in that movement would support the notion of error-based learning in cooperative interaction. Thirdly, the study shows how the degree of error-based learning may be adjusted by varying information available. Namely, the target for object lifting was provided to one or both partners. This might result in a change of dependence between partners such that the partner with the knowledge about the target would be more likely to lead the task and be less affected by movements of the ignorant partner. In contrast, when the target is not known, a person has to actively follow the knowledgeable partner for successful joint outcome. The 'follower' is expected to show stronger adaptation to the 'leader' than vice-versa, with the leader dictating the movement trajectory.

4.3. Method

4.3.1. Participants

20 participants (12 male, 8 female, mean age: 24.4 ± 3.5 years) took part in this study. The participants were randomly paired and completed the study in those pairs. There were four male-male pairs, 2 female-female pairs, and 4 mixed pairs. One of the participants was left-handed and the remaining participants were right-handed. All were naive to the purpose of the experiment and gave informed consent prior to testing. The participants received £6 or course credits for their time in completing the study.

4.3.2. Apparatus

In each trial, participants lifted a 60 cm wooden bar to a specified target height. The target height was indicated on four 60 cm columns which stood 50 cm sagittally and 30 cm coronally apart from each other (Figure 4.1a). In addition to signalling target height, these columns were used to restrict participants from making large horizontal movements. Targets were indicated on horizontal grid lines (0.5 cm calibration) drawn onto the top 20 cm of each column. Five circular indicators, in different colours, were placed every 4 cm between the heights of 46 and 58 cm on the column as possible target heights. Cards with the same set of coloured indicators and one with no indicator were prepared to inform each participant separately about the target heights.

The bar was designed so that its shape and mass distribution were symmetric for the two participants as they sat and faced each other (Figure 4.1b). Two aluminium handles, radius 10 mm, 60 cm apart, were mounted on top of the bar so that their tops were 18cm above the bottom of the bar. At the bottom of each handle a 6 DoF Force/Torque sensor (Mini-45, ATI) was attached to measure the force and torque at 1,000 Hz. The total weight of the bar, handles and transducer was 1 kg.

A 12-camera motion tracking system (Qualisys, Sweden) tracked 4 retroreflective markers attached to the bar at 200 Hz. Although the marker locations were arbitrary, their distances from the two handles were measured in order to extrapolate the positions of the handles (see Design for detail).

Two auditory beeps were presented to each participant through a pair of headphones (MDR-Z700DJ, Sony) to indicate the start of a trial. To prevent participants from using the beeps as timing cues to synchronise movements with their partner, the inter-stimulus interval of the beeps varied randomly between 0.75 – 1.25 seconds. White noise (80 dB) was presented to the participants through the headphones to minimise the auditory feedback from the task. A lightweight screen was placed between partners when they were not performing the task to prevent visual interaction between them.

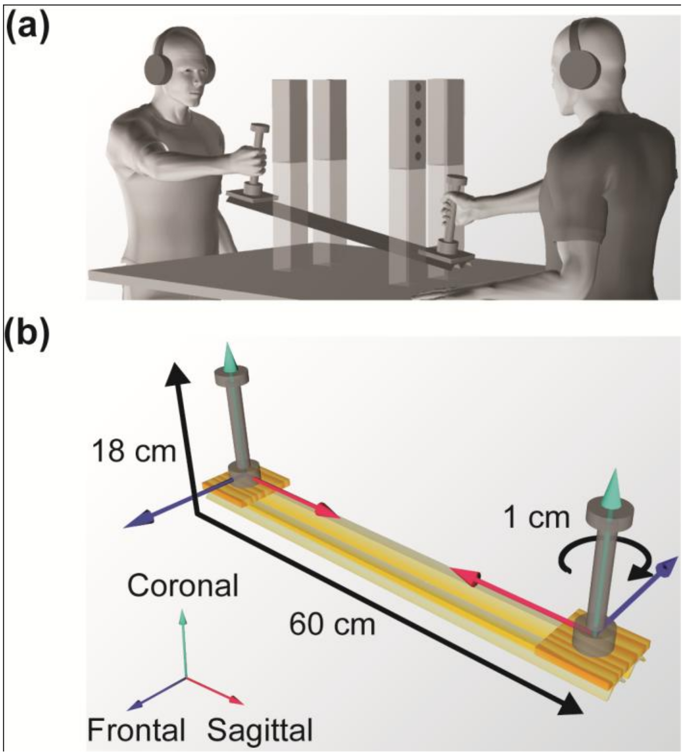

Figure 4.1. (a) Workspace. The participants used a power grip to hold the handle and lift the wooden bar to a target height indicated on the columns in front. The participants were told which target he/she should aim for prior to each block. **(b)** Schematic illustration of the bar and handles. The handles were attached to force transducers attached to the wooden bar. The coordinate axes for each transducer were defined with respect to the participant at each end.

4.3.3. Procedures

Pairs of participants were asked to use arm movements (shoulder and elbow) to lift the bar to a specified target height with their task partner as fast and as nearly in synchrony as possible. The participants sat on height-adjustable chairs and faced each other. The bar was placed on the table in front of them so it was aligned in the frontal plane with the shoulder of their dominant hand. The height of the chair was also adjusted vertically to align the bar with the elbow when the upper arm was at the side of the body. The distance of the bar from the trunk in the sagittal plane was equal to the length of the forearm so that the elbow angle was approximately 90 degrees when the upper arm was at the side of the body while holding the bar on the table. At the beginning of each trial, the participants held the handle with a power grip (i.e., the whole hand).

A card with/without one of the coloured indicators was presented separately to each partner at the beginning of each block. When a target was specified, the participants lifted the bar to the height of the corresponding marker on the column. When there was no indicator, a target was not specified so that the person was required to follow the movement trajectory of their task partner to maintain the vertical orientation of the object. No information was given to the participants with regard to their partner’s target. When the participants had memorised the specified target height, they grasped the handle and waited with eyes closed for the auditory beep.

At the beginning of each trial, two auditory pulses were played; one for preparation, and the second for the start of the trial. When the participants had finished their lifting movement, they maintained the end position and opened their eyes so they could observe how well they had performed the task. The participants then returned the bar to the starting position on the table ready for the next trial.

4.3.4. Design

This study was a repeated-measures design. One independent variable, with three levels, was Role in the task. In one condition, one of two partners played the leading role (Leader) and the other partner played the following role (Follower). The Leader was provided with a target whereas no target was specified for the Follower, who was thus required to coordinate his/her movement with the Leader. In another condition, the Roles of the partners were reversed. In the final condition, the participants had a mutual role (Mutual) such that both partners were presented with the target. Each block consisted of 10 trials and the above three conditions were separately repeated twice to avoid the movements becoming excessively stereotypical and to maintain relatively large interpersonal error compared to sensory and motor noise originating from each individual partner. The order of the blocks was random except that the participants never played the same Role in two successive blocks. The target height was also randomly selected. The experiment took approximately 45 min to complete.

Dependent variables were grouped into two categories, individual and cooperative, which were statistically analysed using different methods (Table 4.1). Individual variables were movement parameters which separately described how each participant performed the task. In haptic cooperative action, there are a number of kinematic and kinetic variables that can be related to error-based learning. To explore which movement parameter would show evidence of adaptation in this task, the variables listed in Table 4.1 were subject to model-fitting. In addition, for mean comparisons, these variables were organised by Role (Lead, Follow, or Mutual), with a total of 20 participants in each case. However, the participants performed the task in pairs, and each variable is potentially correlated between the partners who performed the task together. Therefore, a within-subject ANCOVA was used, which partialled the covariance within the same pair out from the analysis.

The cooperative dependent variables used for describing overall performance were angular error and internal force (i.e., push towards/pull away from the robot). The former was particularly important because the participants were explicitly asked to maintain the object on a horizontal plane. Concerning the latter, it has been suggested that adaptation of biological systems may reflect reduction of redundant interaction (Ito et al., 1999), namely the internal force between the partners in this cooperative task. Since the cooperative dependent variables quantified the performance of each pair as a single parameter, the data were first organised in terms of Mutual and non-Mutual blocks wherein non-Mutual blocks consisted of two levels: Participants who played the Leader first (Lead Start) and participants who played Follower first (Follow Start). The order of the experiment was included as an independent variable for analysis in order to evaluate an order-effect on role-taking and also to keep the sample size equal across three levels. The dependent variables were then submitted to a within-subject ANOVA.

	Kinematics		**Kinetics (vertical, sagittal, coronal)**
Individual	Reaction time (ms)		Peak force (N)
	Movement duration (ms)		Peak force rate (N)
	Peak velocity (cm/s)		Peak torque (mN)
	Peak acceleration (cm/s^2)		Peak torque rate (mN)
Cooperative	Maximum Angular Error (degree)		Internal force (N)

Table 4.1. List of individual and cooperative dependent variables. Note that for kinetic parameters, three orthogonal axes for each variable were separately analysed for individual dependent variables whereas the internal force (cooperative variable) was a vector product.

Kinematic and kinetic data were smoothed using a bidirectional 2nd order Butterworth filter with 12Hz frequency cut-off prior to processing. Using the four reflective markers placed on the bar, the positions and orientations of the two handles were calculated in

Cartesian coordinates using Visual 3D (C-Motion, USA) and Matlab (MathWorks, USA). This procedure was necessary to determine the kinematics of the object despite being grasped by the participants' hands. Using the rotational information of the object, furthermore, the kinetic measurements were transformed into the ego-centric (body-centred) coordinates of each participant (vertical, sagittal, and coronal axes of the participants).

The start of the lift was defined as the first sampling point at which velocity exceeded 5cm/s and continuously increased to at least 20 cm/s. The end of the lift was the first point when the velocity descended below 5 cm/s (Figure 4.2). The reaction time (RT) was defined as the time between the second auditory beep to the start of the lift, and the movement duration (MD) was the time between the start and end of the movement. The maximum angular error was the largest angle in the sagittal plane of the object during a trial. The internal force (*I*) was calculated by subtracting the vector forces applied by one participant (F2) from the other (F1), as expressed below:

$$\mathrm{I} = \left\| \begin{bmatrix} \mathrm{F1_S} \\ \mathrm{F1_F} \\ \mathrm{F1_C} \end{bmatrix} - \begin{bmatrix} -\mathrm{F2_S} \\ -\mathrm{F2_F} \\ \mathrm{F2_C} \end{bmatrix} \right\|$$

eq. 4.1

Note that the sagittal and frontal force axes of the second participant are reversed since the force measurements are expressed in ego-centric coordinates.

4.4. Results

4.4.1. Kinematic and kinetic description of the task

Figure 4.2 illustrates a typical example of kinematic and kinetic profiles. The average duration of lifting movement (MD) was 1207 ± 209 ms with the peak velocity (PV) of 66.74 ± 14.83 cm/s. The velocity trace was smooth and bell-shaped, which is commonly observed during well-practised single-person movement in reaching tasks. The time of the peak velocity (tPV) was observed at 45.0 ± 7.3 % of MD. Concerning kinetics, a large amount of linear force was concentrated at the coronal axis (F_C), as this was a critical component for supporting the object in mid-air. On average, 68.5 ± 10.3% of force was allocated to the coronal axis when the object was stable at the target height (i.e., equilibrium point). The peak force observed over the period of lifting was 7.63 ± 2.45 N. Despite the fact that it was not directly linked to the task goal (i.e., vertical movement), the participants exerted a strong sagittal force (allocation of 19.8 ± 11.7% at the stable position). Across pairs of participants, on an average of 99.5 ± 1.7% of trials, the sagittal force was directed towards (i.e., pushing) their partner, with an absolute peak force in the lifting period of 4.06 ± 3.20 N. More than half of the rotational torque was observed around the frontal axis (T_F: 59.9 ± 15.8 %), and the absolute peak torque was 0.85 ± 0.67 Nm. Across participants, the rotational torque was applied inward (i.e., push towards their partner) on 65.1 ± 19.5 % of trials. The peak torque for Ts (p: 0.25 ± 0.14 Nm) and T_C(0.13 ± 0.11 Nm) were considerably smaller with 25.0 ± 13.8 % and 15.1 ± 10.2 % of torque respectively exerted around these axes.

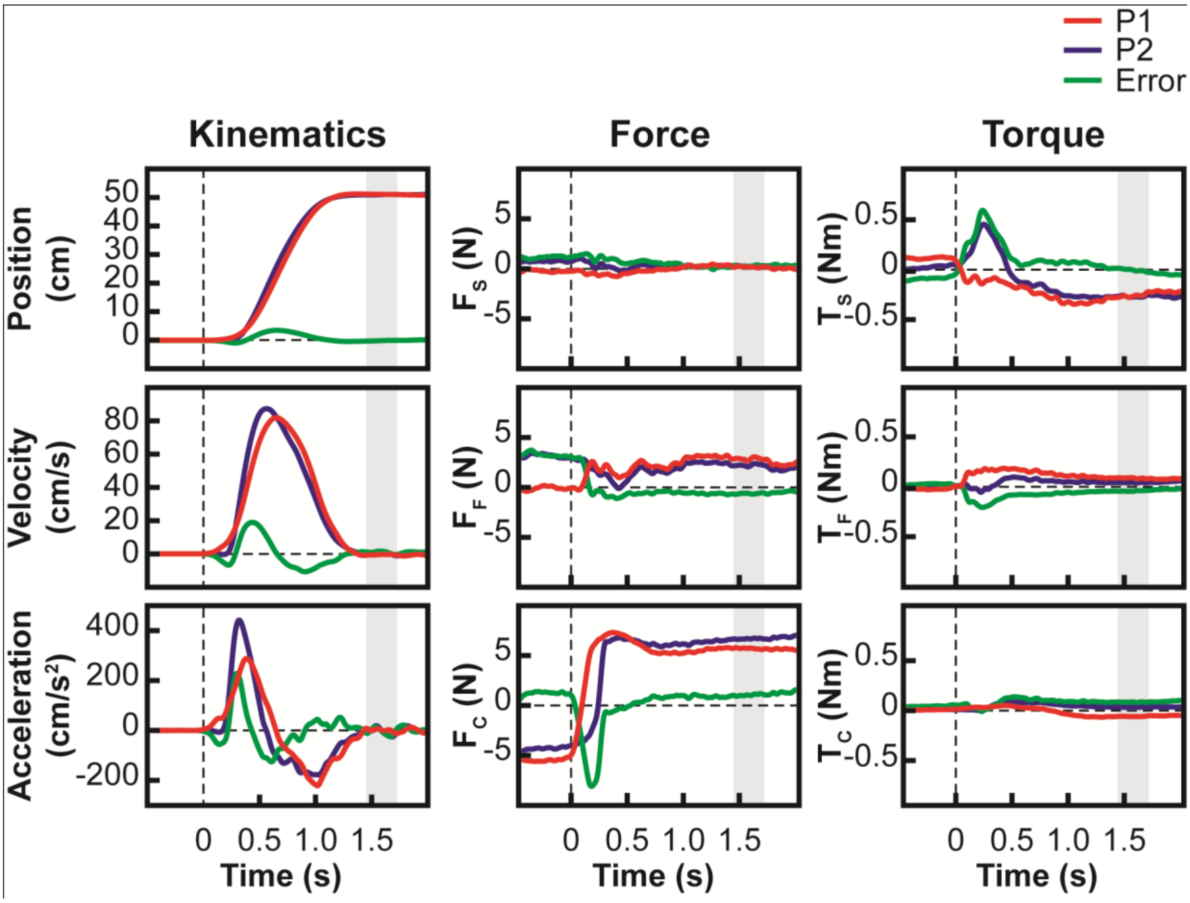

Figure 4.2. An example of kinematic and kinetic profiles. The movements of a pair in a single trial were depicted in red (P1) and blue (P2) lines, with their difference in green (P2 minus P1). The time is locked to the start of the lift. A period of 250ms after the end of the lift was termed the equilibrium point to calculate the force/torque allocations along/around sagittal (F_S/T_S), frontal (F_F/T_F) and coronal (F_C/T_C) axes. At the beginning of the trial, the F_C is measured to be sub-zero. This is due to a participant resting his/her hand on the handle, thus exerting a downward force.

4.4.2. Individual performance

The ANCOVA indicated that the MD was affected by Role, F (2, 36) = 12.267, p< .005, such that the participants spent longer to complete the lift when they were both responsible for the task (Mutual: 1282 ± 239 ms) than when they played either the Follower (1167 ± 225 ms, p < .005) or Leader (1178 ± 235 ms, p < .005). The statistical analysis indicated there was no RT difference between Roles (p = .480), and that their average RT was 571.3 ± 210.2

ms. Similarly, no statistical difference between Roles was observed for tPV (43.1 ± 8.6 %, p = .577). Nor was the peak acceleration (PA) affected by the Roles (281.1 ± 103.4, p = .161).

4.4.3. Cooperative performance

In terms of the overall performance, there was an effect of Role in the maximum angular error during the movements, F (2, 16) = 5.030, p < .03, such that the smallest angular error was observed with the Mutual role (0.4 ± 3.1 degrees), compared to larger angular error in roles of Lead Start group (3.51 ±5.50 degrees, p < .03) or Follow Start group (2.61 ± 5.29 degrees, p < .03). Also the internal force was higher in Lead Start group (8.52 ± 3.60 N) and Follow Start group (7.45 ± 1.74 N) than Mutual role (7.12 ± 1.57N). However, no statistical difference for the internal force (difference in three orthogonal vectors) between these roles was observed (7.70 ± 2.30 N, p = .261).

4.4.4. Model fitting

Dependent variable selection. A simple form of time series model suggests that current performance is adjusted by a product of a previous error to improve the performance in the next trial as expressed below:

$$Z_{An+1} = Z_{An} + \alpha_A (\mathrm{Z_{Bn}} - \mathrm{Z_{An}}) \qquad \text{Model 1}$$

, where Z_{An} is a dependent variable reflecting the performance of Partner *A* at Trial *n*, Z_{Bn} is a dependent variable reflecting the performance of Partner *B* at Trial *n*, and α is the adaptation rate which reduces the difference between partners. In reverse, therefore, the product of change of action over two adjacent trials ($Z_{An+1} - Z_{An}$) over an interpersonal error ($Z_{Bn} - Z_{An}$) should give rise to an adaptive structure of the system. To identify key dependent variables which are relevant to adaptation, change of action was regressed against the interpersonal error for each dependent variable. Table 4.2 lists goodnesses of fits for these variables.

Kinematics	**r^2**	**Force**	**r^2**	**Torque**	**r^2**
Reaction time	0.06(0.03)	F_S	0.04 (0.06)	T_S	0.11 (0.04)
Movement Duration	0.14 (0.08)	F_F	0.08 (0.09)	T_F	0.07 (0.07)
Peak Velocity	0.21 (0.11)	F_C	0.10 (0.06)	T_C	0.10 (0.06)
Peak Acceleration	0.26 (0.08)				
		F_S rate	0.17 (0.11)	T_S rate	0.09 (0.07)
		F_F rate	0.11 (0.08)	T_F rate	0.13 (0.05)
		F_C rate	0.16 (0.07)	T_C rate	0.11 (0.09)

Table 4.2. Goodnesses of fit was calculated for each subject and their averages with standard deviations in brackets (N =20).

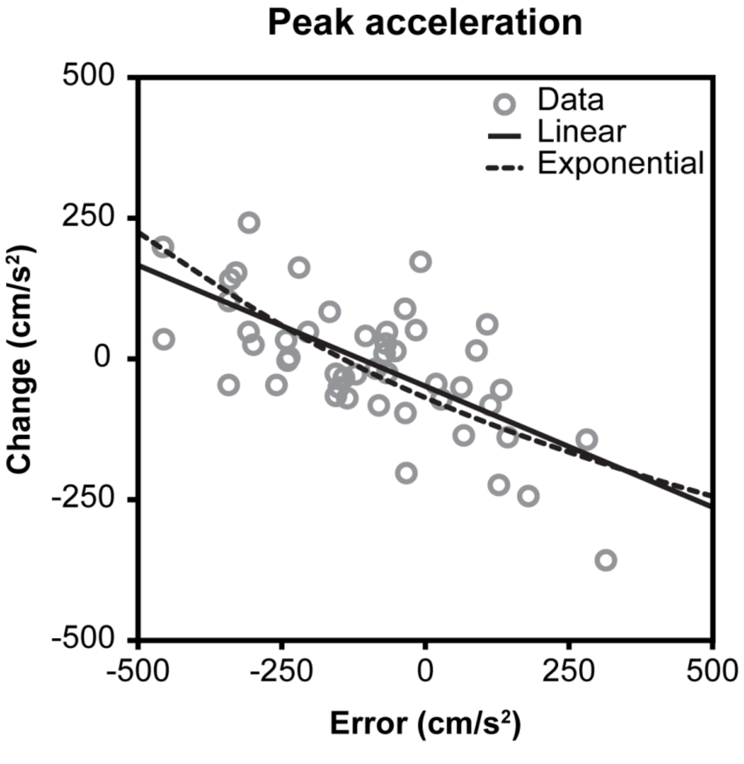

Figure 4.3. A scatter plot of interpersonal errors in the peak acceleration and the change made in the subsequent trials. The data are from a single participant. The relationship between the change and error is well defined linearly (averaged exponential fit across the participants: $y = 96.4^{e-0.001x}$, $r^2 = .304 \pm .092$).

The highest amount of the variance was accounted for by the adaptive model in the peak acceleration (PA, r^2 = 0.26 ± 0.08), followed by the peak velocity (PV, $r^{\mathbf{2}}$ = 0.21 ± 0.11), and the peak force rate at the sagittal axis (F_S rate, r^2 = 0.17 ± 0.11), the peak force rate at the coronal axis (F_C, r^2 = 0.16 ± 0.07), and movement duration (r^2 = 0.14 ± 0.08). Importantly, furthermore, the relationship between the change and error signals was well-defined in terms of linearity (Figure 4.3).

The first order adaptation. To explore how far the preceding error would affect the performance at a current trial, cross-correlation between the behavioural change and the interpersonal error over trials was computed. Results for the three variables with the highest goodness of fit (PA, PV, Fs rate) are described. As Figure 4.4a illustrates, the evolution of cross-correlations was very similar across variables with a strong positive correlation at lag 0 (PA, r = 0.56 ± .10), which was followed by a lag 1 negative correlation (PA, r = -0.47 ± 0.1). Thus, the adaptation model could alternatively include up to n-2 interpersonal errors as described below.

$$Z_{An+1} = Z_{An} + \alpha_A(\mathrm{Z_{Bn}} - \mathrm{Z_{An}}) + \beta_A(\mathrm{Z_{Bn-1}} - \mathrm{Z_{An-1}})$$

Model 2

To evaluate the benefit of including n-2 errors, the standard errors of the estimates of Model 1 and 2 were compared using linear and multiple linear regressions, respectively (Figure 4.4b). For Model 1, the mean adaptation rate was 0.421 ± 0.138. For Model 2, the n-1 adaptation rate (α) was 0.424 ± 0.138 and n-2 adaptation rate (β) was -0.020 ± 0.109. The standard error of the estimates was marginally smaller in Model2 (r^2 = 0.270 ± 0.081, std. error of estimate 92.96 ± 31.99 cm/s^2) than Model 1 (r^2 = 0.264±0.084, std. error of estimate

93.05 ± 31.54). Since the variances were not normally distributed, Friedman Test (non-parametric equivalent of a paired-sample t-test) was used to compare the difference between the two models. The analysis reported χ^2 of 0.20 with an associated probability of 0.655, indicating that there was no statistical difference between these two models.

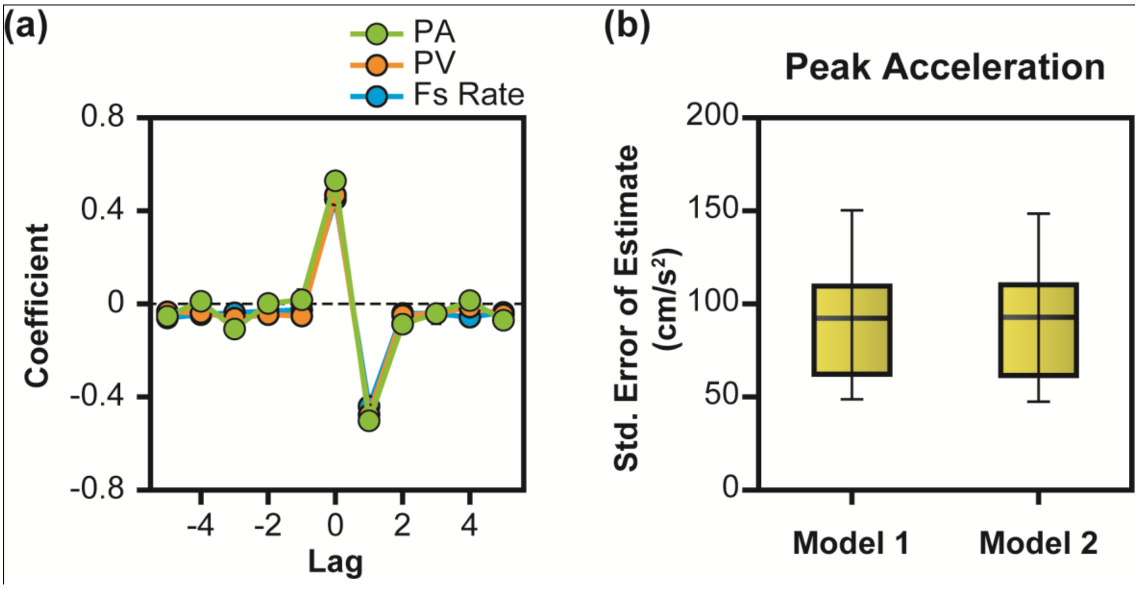

Figure 4.4. Model evaluations. **(a)** Cross-correlation of inter-personal movement error to cross-trial movement changes over 5 lags for peak acceleration (PA), peak velocity (PV) and saggital force rate (Fs rate). **(b)** Standardised error of estimate when the PA were fitted to the data using Model 1 and Model 2. The error bar denotes one standard error.

4.4.5. The role in the task and adaptation

The form of the dependence on their partner during cooperative interaction was investigated in terms of the adaptation rate to their partner. The adaptation rate of each participant was approximated using the slope coefficient of the linear regression, with interpersonal difference of the PA at a previous trial and PA change made from this trial to the next trial as variables (Figure 4.5a). The adaptation rates of each participant when they performed the task as the Leader, Follower, and took an Equal role were analysed using a within-subject ANCOVA wherein participants from the same pair groups entered into statistical analysis as covariates (Figure 4.5b). The results showed that the adaptation rate was the lowest when the participants were the Leader (0.425 ± 0.224). An intermediate level of adaptation was observed when the participants had a Mutual role (0.433 ± 0.189). The highest adaptation rate was observed when the participants were the Follower, (0.566 ± 0.229). One-way within-subject ANOVA confirmed that the Role of the participant affected the size of adaptation rate, F(2, 36) = 5.362, $p < .001$. A post-hoc comparison revealed that the statistical difference was due to the difference in adaptation rates between the Leader and Follower (Bonferroni correction, $p < .03$).

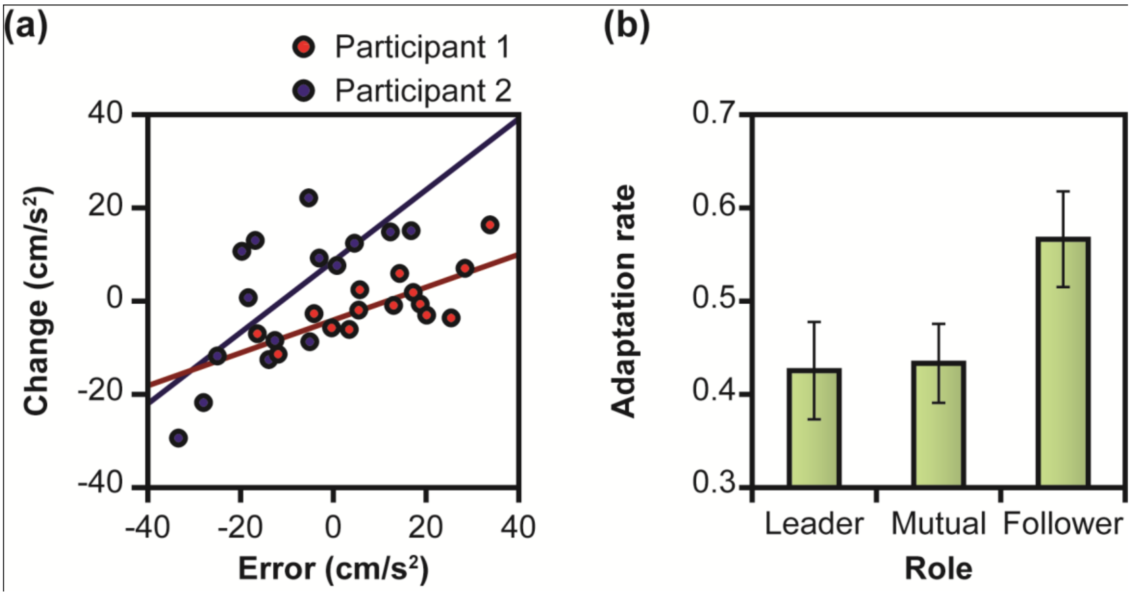

Figure 4.5. (a) A scatter plot of an error and change from a single pair of participants. A scatter plot of the difference in PA between the partners (Error) against PA change made in the subsequent trial (Change) obtained from a single participant. The slope coefficient of the least-square-error represented the adaptation rate. **(b)** Comparisons of adaptation rate due to a change in Roles (n = 20). The error bar denotes one standard error.

4.5. Discussion

Performance error contains vital information for optimising human movement. The aim of the study was to investigate whether the evolution of movement parameters in a cooperative process is governed by error-based learning. The kinematic and kinetic profiles during cooperative object-lifting were expressed in terms of a first-order linear model in which the evolution of the movement was determined by a gain factor of the model and the deviation of movements from those of the partner. This system may be considered as a model of social adaptive behaviour, which enables people to respond flexibly to other people's actions in a wide variety of social interactions and so facilitate goal-directed behaviour in joint actions. Although the inclusion of higher cognitive processes such as motivational factors remains unaddressed, computational approaches to the motor system can capture such interactive flows of sensorimotor coordination. Thus, this study extends current understandings of error-based learning and presents evidence for motor adaptation to a partner during a cooperative task.

Overall, the results indicated that kinematic profiles reflected error-based learning during interpersonal interaction such that interpersonal errors in variables such as peak acceleration and peak velocity were strongly correlated with resultant change in these variables over successive trials. It is important, however, to note that the error-based learning in the kinematic variables as observed in this study may be task-dependent. In this experiment, kinematic coordination was the primary goal of the task partners. In these types of movements, various kinematic parameters, such as the peak velocity and the peak acceleration tend to correlate strongly as proposed by several movement models such as the minimum-jerk model (Flash & Hogan, 1985). When the primary task goal is coordination of movement at the kinetic level, on the other hand, error-based learning may be realised kinetically. In a study by Reed and colleagues (2006), for example, paired participants held a handle each and cooperatively rotated an object to a target orientation. In such tasks, the rotation of the table by one handle causes the same movement in the other handle (controlled by their partner), and no kinematic difference is observable. Nevertheless, these participants improved the joint performance as they repeatedly interacted with the same partner. Thus, the learning is more likely to take place at the kinetic level in this example.

The size of adaptation rate determines the rate and form of the error reduction over successive trials. In principle, cooperative performance at the net adaptive rate of 1 leads to the most rapid interpersonal error reduction although the adaptation rate should drop for a stable performance when there is appreciable random noise in the environment (Burge et al., 2008), an example in a cooperative scenario being the motor noise of the task partner. When the motor variability of a task partner is large, adapting to this person may exacerbate the cooperative performance since the evolution of the movement parameters would fluctuate with the perceived motor variability of the task partner. Thus, this variability may be damped by reducing the adaptation rate. An active adjustment of the adaptation rate was demonstrated by changing the task instruction between two interacting partners. In the study, the target height for lifting the bar was presented either one or the other partner, or both partners. The results showed that the adaptation rate became larger when the person was not informed of the target height compared to when he/she knew the target, demonstrating the adjustment of a movement parameter by the Follower to that of the Leader.

In the present study, the net adaptation rate of the Leader and Follower in the task comes close to 1. This unusually high net adaptation rate may be due to a statistical confound in how the adaptation rate was obtained. Previously, in individual movement studies, Vorberg and Schulze (2002) noted that adaptation rate estimation using autoregressive structure of the data tends to lead to overestimation of true adaptation rate because the presence of positive lag-1 autoregression (i.e., random drift of a movement parameter over responses) inflates the correlation of the two variables. Since the adaptation rate estimated in this chapter relies on the regression between the real error-signal and change signal, the adaptation rates reported in this study are likely to be overestimated since the interpersonal error and the subsequent change in the behaviour are derived from the same set of data. One way to avoid this statistical confound in the adaptation rate estimation is to insert a probe in the system as an error signal and observe the response, hence eliminating inherent correlation between the interpersonal error and the subsequent change. This approach is taken in the next chapter of this thesis.

It is important to note that there are other models which could better account for cooperative interaction. For example, the model-fitting showed that the prediction of a task partner's movements was marginally improved by taking more errors into account. However, the strong negative cross-correlation at Lag 1 (the error 2 trials before the current trial) observed in this study was largely due to the carry-over of correlation from Lag 0. This is similar to a previous suggestion concerning individual adaptive movement, namely that movement errors at an order of 2 or higher are typically negligible unless the temporal gap between successive responses is very short (Repp & Keller, 2008). Furthermore, this adaptive model predicts the evolution of a participant's movement deterministically, while computational literature often suggests that stochastic modelling outperforms deterministic modelling (Todorov & Jordan, 2002; Sarkar et al., 2002). The primary focus of this study, nonetheless, is to highlight the relationship between interpersonal error and the evolution of movements, and the adaptive model presented here is sufficient for generating tangible theoretical and analytical predictions about cooperative behaviour, as will be shown in the next chapter.

The error-dependent adaptation observed in the current study can also be explained in terms of mimicry, where the participants unidirectionally shift their movements towards the movement of the partner in the previous interaction as opposed to optimising the performance outcome as a cooperative partner. In the joint adaptation model presented here, there is an implicit mimicry characteristic expressed since the behavioural adaptation is always derived with regard to how their partner performed in the previous interaction. Thus, although the behaviour appears to be error-dependent, this phenomenon could be linked to the copying of behaviour rather than the improvement of interpersonal performance in the next trial. Indeed, there is much evidence suggesting that there is an inherent tendency for humans to mimic the movement of others, and research has suggested that the observation of an action performed by a third person covertly primes the movement trajectory of one’s own action performed subsequently (Griffiths & Tipper, 2009). Thus, this account potentially controverts the existence of error-based learning in cooperative action. The next chapter will address this issue in detail by demonstrating how changes in the statistical properties of their partner influence the adaptation rate of the participants, indicating that adaptation rate is negotiated with a view to optimising joint outcome rather than as a result of one-directional mimicry. (See Appendix I for numerical contrasts between the error-based learning and mimicry models).

Chapter 5

Joint Adaptation in Cooperative Action

5.1. Abstract

When two people attempt to coordinate an action, either or both may take responsibility for adapting their movement to that of their partner in order to improve performance. This study demonstrates how paired participants learn to conform to each other's motor strategy. Participants performed a joint visuo-motor task in which they each moved a virtual object together to a target, attempting to keep it as horizontal as possible. In some conditions, unbeknownst to participants, the partner was replaced by a simulated agent that adapted the timing of action on the current trial at a fixed rate to reduce their timing difference from the previous trial. Results showed that participants' adaptation rate decreased as the adaptation rate of the simulated agent increased. We conclude that, in cooperative action, people are sensitive to a partner's adaptation strategy and modulate the degree to which they adapt their own movement accordingly.

5.2. Introduction

When two people coordinate their actions in order to achieve a shared goal, there may be several options for completing the task. However, whether lifting a table, rowing a boat or playing a musical duet, the movements of a dyad engaged in joint action must relate to each other in time and space. Take the example of pushing a car stuck in snow. To free the car, the partners in a dyad should synchronise the times they apply force. In this situation, the dyad might agree to use verbal cues to help synchronise their timing with one of them counting out “1-2-3-push”. However, this would still not guarantee synchrony of force application as the partners might vary in their count times, in when they initiate the push relative to the count and in the rate at which they increase their force. If freeing the car requires a series of pushes, such movement differences in the dyad could be progressively corrected over successive pushes by either or both partners. For instance, if A observes that B pushed the car earlier than A on one trial, A might try to advance his or her push on the next trial. However, B might also observe the error and adjust on the next trial by delaying his or her push. In such a case, if the combination of their adjustments is too large, the dyad risks over-correcting and this could result in the partners being alternately early and late. On the other hand, if the combined adjustment is too small, the timing discrepancy will persist over several trials. Thus, it is not only important to adapt movement, given information about how one’s partner performed previously, but it is also important to predict how one’s partner will adapt, and then to alter one’s own degree of adaptation accordingly. Here we provide the first quantitative evidence of complementary adaptation in dyads achieved without verbal interaction.

Adaptation of actions based on previous errors has been studied extensively in the context of individual movements. Adaptive behaviour can be accounted for by a simple linear model which adjusts the current movement by some proportion of the observed error in the previous movement (Thoroughman & Shadmehr, 2000; Vorberg & Wing, 1996). This proportion - the adaptation rate - determines the form and speed of error reduction over successive trials. For optimal performance, the adaptation rate should relate to the source of the errors in task performance (Behrens et al., 2008; Burge, Ernst & Banks, 2008). For example, if the environment changes quickly, people should adapt rapidly to reduce errors. On the other hand, when errors are largely due to random noise in sensory or motor processes, it is better to adapt performance to a lesser degree.

In the present study, we ask whether the adaptation rate of one partner influences that of the other in joint action. In order to investigate this we designed a novel cooperative paradigm. During the trial, the participants were asked to hold opposite ends of a virtual bar and, on external command, lift the bar into a target zone as quickly as possible, without tilting it. Thus the task required the two players to start in synchrony with each other and to move at similar speeds. To measure adaptation rates, we randomly inserted ‘probe’ trials, in which the feedback to each participant was manipulated such that their partner was perceived as moving either earlier or later than was actually the case. We then measured the change in partner action on the following trial, which shows how much the partner adapted to this perceived error. Furthermore, in some conditions, we replaced the visual display of the partner’s action with a simulated agent calculated by a computer algorithm. This simulated partner adapted to the joint error by varying amounts. This allowed us to manipulate the partner’s adaptation rate explicitly and to measure its influence on the participant’s own adaptation rate, while maintaining the illusion of interaction with a real partner.

5.3. Method

5.3.1. Participants

44 right-handed participants (25 male, 19 female, mean age: 22 ± 3.8 years) took part in this study, receiving £6 for their time. Participants were randomly paired and assigned into one of four groups. 10 people were assigned to a Real Partner group. The rest were assigned to one of 3 Simulated Partner groups, which differed only in the simulated adaptation rate (Sim0%, n=10; Sim60%, n=12, Sim90%, n=12). Participants were all told that they would be performing the task with another participant. All were naive to the purpose of the experiment and gave informed consent prior to testing. The study was approved by the ethics committee of the School of Psychology at University of Wales, Bangor.

5.3.2. Stimuli and Apparatus

Two identical setups were prepared in adjacent test compartments separated by a lightweight screen that prevented direct view between the participants (Figure 5.1a). In each compartment, the participant sat in front of the apparatus and used the right hand to hold a stylus connected to a robotic device (PHANToM 3.0, SensAble Technologies). The robot recorded the position of the stylus in Cartesian coordinates at 200 Hz. Each participant had a computer screen that displayed two red spheres (8mm in diameter) which represented the positions of his or her own stylus and the stylus of the partner. A white line was drawn between them as a virtual object (Figure 5.1b). At the bottom of the screen, two horizontally-aligned white spheres (8mm in diameter and 6cm on either side of the midpoint) served as starting positions. A 120 x 10 mm rectangle, 120 mm above these starting positions, constituted the target.

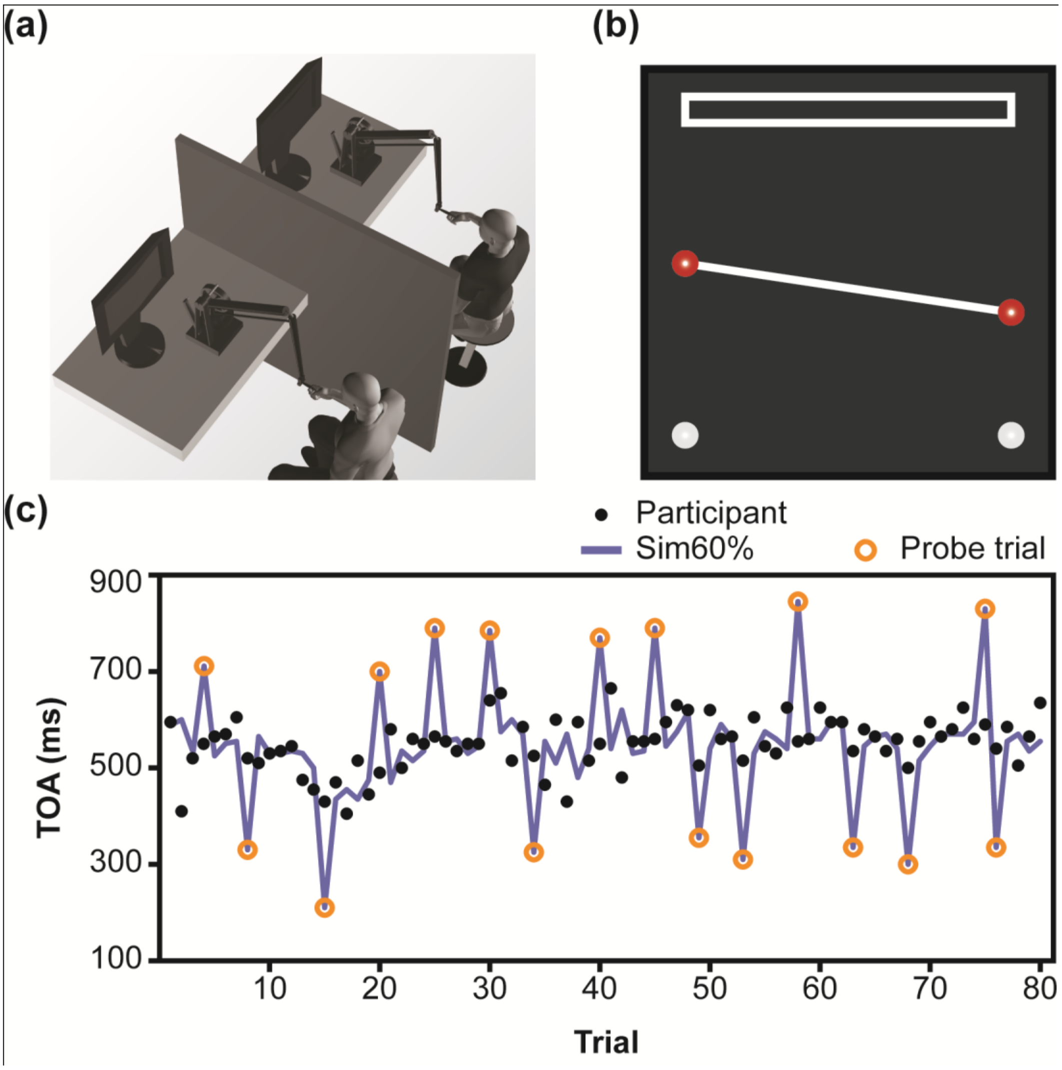

Figure 5.1. (a) Schematic illustration of the experimental setup. Two participants sat next to each other and each one hand-held a stylus attached to a robotic arm. A divider was placed between them to block a mutually direct view. **(b)** Each participant viewed their own and their partner's action on a computer screen. The participants' task was to move the two red spheres to a target box, while keeping the white line connecting the spheres horizontal. Three pacing tones helped the participants synchronise their actions. **(c)** An example of time of action (TOA, measured at the moment the hand reaches 70% of the movement amplitude, timed from the last pacing tone) over one block from a single participant (black circles). The same measure for the computer simulated partner is shown in the blue line. Probe trials are indicated by orange open circles.

5.3.3. Procedure

The partners in a dyad were seated in the left or right compartment, and received instructions together. Movements were performed in the natural reaching space in an upward-forward direction, involving shoulder and elbow movements, with the elbow pointing down. The chair was adjusted so the height of the stylus came slightly above the waist. At the beginning of each trial the participants moved their respective cursors to the start positions. Facing the display, the participant in the left compartment used the left starting position, and the right participant used the right starting position. The two cursors had to be positioned within their own starting spheres to commence each trial. After 1 second, three tones were played at 600 ms intervals to indicate trial start. The participants lifted the cursor to the target box on the third tone. The task of the participants was to jointly move the object into the target box, while keeping it horizontal.

A point was awarded for each successful trial based on movement duration and the maximum angular departure from the horizontal. The start of the movement was registered when the velocity of the cursor exceeded 35 mm/s. The end of the movement was registered when the velocity of the cursor dropped to lower than 15 mm/s within 25 mm of the target. The movement duration had to be less than 900 ms, and the movement speed had to reach at least 40 cm/s for success. The angular limit on departure from the horizontal was initially set at 40 degrees and was subject to a change at the end of each block in order to keep the success rate at around 50%. A point was deducted on each trial that the angular limit was exceeded. When the movement was too slow or the angle was too large, the colour of the target box turned into blue or red, respectively. The participants performed 7 blocks of 60 trials. The first block was a training block. The remaining 6 blocks contained probe trials.

In the following analysis, the main outcome measure for each trial was the time (relative to the last pacing tone) which the cursor reached 70% of the movement amplitude (Figure

6.2). This time of action (TOA) measure, rather than reaction time, was chosen because it is sensitive to changes both in reaction time and movement speed. Moreover, the difference in TOAs of the two partners better reflects the task-relevant variable, the tilt of the object.

5.3.4. Partner Simulation

In all experimental groups except for the Real Partner group, each participant performed the task with a computer simulation defining the partner's movements. However, participants still performed the task in pairs. That is, they saw the other participant locate his or her cursor in the starting position and the three pacing tones at the start were played to both participants. During the movement, however, the starting time of the partner's cursor was dictated by the computer simulation, and the trajectory followed a minimum-jerk trajectory (Flash & Hogan, 1985) set by the simulation. The vertical movement amplitude of the simulation was 120 mm with some added variability (SD = 10 mm) to resemble human characteristics. Furthermore, the horizontal position of the cursor was the true position of the partner's cursor, making it believable that the cursor was indeed controlled by a person. The simulation target TOA was updated trial-by-trial using the following adaptation rule:

$$\mathrm{TOA}_{\mathrm{A}n+1} = \mathrm{TOA}_{\mathrm{A}n} + \alpha_{\mathrm{A}}(\mathrm{TOA}_{\mathrm{B}n} - \mathrm{TOA}_{\mathrm{A}n}) \qquad \text{eq. 5.1}$$

where TOA_{An} is the time to attain 70 % of simulated Partner *A*'s movement amplitude on Trial *n* and α is the adaptation rate which reduces the time difference with Partner *B.* For each experimental group, the adaptation rate of the simulation was fixed at high (Sim90%, α = 0.9), intermediate (Sim60%, α = 0.6), or zero (Sim0%, α = 0.0) values. In the Real Partner group, the performance of the partner displayed on the screen was veridical.

At the end of the experiment, an exit interview was conducted to gather subjective impressions about the task partner. In particular, participants were told that half of the participants performed the task with a computer simulation and they were asked to answer whether they thought their partner was another participant or a computer simulation. One participant in the Real Partner and two participants in each Simulation group reported that they thought they performed the task with a computer simulation. A Kruskal-Wallis one-way ANOVA indicated there was no difference in the number of participants reporting their partner was a simulation across the four experimental groups (p = .943).

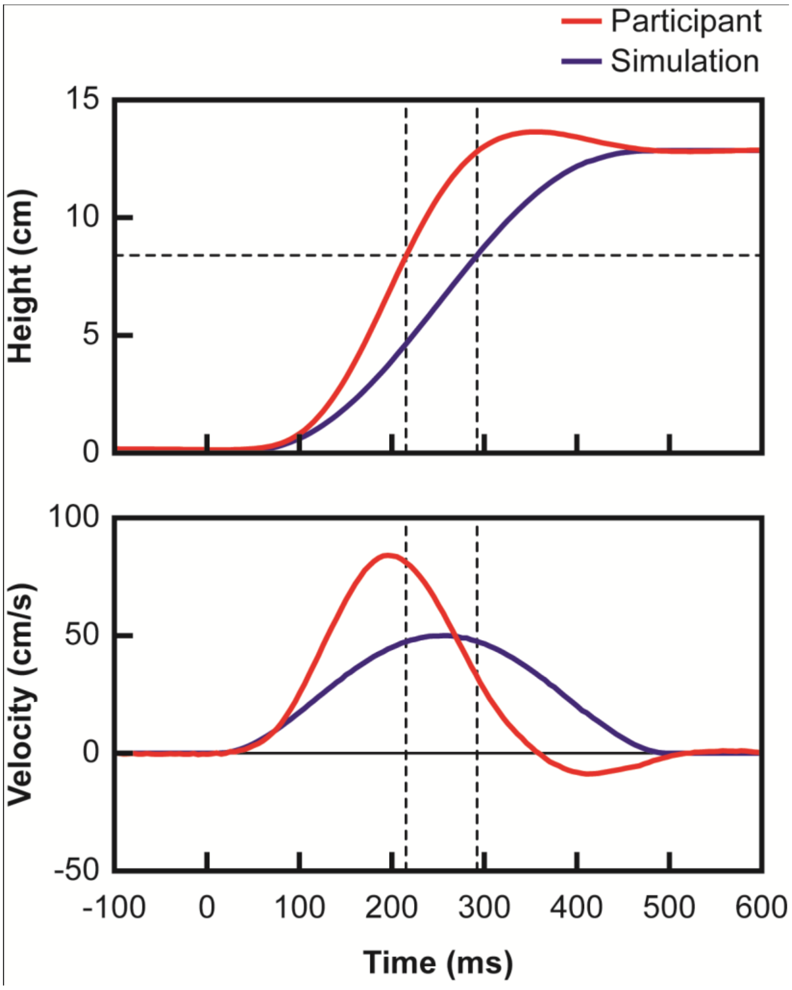

Figure 5.2. Position and vertical velocity profiles of a participant (red line) and a simulation (blue line) from a single trial. The time at which the position reached 70 % of the target movement amplitude (= 12 cm) was used to index cross-trial adaptation of participants and simulation (indicated by the dotted lines).

5.3.5. Probe trials

Probe trials were randomly interleaved with regular trials to estimate the amount of within-trial, online correction and the amount of across-trial adaptation. In probe trials, the movement of the partner or the computer-simulated movement was shifted, either forward or backwards, by 250 ms. To achieve this, the movement was simulated using a minimum jerk trajectory (see above), where current TOA, was predicted using Equation 5.1, with α set to 0.1 for the Real Partner and to the computer's adaptation rate for the Simulated Partner conditions. The estimated current time was then shifted by -250 ms (TOA advanced trials) or by +250ms (TOA delayed trials). Successive probe trials were separated by at least 3 normal trials but otherwise they occurred at random. There were 8 delayed and 8 advanced trials in each block, giving a total of 96 probe trials per participant. Probe trials always occurred for both partners on the same trials, and the shift directions could either be the same or opposite.

5.4. *Results*

Figure 5.2 shows how the TOA changed in response to a probe trial (trial 0). Because participants could not predict the occurrence or direction of a probe trial, any difference between advanced and delayed trials must reflect online corrections based on visual feedback in that trial. Persistent changes of the TOA after the probe trial (trial 1 and following) are due to adaption, and the size of this effect was used to estimate the adaptation rate (see below).

5.4.1. *Online correction*

The change in the TOA from trial -1 to 0 signifies the strength of visual online corrections. Here, we observed an asymmetry: If the partner appeared to achieve TOA 250 ms earlier than expected, participants were able to partly correct for this by reducing their TOA (-43.6 ± 22.3 ms) – i.e., by starting the movement earlier or by speeding up. In contrast, when the partner appeared to achieve TOA 250 ms later, there was only a small increase in TOA (4.6 ± 16.2 ms). We analysed the change in the TOA (with reversed sign for the delayed trials) using a 2 (Probe Type) x 4 (Partner Type) mixed ANOVA. There was a main effect of Probe Type, $F(1, 40) = 80.32$, $p < .0005$, $\eta^2 = .668$, confirming the asymmetry in online correction for advanced and delayed probe trials. There was no main effect of Partner Type ($p = .724$), nor was there any interaction ($p = .225$), showing that the participants did not change the amount of online correction according to the adaptation rate of the simulated partner.

5.4.2. *Adaptation gain*

The adaptation rate was estimated by studying how the probe trials affected the TOA on the trial following the probe trial. Because of the presence of online correction in trial 0, we used the TOA change from trial -1 to trial 1. As a measure of adaptation rate, we determined the average size of the change, divided by induced interpersonal error (250ms) on the probe trial. These adaptation rates (Figure 4) show a significant difference between groups, F(3, 40) = 5.80, $p < .001$, $\eta^2 = .303$. Post hoc tests (Bonferroni) revealed that the Real (0.140 ± 0.066), the Sim0% (0.148 ± 0.039) and the Sim60% (0.156 ± 0.053) conditions did not differ significantly from each other. In contrast, the adaptation rate in the Sim90% (0.071 ± 0.060) was significantly lower than the other two Partner Types (ps. < .02).

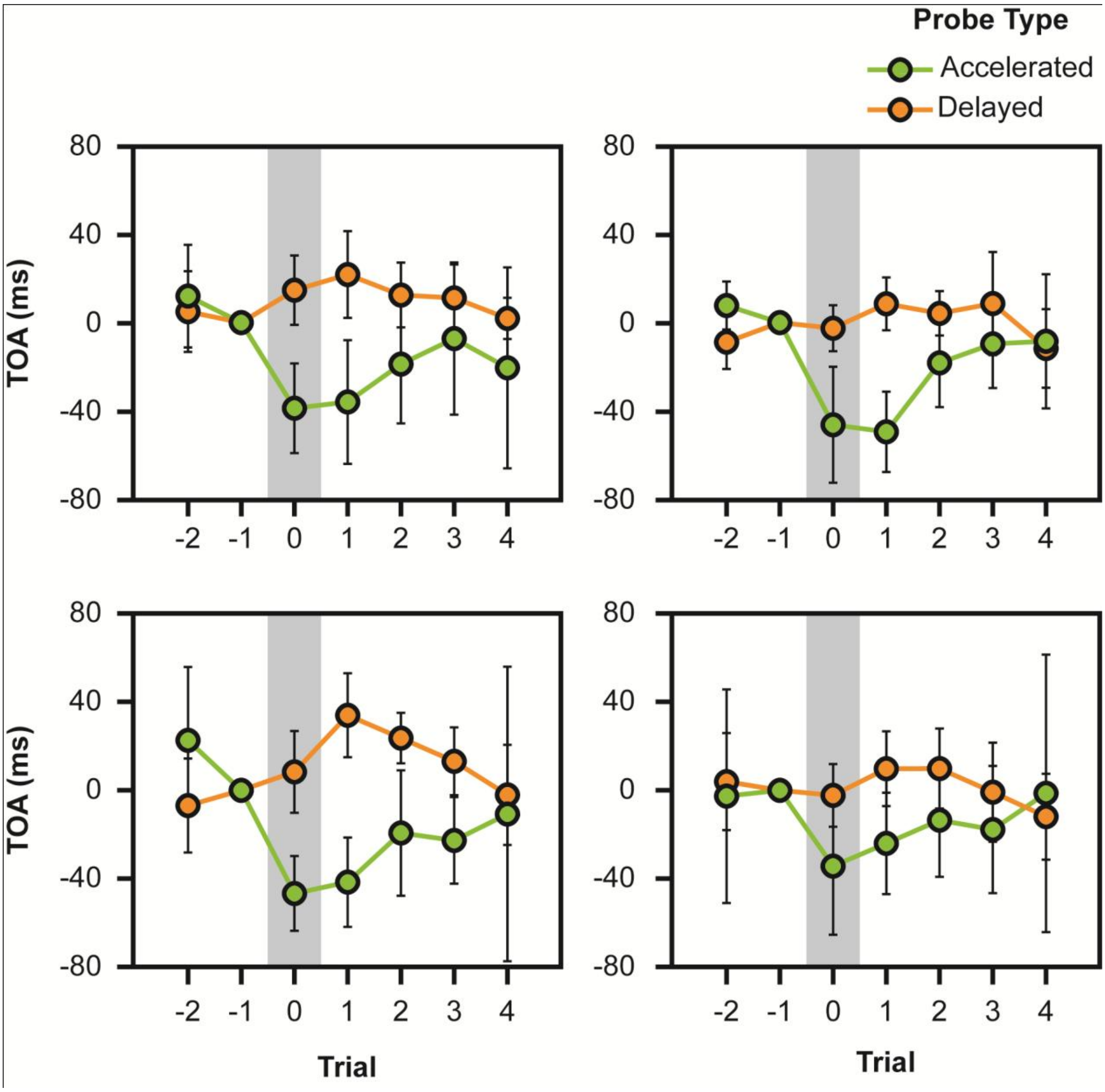

Figure 5.3. The time of action (TOA) before (trial -2 to -1), during (trial 0) or after (trial 1 to 4) an advanced or delayed probe trial. TOAs in the figure were adjusted so the TOAs at trial – 1 was set to zero. A change in the TOA is observed on the probe trial (gray underlay), indicating the presence of online corrections. An influence can still be seen on the TOA multiple trials after the probe trial, indicating adaptation. The error bars represent the between-person SD of the TOA.

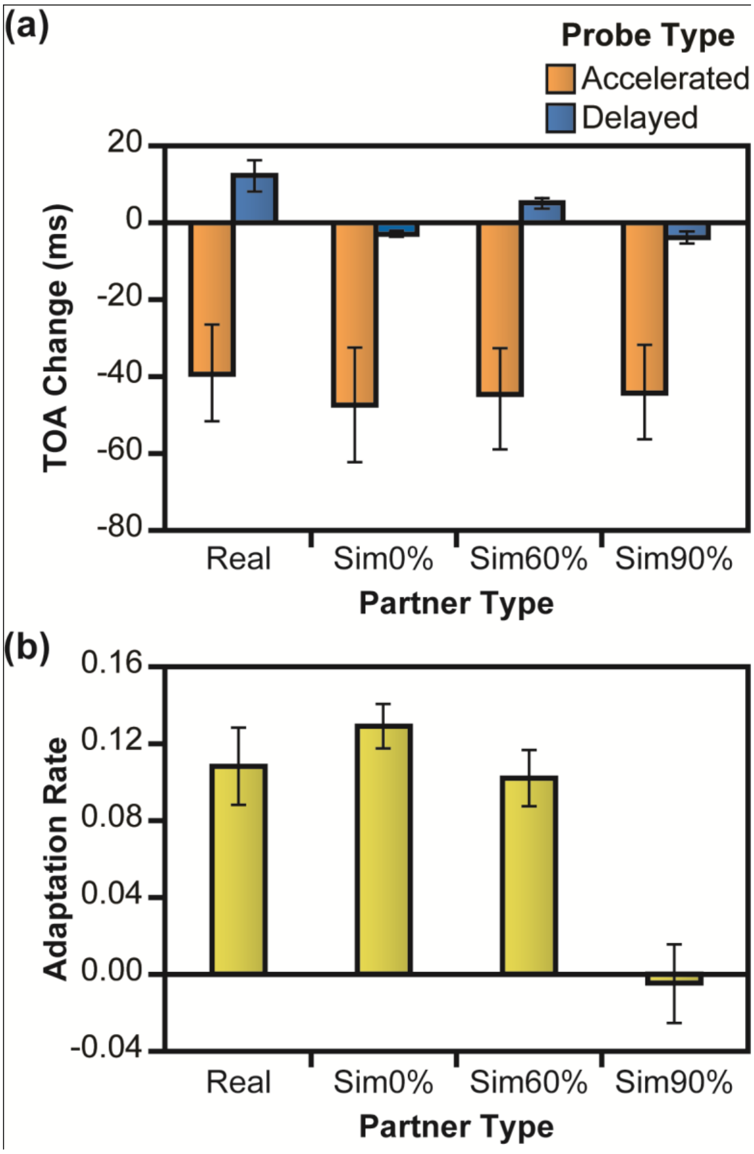

Figure 5.4. Correction gains and adaptation rates in the 4 experimental conditions. **(a)** TOA difference between the probe trial and one previous trial. The size of the change indicates the presence of online correction. **(b)** The adaptation rates, calculated as the average change from the trial before to the trial after a probe trial. The error bars denote between-subject standard error.

5.5. Discussion

In two-person joint action, either member of the dyad may use observed error on one trial to correct his or her movement on the next, and so there is a risk of over-correction. For successful cooperative action, members of the dyad should therefore be sensitive to the movement adaptation rate employed by their partner when adapting their own movement. Using a computer-simulated partner whose movements adapted to error at various rates, the present study provides clear evidence that people adjust their adaptation rate to that of their partner without need for verbal communication. Our results show that, as the adaptation rate of the simulated partner increased, participants' adaptation rate reduced.

Studies of single-person adaptation have shown that people change their adaptation rates according to the perceived stability of the environment, and this depends on the statistical nature of the variability. For example, participants tend to increase their adaptation rate in response to strongly fluctuating environments, provided these fluctuations evolve slowly over successive trials, associated with positive lag-1 autocorrelation between trials. In contrast, if the trial-to-trial changes are more rapid (zero or negative lag-1 autocorrelation), adaptation rate remains constant (Burge et al., 2008). In the present study, the small adaptation rate may reflect uncertainty about the partner's correction in joint performance. Interestingly, however, in our Sim90% condition the TOA of the computer simulation fluctuated much more (SD = 268.2 ms) than in the Sim0% (SD = 4.3 ms). The fluctuations in Sim90% were on a relatively slow timescale with positive lag-1 autocorrelation (lag-1 = 0.33), which might have been expected to lead to an increased adaptation rate (see Appendix II for an optimal adaptation rate in the presence of various sources of noises). However, our participants significantly decreased their adaptation rate in Sim90%. This suggests that participants are sensitive not only to the nature of variability, but also that they react to the adaptive characteristics of the partner. Specifically, in our experimental manipulation, slow fluctuations of the interpersonal error over trials reduced with an increase of the adaptation rate (lag-1 autocorrelation; Sim0% = 0.05, Sim60% = -0.14, Sim90% = -0.22). Thus, the participants might have adapted to the statistics of the interpersonal error.

To our knowledge, ours is the first study to examine between-partner adaptation of spatial characteristics of movement. However, adaptation between partners has previously been studied in timing tasks. When people work in pairs to produce repetitive/cyclic movements, ranging from using arm movements to oscillate two pendulums (Schmidt, Bienvenu, Fitzpatrick, & Amazeen, 1998) to oscillate their index fingers (Oullier et al., 2008), relative phase tends to converge on a stable (in-phase) state depending on the available sensory feedback. This has been modelled in terms of a dynamical system in which the two separate sets of movement continuously interact and mutually influence each other's state and, as a result, converge on a stable solution. In this approach, reciprocal coupling terms (which may be likened to reciprocal adaptation) have been stated (Haken, Kelso & Bunz, 1985); however, these studies have focused on the description of emergent behaviour as a result of interpersonal interaction and, to our knowledge, the processes behind such interaction have not previously been investigated. A complement to this approach based on discrete timing has been provided by Repp and Keller (2008). Following Vorberg (2005), they suggested that 2-person synchronisation tapping involves reciprocal phase adjustment. They sought, but failed to find, evidence of flexible setting of adaptation rate in a paradigm in which an adaptive metronome played the role of one partner. However, the correction parameter of the metronome changed every trial in a random order for each participant. Thus, an adaptive response by the participants may have been missing due to the lack of time for them to adapt to the new parameter; or it may have been suppressed by the constant change of metronome type.

The adaptation model used in this discussion assumes that the interpersonal error was reduced across trials. Nevertheless, there was evidence of concurrent online correction. In probe trials where the time of arrival (TOA) variable determining success was advanced, approximately 20% of the error was compensated within the trial. However, the size of the online-correction was constant across the three adaptation rates of the simulated partner. Furthermore, our simulation suggests that presence of online correction does not statistically affect the adaptation rate (see Appendix III). Thus, it is unlikely that the presence of on-line correction induced a change of adaptation rate.

It has been suggested that social interaction is a process in which two or more autonomous agents mutually influence each other’s behaviour to regulate behavioural outcome at a collective level (De Jaegher, Di Paolo & Gallagher, 2010). In this view, the modulation of adaptation rates observed in the present study comprises social interaction. This suggests the paradigm might be used to explore further aspects of social influence. For instance, evidence suggests that people are less responsive when they believe they are coordinating their movements with a robot as opposed to another human. It has been shown that the entrainment of arm movement to a moving cursor becomes stronger when people believe the cursor movement represents human motion rather than robot motion (Stanley, Gowen & Miall, 2007). Thus, it seems that cooperative action is not just a mere low-level coordination of movements by two actors, but it is also strongly related to cognitive expectancy about the partner. Given the social nature of the task we report, it is also possible that the modulation of the adaptation rate may depend in part on perceived social attributes of the partner. Understanding how this joint adaptation is modulated by social context and whether people can retain the adaptive information about a specific partner and differentiate among multiple task partners could provide further important insights into how the CNS supports cooperative interaction.

Chapter 6

Joint Adaptation in Rhythmic Motor Coordination

6.1. Abstract

Previous chapters provided evidence for joint adaptation of two partners in order to maximize the effect of the motor performance at a cooperative level. This study applies this joint adaptation model to continuous movement and their associated kinematic parameters are reported in detail. In the study, the participants made a vertical handshaking-like movement with a robot which adapted its movement frequency to the participant at various different rates. The results showed that participants' adaptation rates to the robot's frequency were negatively modulated with those of the robot, so keeping the net adaptation rate constant. The results showed that participants' adaptation rates to the robot's frequency were negatively modulated with those of the robot, so keeping the net adaptation rate constant. The study suggests that the joint adaptation model observed in the previous chapter is also present in an interpersonal continuous motor task. Kinematics analyses further suggested that feedback and feedforward controls are present for correcting frequency errors, while the degree of feedback correction is unaffected by the adaptive characteristics of the robot.

6.2. Introduction

Chapter 5 demonstrated that the movement adaptations made according to the movements of a task partner are dynamically modulated, given the adaptive characteristics of this partner so that the motor outcome becomes optimal at a cooperative level. This adaptive behaviour was described in terms of error-based learning wherein each participant reduced the interpersonal movement error that was present in a previous trial at a certain rate. Since the net adaptation rate of the two partners determines the success of cooperative action in a subsequent trial, it was hypothesised that the adaptation rate of one person would drop as the adaptation rate of a task partner increased. Using a computerised task wherein a simulated task partner adapted to the participants at various rates, the study confirmed inversed modulation of the adaptation rate by the participants. This indicated as hypothesised that the participants adjusted their adaptation rate to avoid excessively high/low net adaptation rate.

Since the joint adaptation model of the previous chapter describes discrete changes in the cooperative interactions between partners across trials, it is interesting to examine the applicability of the model under continuous movement. One motivation for using continuous movements as an application of this adaptation model was that previous studies on individual upper-body movements have shown that continuous movements and discrete movements are controlled differently by the CNS (Diedrichsen, Hazeltine, Ivry, Kennerley, & Spencer, 2002; Huys, Studenka, Rheaume, Zelaznik, & Jirsa, 2008; Schaal, Sternad, Osu, & Kawato, 2004). Discrete movement is a term commonly used to describe movements, such as reaching and grasping. These types of movements are short in duration with a clear termination of the movement, therefore providing a useful timing framework for interpersonal interaction. In contrast, continuous movement is a term applying to movements, such as walking or scratching. A continuous movement usually consists of cyclic repetition of elements connected without appreciable pause or stops between the cycles and the movement lasts considerably longer. Continuous movements are considered to be phylogenetically older than discrete movements (Schaal et al., 2004) and low-level movement coordination can be achieved without cortical structures as shown by the decerebrate cat's sustained ability to walk (Whelan, 1996). Nevertheless, explicit coordination of continuous movements may pose more challenges than discrete movements under a cooperative scenario.

For instance, a specific temporal cue about a task partner's movement is known to enhance the cooperative performance. In a study by Knoblich and Jordan (2003), paired participants controlled a speed of moving cursor presented on a computer screen using left and right button press. The left button increased speed of the target to the left and right button increasing speed for rightward movement as each participant in a pair controlled one or the other button. Their task was to track a laterally moving object which randomly changed its direction. Since the effect of the button press was merged into the movement of a single cursor, there was uncertainty in when the task partner pressed the button. When every button press elicited a sound, however, the timing of the button press was precisely perceived by the other partner, and it led to improvement of the tracking performance. In terms of continuous movement for cooperative interaction, it may be more difficult to extract temporal features of individual cycles about their partner compared to a discrete movement task since the partner continues to move without clear pauses between cycles of movements.

Another challenge for continuous movement is that there are more stringent temporal constraints in gathering statistical characteristics of the partner. In Chapter 3 of this thesis, feedback control during vertical object lifting was examined wherein a participant jointly lifted an object with a humanoid robot. When the trajectory of the robot unexpectedly changed from usual trajectory, the participants responded to this sudden perturbation with an average delay of approximately 140 ms. Thus, the actor has to recognise the delay of corrective movement as the participants adapt their movements to their partner in a continuous movement paradigm.

A good example of the need to negotiate the demands of cooperative movement in the context of continuous rather than discrete movement is found in the practice of handshaking. Handshaking is a commonly used as a form of greeting in the Western culture in which two people engage their hands and jointly make vertical cyclic movements. There are many movement parameters in handshaking that are coordinated between the partners, including amplitude, speed, and number of "shakes". Due to social and cultural influences, these factors may vary across pairs of individuals (Chaplin, Phillips, Brown, Clanton, & Stein, 2000). As demonstrated throughout this thesis, movement error due to a lack of coordination between partners can be actively reduced by one partner adjusting his/her own preferred course of action to the partner's action. In complementary fashion, one may expect a task partner to adjust his/her movement to oneself.

This study therefore employed an up-down handshake-like oscillatory movement to investigate whether error-based learning is present during a cooperative task. In this study, participants cooperated with a robot to rhythmically move a bar up and down while the robot acted as a partner. The adaptation rate of the robot was manipulated to investigate whether a change in this rate would influence the adaptation rate of participants. Reduced adaptation rate of the robot was predicted to increase a participant's adaptation rate if the CNS incorporates the adaptive model of a task partner when planning cooperative action, thus leading to more efficient interpersonal error reduction across cycles owing to a pertinent net adaptation rate of the partners. Detailed kinematic analyses are provided to present the manner in which the interpersonal motor errors were corrected during interpersonal rhythmic coordination. Furthermore, this study employed haptic feedback as modality of interpersonal interaction to contrast with results in Chapter 5 wherein the participant visually interacted with a simulated partner through a computer screen (see Appendix IV for an equivalent cooperative lifting task with haptic feedback). As demonstrated throughout this thesis, the haptic feedback is a central source of information for perceiving the dynamics of the object and manipulating it. Thus, it was expected that haptic error feedback about interpersonal coordination might invoke a stronger adaptive response by the participants. In this study, therefore, a robot played a role of task partner, and the participant and the robot translated a real object together.

6.3. Methods

6.3.1. Participants

24 right-handed participants took part in this study. The participants were randomly assigned into one of three groups of eight people each: Adaptor 0 %, Adaptor 60 %, or Adaptor 90 %. The average age was 26.1 ± 4.2 years old and four of them were female. All the participants gave informed consent prior to testing. As compensation for their time, the participants received €10.00. Ethical approval was obtained from the ethical board of the clinical centre of Grosshadern, Ludwig-Maximilians-Universität (LMU) in München, Germany.

6.3.2. Apparatus

A 10 degrees-of-freedom (DoF) robotic arm ViSHaRD10 (Ueberle, Mock, & Buss, 2004) served as task partner for participants, who were tested individually (Figure 6.1a). In the task, the robot and the participant held a metal bar at each end and moved it vertically up and down. The distance between the grip positions of the participant and robot on the bar was 30cm, and the total weight of the bar was approximately 1kg.

To achieve the joint task with the robot, 2 DoF of the robot were enabled: one for vertical translation and the other for rotation around the pitch axis, along which the robot and a participant faced each other. Each of the 2 DoF motions was controlled by a different type of controller. The vertical translational DoF was controlled by a pure position controller with a reference trajectory, while the rotational DoF was controlled by a position-based admittance controller. In the translational DoF, the robot followed the reference trajectory veridically, without being affected by the participants. In contrast, in the rotational DoF, the robot was compliant so that the bar could rotate if the trajectories executed by the participant and the robot were different.

The motion of the robot was measured by incremental encoders with a sample rate of 1000Hz. Given that the bar was rigidly connected to the robot end-effector, the hand motion of the participants was estimated by calculating the forward kinematics, taking into account the geometry and orientation of the bar.

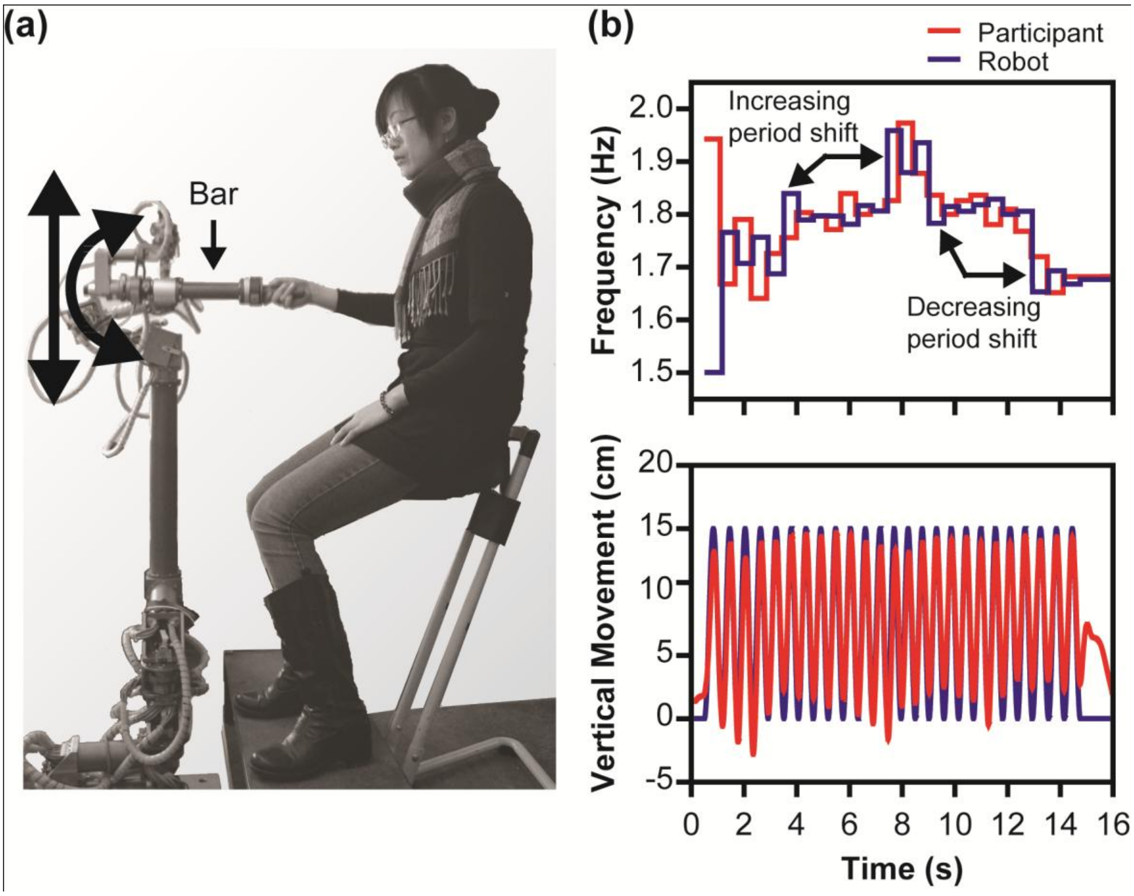

Figure 6.1. The experimental setup and an example of movement profiles. **(a)** The participants held a bar and performed a vertical motion with a robot. The vertically structured robotic arm horizontally supported the bar at its end and moved in the vertical axis (indicated by the up-down arrow). The bar was freely rotated around the pitch axis (indicated by the arc arrow). **(b)** An example of vertical frequencies and movements of the participant and the robot in a single trial. The frequency of the robot either increased or decreased by 0.15 Hz at period shifts. In this example, the robot adapted its movement at every cycle by 60 % of the frequency error on the previous cycle.

6.3.3. Procedure

The participant’s task was to cyclically transport the bar in the vertical axis in synchrony with the robot with their eyes closed. The participant sat in front of the robot to perform the task. At the start of each trial, the participant held the bar with the right hand, the elbow flexed at about 90° and the upper arm externally rotated with respect to the torso. In order for the participant’s arm in this position to match in height the robotic arm mounted on the floor, a platform was placed under the participant’s chair.

Initially, the robot supported the entire weight of the bar so the bar was kept pointing horizontally towards the participant. Once the participant held the bar with a power grip, the operational mode of the robot was switched and the rotational DoF was enabled. Thus, from this point on, the weight of the bar was supported by participant and robot.

When the participant was ready, with eyes closed, three beeps (500 ms interval) were played to warn of movement initiation by the robot. On the third beep, the robot initiated the movement and performed 25 cyclic movements (see Design for detailed description of the movement). At the end of each trial, the maximum angular deviation of the bar in the vertical axis was verbally provided to the participant as an indication of the synchronicity achieved with the robot. Participants were encouraged to reduce this angle as much as possible in successive trials. The robot then slowly came back to the starting position for the next trial. The experiment took approximately 1 hour including time for providing instructions, obtaining informed consent and allowing for breaks between trials.

6.3.4. Design

In each trial, the robot executed 25 vertical cyclic movements with an amplitude of 15 cm (Figure 6.1b). The trajectory of the robot was composed of a series of sinusoidal curves, each lasting for one cycle and connected at the lowest point of the amplitude. The frequency of the cycle was updated at every cycle. Once the desired frequency of the next cycle was determined according to the algorithm discussed below, a sinusoidal curve with a new frequency was generated for the next cycle.

The frequency of the movements varied between 0.5 Hz – 2 Hz, and the frequency for each movement cycle was selected as follows.

$$F_{r\,n+1} = F_{r\,n} + \alpha_r\,(F_{p\,n} - F_{r\,n}) \qquad \text{eq. 6.1}$$

where $F_{p\,n}$ is frequency of a participant and $F_{r\,n}$ is frequency of the robot at the n-th cyclic movement. Thus, the robot was controlled so it reduced the frequency difference in the previous cycle at an adaptation rate, α_{r}.

Three different adaptation rates were applied in this study. In one condition, α was set at 0.0 (Adaptor 0 %), meaning that the robot did not adapt to the interpersonal frequency error (i.e., $F_{p\,n} - F_{r\,n}$). In another condition, α was set at 0.6 so that the robot adapted to the interpersonal error by 60 % (Adaptor 60 %). In the remaining condition, α was set at 0.9 (Adaptor 90 %). The frequency of the first cyclic movement was randomly selected for each trial from a normal distribution with a mean of 1.5Hz and a standard deviation of 0.1 Hz. From the second cycle on, the frequency changed according to Equation 6.1 and the prescribed adaptation rate.

In each trial, period shifts were applied to groups of four cycles to measure the participants’ adaptation rate. In these cycles, the frequency was increased (increasing period shift) or decreased (decreasing period shift) by 0.15 Hz from the last commanded frequency. Out of four period shifts, two of them were Decreasing and the other two were Increasing. The time of the period shift and the types of those shifts were randomised with the following constraints: no period shifts occurred during the first and last three cyclic movements, and two adjacent shifts were separated by at least two non-shifted cycles.

For the analyses, the period of each movement cycle was calculated between the two adjacent lowest points of the vertical movement (Figure 6.2). Subsequently, the evolution of the movement frequency was tracked over the course of the trial in terms of Equation 6.1 with the human and robot terms switched around to obtain the adaptation rate of the participants (see Results for details). In addition, in order to determine whether the period shift led to reliable changes in kinematic landmarks other than the cycle frequency, the following four kinematic parameters were studied: maximum angular error, movement amplitude, peak velocity and the time of peak velocity. The time of peak velocity was normalised to the duration of each cycle. A sinusoidal trajectory executed by the robot consisted of two velocity peaks in each cycle; one at the first quarter (25% of the whole trajectory) for the upward part and the other at the third quarter (75%) for the downward part. The peak velocities were, therefore, obtained for the upward and downward parts of the cycles and analysed separately.

The experiment consisted of 30 trials, giving a total of 60 Increasing and Decreasing period shifts each. The experiment was conducted in a three-way mixed design whereby each group performed the task with a different adaptation rate of the robot. There were three independent variables in this study. The between-groups factor was Adaptor wherein the adaptation rate of the robot was set to one of three values (0 %, 60 %, or 90 %). The first within-subject factor was Shift Direction such that the period shift involved either shortening or lengthening a cycle. The second within-subject factor was Time of the cycle. The kinematic parameters at one cycle before (Cycle -1), during (Cycle 0), and one cycle after (Cycle 1) the period shifts were statistically analysed to investigate effects of the period shift on the shape of the trajectory. Mixed ANOVAs were used to report statistical differences in the group means and Greenhouse-Geisser correction was applied when the assumption of the sphericity for the within-subject variables was violated. Alpha levels of 0.05 were used for significance of the tests.

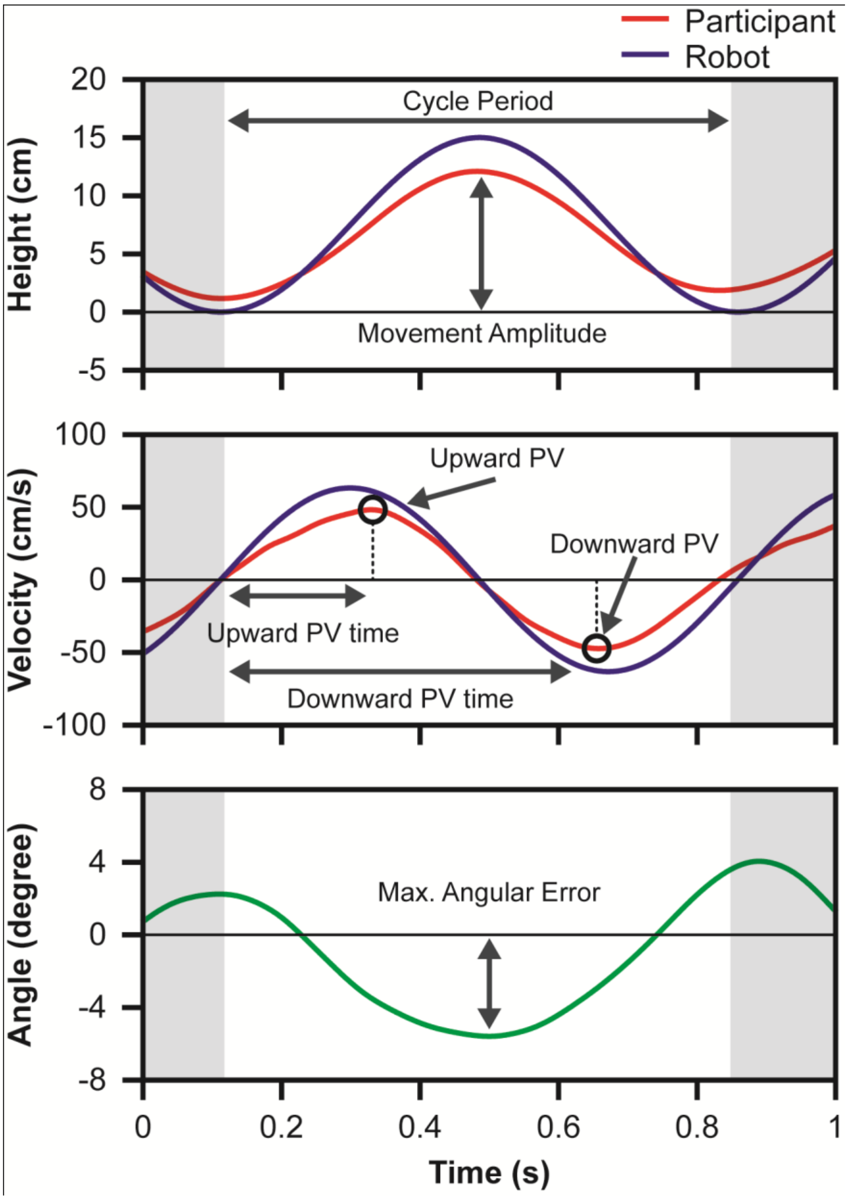

Figure 6.2. Illustrations of kinematic parameters obtained in this study. Height of the participant’s hand and the end effector for the robot are represented by the red and blue lines, respectively. One cycle is defined as the time between the two lowest points in the trajectory. The peak velocities (PVs) during the upward and downward movements within a cycle are expressed as positive and negative peaks in the velocity profile, respectively. The maximum angular error was defined as the largest absolute angle within a cycle.

6.4. Results

The results are divided into three sections, and indicate how the relative proportions of proactive and reactive components of the participants' actions relate to the manipulated characteristic of the robot partner. The first section deals with kinematic changes as participants adapt to the period shift in terms of movement amplitude, velocity profile (including the peak velocity and the time of peak velocity) and maximum angular error. The second section compares movement frequencies and their variability across three types of Adaptors. These results help us to understand if cooperative movements incur different costs to temporal coordination between partners (either its mean accuracy or variability) according to the degree of adaptation implemented by the robotic partner. The final section addresses changes in the participants' adaptation rates in relation to the adaptation rate of the robot.

6.4.1. Kinematic changes due to the period shift

Movement Amplitude. Effects of the period shift and the adaptation rate of the partner on the movement amplitude were investigated using a 2 (Shift Direction) x 3 (Time) x 3 (Adaptor) ANOVA (Figure 6.3). The ANOVA revealed a trend in Adaptor ($p = .084$). The movement amplitude was larger than the robot's amplitude (= 15 cm) with Adaptor 90 % (16.34 ± 2.60 cm) and smaller with Adaptor 0 % (13.64 ± 3.13 cm) as well as with Adaptor 60 % (13.53 ± 2.28 cm). The movement amplitude was not, on the other hand, different across Time ($p = 0.603$) or Speed ($p = .137$). Furthermore, none of the interaction terms was significant (ps. $> .11$). Thus, the analysis suggests that period shifts did not have a notable influence on the movement amplitude.

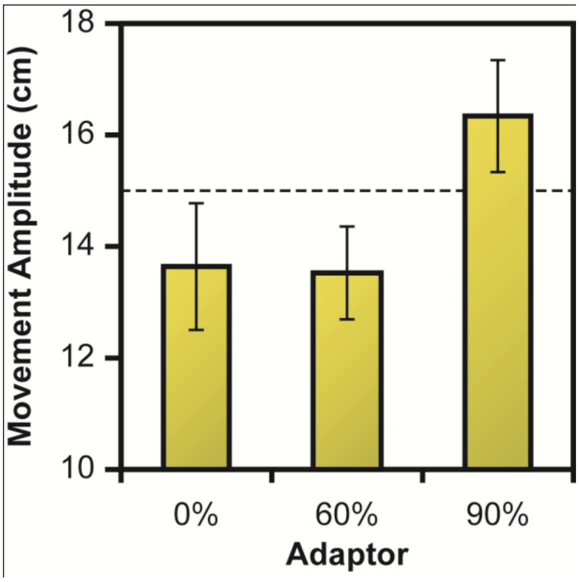

Figure 6.3. Movement amplitudes across Adaptor. The dotted line indicates the movement amplitude of the robot (15 cm).

Peak Velocity. Figure 6.4 shows velocity profiles around the time of period shift. A 2 (Shift Direction) x 3 (Time) x 3 (Adaptor) ANOVA was used for statistical analyses to compare the effect of the period shift on the peak velocities. ***Upward Movements*:** In the presence of Increasing period shift, the peak velocity gradually increased from Cycle -1 (64.89 ±11.70 cm/s), through Cycle 0 (68.98 ± 11.63 cm/s) to Cycle 1 (69.34 ± 12.17 cm/s). In contrast, the peak velocity decreased from Cycle -1 (70.17 ± 12.43 cm/s), through Cycle 0 (66.09 ± 12.69 cm/s) to Cycle 1 (64.33 ± 11.94 cm/s) with Decreasing period shift. A mixed three-way ANOVA supported mean differences across Shift Direction, F (1, 21) = 14.363, p < .002, and an interaction effect between Shift Direction and Time, F (2, 4) = 140.933, p < .0005. A main effect for Time was also observed, F (2, 42) = 39.576, p < .0005. Overall, the peak velocity was smaller at Cycle 1(66.84 ± 12.19 cm/s) than Cycle -1 (67.53 ± 12.24 cm/s) and Cycle 0 (67.53 ± 12.13 cm/s). The post-hoc comparisons revealed that peak velocity at Cycle -1 was larger than the peak velocity at Cycle 1 (p < .0005). If the continuous movements were strictly evolved in a predictive manner as proposed by the model, no corrective response to the period shift by the participants at Cycle 0 should be expected. Namely, the medium shift of the velocity at Cycle 0 indicates that there was a degree of on-line correction immediately after the phase shift. In addition, a main effect for Adaptor was revealed, F (2, 21) = 4.657, p < .03, such that the peak velocity was higher with Adaptor 90 % (76.44 ± 11.93 cm/s), than Adaptor 60 % (61.56 ± 20.06 cm/s) and Adaptor 0 % (63.89 ± 11.93 cm/s). Post-hoc comparisons indicated the peak velocity at Adaptor 90 % was statistically larger than at Adaptor 60 % (p < .04). A three-way interaction was also detected, F (4, 42) = 3.434, p < .05. ***Downward movements***. Unlike the upward movements, the peak velocity evolved asymptotically across Time. For Increasing period shifts, the peak velocity increased from Cycle -1(65.71 ± 11.59 cm/s) to Cycle 0 (71.85 ± 10.84 cm/s) and remained in the same range at Cycle 1 (69.75 ± 11.71cm/s). A reversal of asymptote was observed with Decreasing period shifts such that the peak velocity at Cycle -1 (71.07 ± 11.66 cm/s) was higher than PVs at Cycle 0 (63.97 ± 12.42 cm/s) and at Cycle 1 (65.77 ± 12.20 cm/s). An ANOVA showed that there are main effects on peak velocity for Shift Direction, F (2, 21) = 73.164, p < .0005, and Time, F (2, 42) = 12.819, p < .0005. Furthermore, an interaction between Shift Direction and Time was statistically significant, F (2, 48) = 198.587, p < .0005. With respect to Adaptor, the PVs were higher for Adaptor 90 % (76.62 ± 7.94 cm/s) than Adaptor 60 % (63.29 ± 10.33 cm/s) or Adaptor 0 % (64.15 ± 11.68 cm/s), F (2, 21) = 4.182, p < .04. Three-way interaction was also statistically significant, F (4, 42) = 8.048, p < .0005.

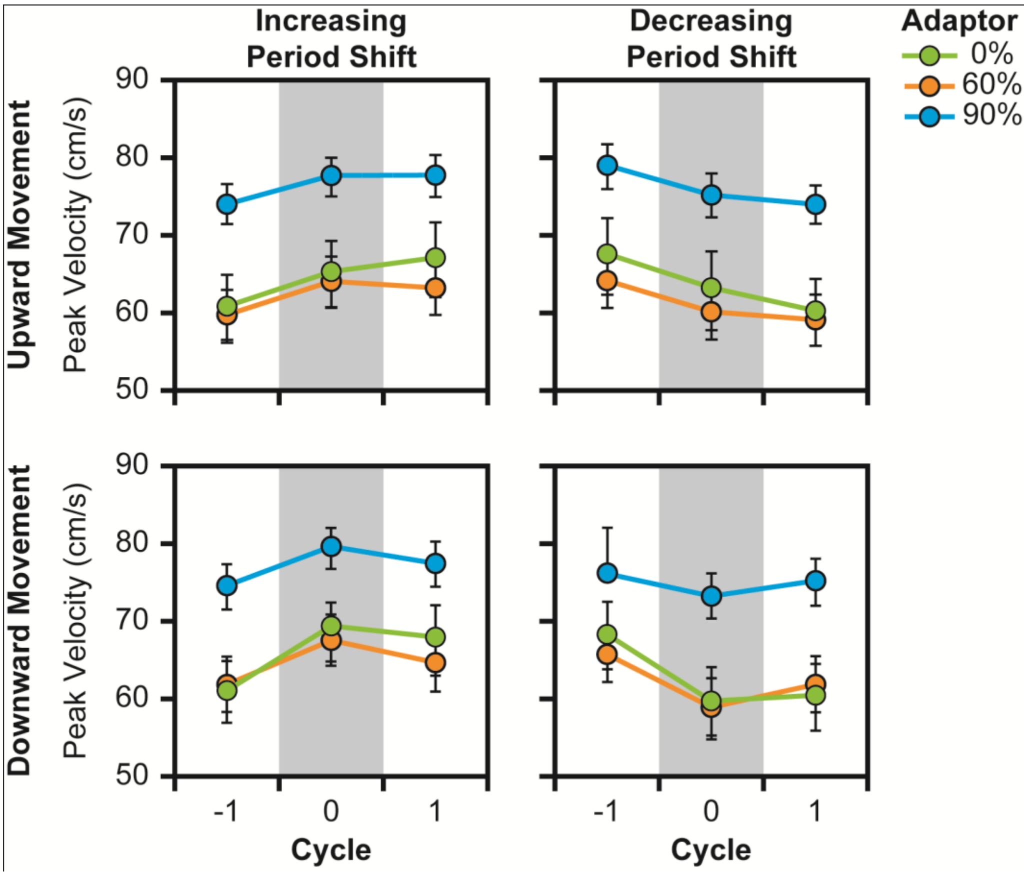

Figure 6.4. The peak velocity at a cycle before (Cycle -1), during (Cycle 0) and a cycle after (Cycle 1) the period shift which Increased or Decreased the movement frequency of the robot. The velocity profiles of a cycle consisted of two peaks. Peak velocities for the upward movement and the downward movements were presented separately.

Time of Peak Velocity. Changes in the time of peak velocities were investigated by administering three-way mixed ANOVAs for statistical comparisons (Figure 6.5). ***Upward movements***: For the Increasing period shift, the time of peak velocity was delayed at Cycle 0 (27.40 ± 1.12 %) compared with at Cycle -1 (25.84 ± 1.01 %) and at Cycle 1 (25.23 ± 0.57 %). When a Decreasing period shift was implemented, in contrast, the time of peak velocity was earlier at Cycle 0 (24.14 ± 0.73 %) than at Cycle -1 (25.63± 0.65 %) or at Cycle 1 (26.02 ± 1.09 %). The ANOVA supported the statistical difference in times of peak velocity due to Shift Direction, F (1, 21) = 135,170, p < .0005, as well as an interaction effect between Shift Direction and Time, F (2, 42) = 222.554, p < .0005. No main effect for Time (p = .143) or

Adaptor (p = .835) was observed. ***Downward movements***. The changes in the time of peak velocities during downward movements were similar to those during the upward movements. The Increasing period shift significantly delayed the time of peak velocity in Cycle 0 (77.2 ± 0.9 %) compared with Cycle -1 (76.8 ± 0.8%), but by Cycle 1 it had returned to the original level (76.5 ± 0.8 %). In reverse, the Decreasing shift resulted in advancement of the time of peak velocity in Cycle 0 (76.0 ± 0.9 %) with respect to Cycle -1 (76.6 ± 0.9 %), with values returning to a similar range by Cycle 1 (76.9 ± 0.9 %). The ANOVA indicated there is a main effect for Shift Direction, F (1, 21) = 21.535, p < .0005 as well as an interaction effect between Shift Direction and Time, F (2, 42) = 61.744, p < .0005. There was no main effect for Time (p =.120) or Adaptors (p = .709).

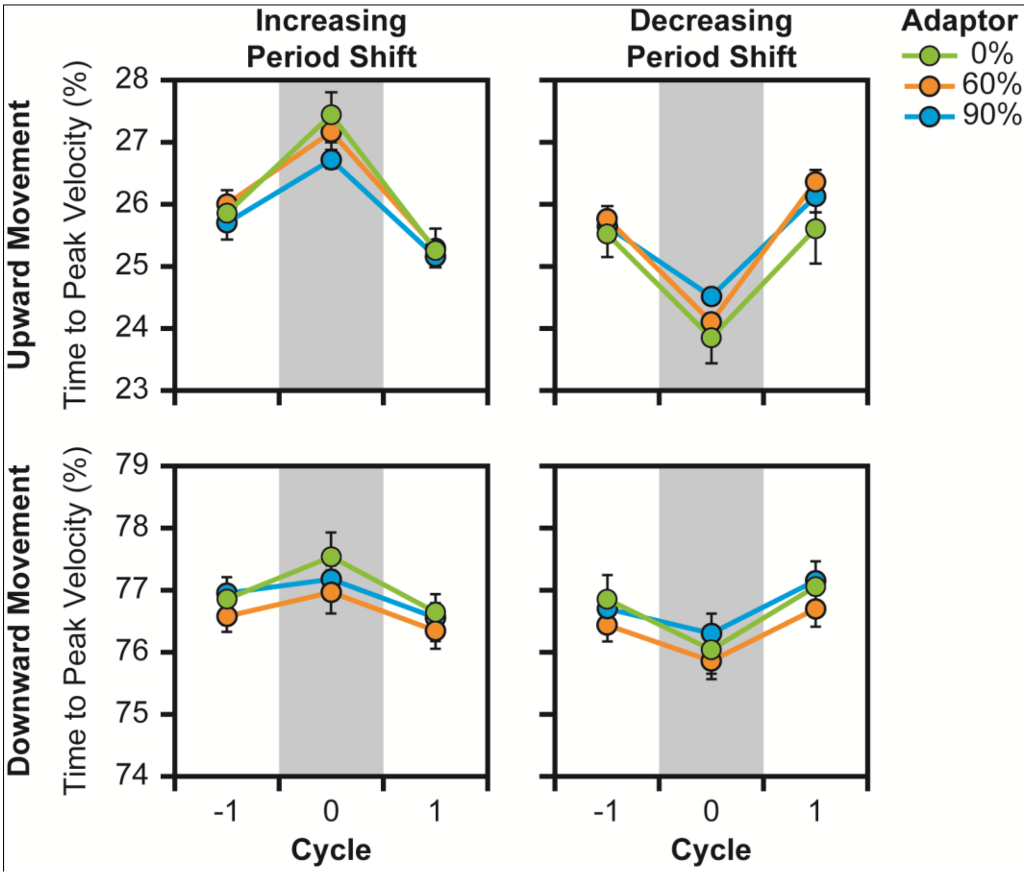

Figure 6.5. The time of the peak velocity at a cycle before (Cycle -1), during (Cycle 0) and a cycle after (Cycle 1) the period shift.

6.4.2. Angular error

Figure 6.6 shows the maximum angular deviation of the bar in the vertical plane at each cycle as a function of Shift Direction, Time and Adaptor. A three-way mixed ANOVA revealed a main effect for Shift Direction, F (1, 21) = 60.254, p < .0005, as well as an interaction between Shift Direction and Time, F (2, 42) = 72.864, p < .0005. The angular error was the highest for Adaptor 0 % (3.78 ± 2.92 degrees), slightly smaller for Adaptor 60 % (3.31 ± 1.78 degrees) and the smallest for Adaptor 90 % (1.55 ± 3.23 degrees). At the time of the increase in frequency (Cycle 0), the angular error was exacerbated by 1.22 degrees whereas the error was reduced at the time of the Decreasing period shift by -1.14 degrees on average. Furthermore, there was a main effect for Time, F (2, 42) = 3.693, p < .04. No main effect for Adaptor was observed (p = .247) and the remaining interaction terms were not significant (ps. > .10).

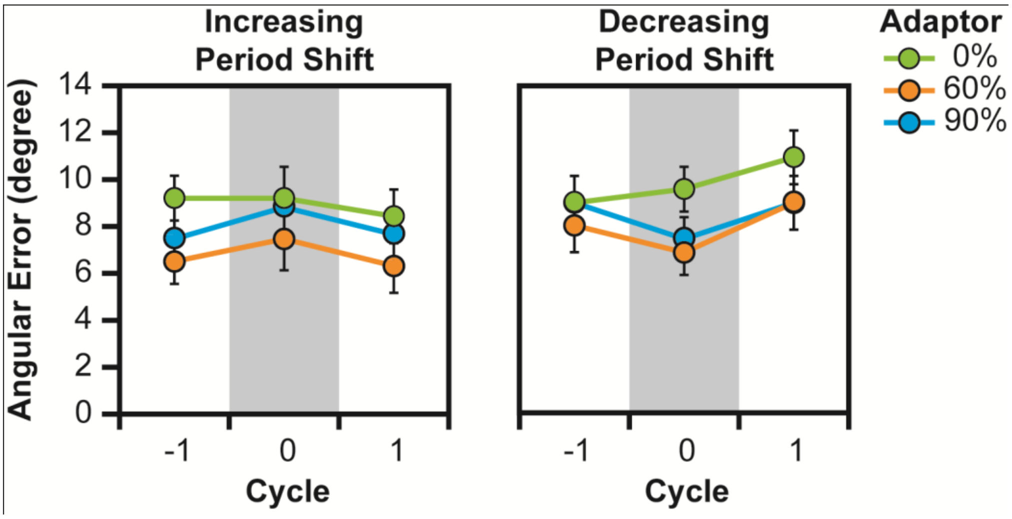

Figure 6.6. Average maximum angular error as a function of cycle. The maximum angular deviation in the vertical axis was calculated for each cycle.

6.4.3. Movement Frequency

Here, overall movement frequencies for each Adaptor are described. Figure 6.7a shows mean frequencies of the movements produced by the participants. A one-way between-groups ANOVA revealed a significant difference in the mean frequency between Adaptors, F (2, 21) = 5.929, p < .01. A post-hoc multiple comparison with Bonferroni correction indicated that the main effect was due to a difference in the mean frequency between Adaptor 0 % and Adaptor 90 % (p < .001 It is also important to note that most of the participants in Adaptor 60 % and Adaptor 90 % had evolved their movements to ones of higher frequency (Figure 6.8). In Adaptor 0 % the frequency remained at around the starting frequency of 1.5 Hz with a small variability (1.49 ± 0.02 Hz). This was predicted due to the non-adaptive feature of the robot in this condition. For Adaptor 60 % and Adaptor 90 %, the mean frequency slightly increased from the initial value (1.60 ± 0.19 Hz and 1.69 ± 0.05 Hz, respectively).

Since the variability (i.e., standard deviation of the data) is not normally distributed, a Kruskal-Wallis one-way ANOVA was performed on the three Adaptors to investigate whether the Adaptors had influenced the variability of the performance (Figure 6.7b). The median frequency variability was similar between Adaptor 0 % (0.133 Hz) and Adaptor 90 % (0.121 Hz) and Adaptor 60 % (0.130 Hz). The analysis did not identify significant difference between the Adaptors (p = .104).

In order to verify whether the participants performed the task more successfully in one condition than another, mean frequency error was calculated by subtracting the position frequency of the participants from that of the robot. Frequency errors at the period shifts were excluded from the analysis since the error was externally inserted for those cycles. As shown by the negative frequency error across Adaptors in Figure 6.7c, the frequency was lower for the participants than the robot. The error was the largest in Adaptor 0 % (-0.0065 ± 0.0165 Hz). The frequency error was smaller in Adaptor 60 % (0.0029 ± 0.0061 Hz) and the smallest in Adaptor 90 % (0.0017 ± 0.0013 Hz). However, a one-way between-groups ANOVA indicated that there was no statistical difference across Adaptors (p = .623).

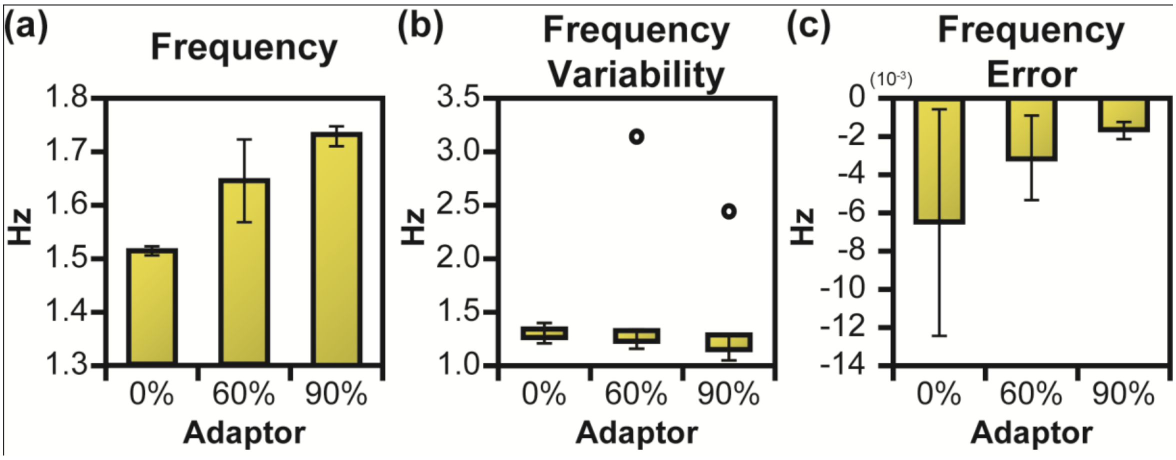

Figure 6.7. The movement frequency, frequency error and their variability. Error bars represent between-subject standard error. **(a)** Frequency of the movement became higher as the adaptation rate of the robot increased. **(b)** A box plot of the variability of the frequency. Outliers are represented in open circles. **(c)** Frequency error was calculated by subtracting the frequency of the participants from that of the robot. Thus, negative value indicates that the participant's frequency was higher than the robot's frequency.

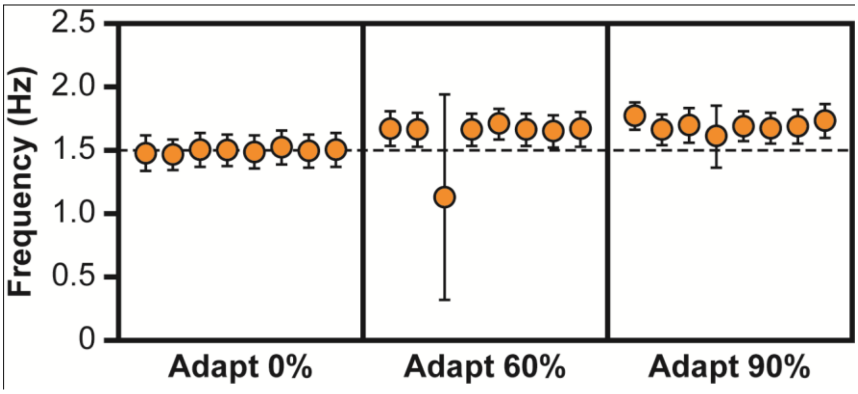

Figure 6.8. Mean frequencies of all participants. At Adaptor 0 %, the robot's movement frequency was constrained to the initial frequency (i.e., around 1.5 Hz). For this reason, the participants' frequencies always dwelled at around the initial frequency. For the remaining two Adaptors, the robot could increase or decrease the movement frequency depending on how the participants interacted. Nevertheless, all participants but one in Adaptor 60 % showed a tendency to increase the frequency from levels in the initial state, to a value of around 1.6 – 1.7 Hz.

6.4.4. Joint Adaptation Rate

This study investigated whether modulation of the adaptation rate would be observed in a continuous rhythmic movement. Figure 6.9 shows the mean movement frequency at the period shift (Cycle 0), a previous cycle (Cycle –1) and four cycles after the shift (Cycle 1 to 4). At Cycle –1, the frequencies of the participants and the robot are very close. A large difference in frequencies is evident at Cycle 0 due to the unpredictable period shift. This difference then gradually reduces over the following Cycles 1 to Cycle 4. The adaptation rates of each participant were calculated as follows. Firstly, an averaged frequency change from Cycle 0 to Cycle 1 and an averaged frequency error at Cycle 0 were obtained. The adaptation rate was then calculated by taking the ratio of the change term over the error term. To investigate the effect of the directionality of the period shift, the rates for Increasing and Decreasing period shifts were then analysed separately.

The movement frequency of the robot was determined by Equation 6.1 with a pre-defined adaptation rate, α. Thus, the frequency of the robot should be constant following the period shift at Adaptor 0 %. On the other hand, the robot frequency at Adaptor 90 % should move towards the participant's movement frequency by 90 % of the frequency error observed in the previous cycle. In Figure 6.9, however, the error amendments by the robot at Cycle 1 due to the error at Cycle 0 appear to be smaller than expected in Adaptor 60 % and Adaptor 90 %. The main reason for this is that the model assumes the acquisition of the error signal and the adaptation of the frequency take place concurrently for statistical simplicity. To achieve the adaptation in the robot, however, a time lag between sampling the frequency error with the participant and the implementation of a new trajectory was necessary. The frequency of the participant was calculated in real-time by sampling the time when the height of the participant passed a threshold of 3 cm during downward movement, descending from a position higher than at least 4.5cm. This procedure induced the average lag of 109.3 ms (±

7.5 ms) compared to the movement frequency defined as a trajectory between two adjacent local minima in amplitude. For this reason, the adaptation rate of the robot appears different when a cycle is defined as a trajectory between two adjacent local minima in amplitude. In order to show how the adaptation rate of the robot was affected by this frequency calculation method, this ‘observed’ adaptation rate of the robot was calculated using the actual movement frequency in the same way as the adaptation rate was obtained for the human participants.

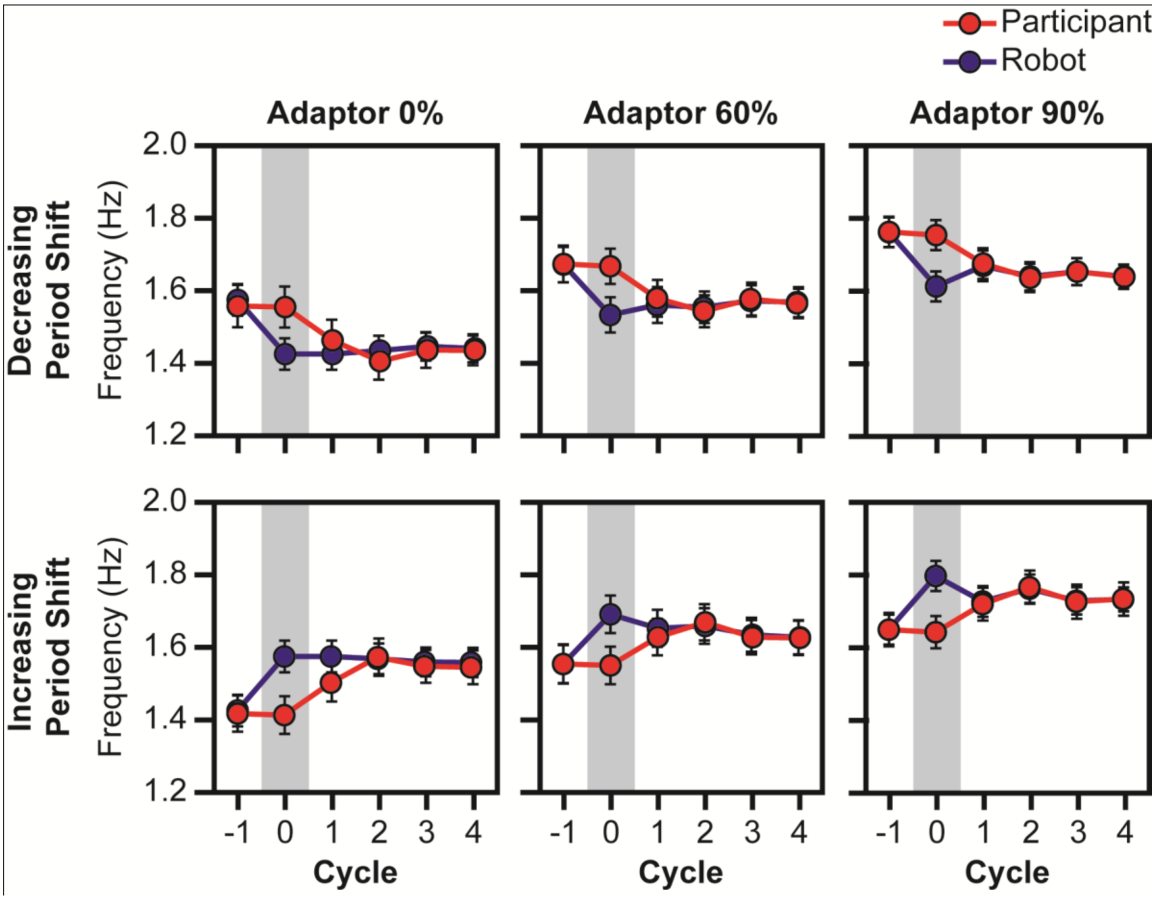

Figure 6. 9. Changes in frequency due to the period shift. The frequency at each movement cycle, at (Cycle 0), before (Cycle -1) or after (Cycle 1 to 4) the period shifts. Note that the frequency of the robot fluctuates at Adaptor 0. In the study, the period shift occurred at random with a minimum of 2 cycles separating successive shifts. Thus, the number of samples at each cycle varies after Cycle 2 and this causes small fluctuations in average frequency after this point. The dotted lines indicate expected frequencies if the adaptation rate of the robot were veridical to the prescribed adaptation rate. The error bars represent averaged within-subject standard error.

Figure 6.10 shows the estimated adaptation rates of the participants and the robot. For the robot, the estimated adaptation rate at Adaptor 0 % matched the model parameter (0.00 ± 0.00) for both Increasing and Decreasing period shifts (Figure 6.10). For the Increasing period shift, the rate was 0.21 ± 0.04 for Adaptor 60 % and 0.40 ±0.05 for Adaptor 90 %. For the Decreasing period shift, the rate was slightly higher at 0.28± 0.06 for Adaptor 60 % and 0.45 ± 0.04 for Adaptor 90 %. Despite the overall reduction in rate, overall the estimated rates were linearly correlated with the originally prescribed rates ($r^2 = 0.89$). The adaptation rates of the participants linearly decreased from Adaptor 0 % (0.78 ± 0.28), Adaptor 60 % (0.66 ± 0.06) and to Adaptor 90 % (0.56 ± 0.06) for the Increasing period shift. Similarly, though the rates were smaller, adaptation rates for Decreasing shift decreased from Adaptor 0 % (0.55 ± 0.07), Adaptor 60 % (0.55± 0.06) and to Adaptor 90 % (0.50 ± 0.05). 2 (Shift Direction) x 3 (Adaptor) mixed ANOVA confirmed that there were main effects for Adaptor, F (2, 21) = 3.488, p< .05, and Shift Direction, F (1, 21) = 17.889, p < .0005. No interaction effect was found (p = .104). Post-hoc tests (Bonferroni correction) indicated that the adaptation rate at Adaptor 0 % was statistically larger than that at Adaptor 90 % (p < .05).

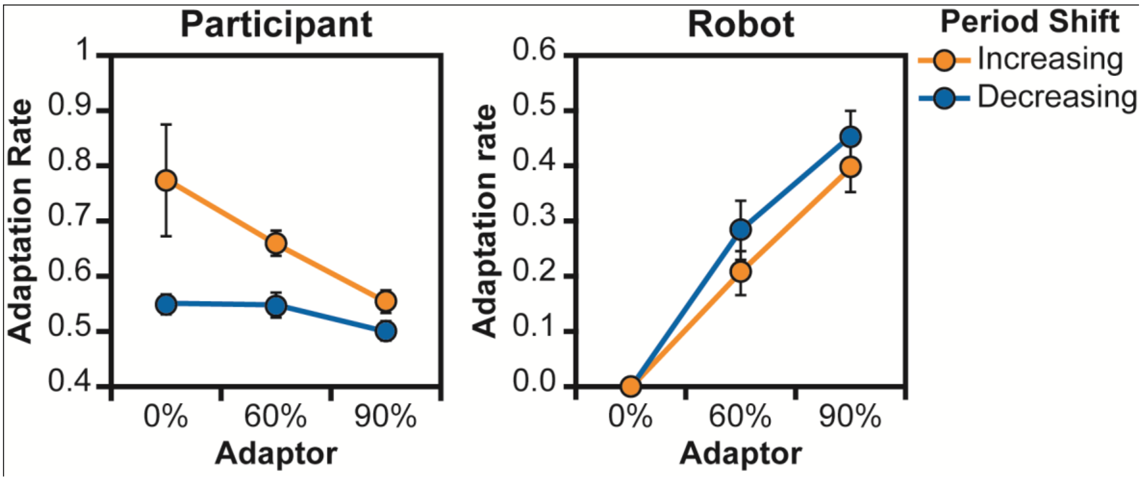

Figure 6.10. Adaptation rate of the participants and the robot for increase and decrease in frequency. There was a tendency for the participant's adaptation rate to decrease as the rate of the robot increased. The estimated adaptation rates of the robot were smaller than the prescribed rates, but the linear step change in the adaptation rate was preserved in the estimated adaptation rates. The error bars represent one standard error.

6.5. Discussion

The present study describes changes in kinematics and motor adaptation rate in the presence of an adaptive robot as a task partner when the partners rhythmically translated a bar between two points in space together. In this study, motor adaptation was expressed in terms of a first-order linear model in which the evolution of movement frequency was determined by linear adaptation law operating on the frequency error between task partners. The adaptation rate of the robot was manipulated to investigate whether this rate change would influence the movement characteristics of participants.

6.5.1. Kinematic Changes due to a Period Shift

Here we were interested to characterise the kinematics of how participants adapted to the period shift. Changes in detailed kinematic characteristics due to unexpected period shifts of the robot were studied to investigate whether changes in the adaptability of the robot would result in systematic change in feedback correction by the participants.

One way of modulating timing both in terms of variability and accuracy is via movement amplitude change (Doumas, Wing, & Wood, 2008). Nevertheless, the results show that, at least in this context, amplitude change was not how the participants modified their timing behaviour in response to the period shifts. This indicates that the participants were properly following the task instruction of synchronising the movement with the robot. However, it is equally probable that two people shaking hands with each other would adapt their movement amplitude over repetitions in addition to movement frequency. For simplicity, this study focused on adaptation of movement frequency. Thus, exploring how these two potentially depending factors that are affecting the timing behaviour would be adapted may provide a richer context for exploring interpersonal interaction.

Separate measures of peak velocity and time of peak velocity for upward and downward movements within a single cycle enabled a closer look at the local evolution of frequency change. The analyses of the time of peak velocity addressed the question as to whether the effect of period change was distributed over the subsequent movement cycles or compensated abruptly for at a particular point in the movement. The results indicated that the participants started engaging in period correction within the first half of a phase shift cycle. On the other hand, observation of the peak velocity during the downward movement suggests that change in the peak velocity from the period shift cycle (Cycle 0) to the next one (Cycle 1) was much smaller than the change from Cycle -1 to Cycle 0, in either direction of period shift. Taken together, it seems that the participants gradually corrected the movements by the time of downward peak within the period shift cycle. Furthermore, the time of the peak velocity shifted forward and backward at the time of decreasing and increasing period shift, respectively. Thus, it seems that the participants controlled the velocity profile, both in terms of the distribution of the velocity profile as well as its peak size, to cope with a sudden period shift by the partner.

Angular error could be a source of information prompting adjustment to a period change and to any variability in the partner’s movement. Despite the fact that the analyses on the velocity profile indicated the participants corrected the period shift within the same movement cycle, the maximum angular error at this cycler was larger than the rest of the cycles. This suggests that the immediate within-cycle correction of the frequency was incomplete. Interestingly, the size of the error was the largest when the robot did not adapt to the participant (Adaptor 0 %) and the error with increasing adaptation rate of the robot. This is consistent with that the summed adaptation rate of the participant and the robot being closest to 1 at Adaptor 0.9, indicating that in this condition a larger proportion of error was corrected by the two partners at each cycle.

6.5.2. Movement Frequency

Overall, there was a tendency for the movement frequency to evolve to higher frequency as the adaptation rate of the robot was increased. The results show that when the robot is more accommodating, participants do not stay as close to the original frequency, but continue to increase their frequency. This may be due to the nature of the period shift, previous research has suggested that people have a tendency to increase movement frequency under stress (Yarrow, Haggard, & Rothwell, 2004). Thus, a sudden increase of the movement speed might have triggered a neural circuit that processes arousal and influences the motor system. Another possibility is that people preferred to produce a frequency higher than 1.5 Hz due to the biomechanics of the arm (de Rugy, Salesse, Oullier, & Temprado, 2006). It has been suggested that the oscillation frequency of a handheld object is dependent of a resonance frequency of the end-effector. Thus, the mechanical properties of the object may have contributed for the participants to produce a particular movement frequency.

6.5.3. Joint Adaptation Rate

The final section addressed the changes in the participants' adaptation rates in relation to the adaptation rate of the robot. Consistently to the previous finding presented in Chapter 5, an inverse modulation of adaptation rate was observed in this continuous movement task. The parametric reduction in human adaptation along with the manipulated increase in the robot adaptation indicates that cooperative behaviour is very sensitive to partner accommodation during interpersonal rhythmic motor coordination.

The combined adaptation rate of a participant and the robot was much higher than the adaptation rates observed in Chapter 5 where the adaptation rates varied between 0.05 and 0.15 for the same set of partner adaptation rates. Previously, an error-based learning model has been used to explain both discrete (Thoroughman et al., 2000) and rhythmic (Vorberg et al., 1996) individual movement tasks. During a discrete movement paradigm, the adaptation is induced by artificially changing the sensory-motor mapping by, for example, using a prismatic displacement (Redding & Wallace, 1996) or modifying the force field of a task environment (Shadmehr et al., 1994). In rhythmic studies, participants are typically asked to tap their fingers to a metronome in synchrony and a sudden change in the rhythm is introduced to study how quickly they could recover from this error. Interestingly, however, there is a large difference in the optimal adaptation rates in the two movement tasks such that the optimal adaptation rates are usually reported to be at around 0.8 for rhythmic synchronisation tasks whereas the adaptation rate in the discrete movements such as learning to reach to a target in a new force field falls in at around 0.1- 0.2. Thus, there may be fundamentally different mechanisms involved in how people learn to coordinate movement with a task partner in a discrete movement task and in rhythmic continuous. Another major difference of this study from the study presented in Chapter 5 is that the task involved haptic coordination of two people. As shown in previous chapters, haptic feedback provides rich information about dynamics of the task as well as the movement of a person manipulating the same object from the other side. Thus, it is plausible that people were more sensitive to haptic errors than visual errors and this might have tapped into higher adaptation rates in this experiment than previously found.

6.5.4. Social Cooperative Interaction

This study used the task of handshaking as an example of continuous interpersonal coordination of movements. It has been suggested that the form of the handshake can be prone to a variety of social factors such as sex and culture as well as action-related factors such as the weight and morphology of the hand. People often offer a handshake as a means of indicating their presence to the social partner. For this reason, some have proposed that the handshake plays a significant role exchanging psychological meanings. Schiffrin (2009), for example, viewed handshake as a culturally derived ritual to prove trust and familiarity to the social dyad by allowing the partner in the physically proximal space. Accordingly, researchers hypothesised handshake as an invariance that reflected the actor's personality (Astrom, 1994; Chaplin et al., 2000) and their psychopathological state (Astrom, Thorell, Holmlund, & Delia, 1993). In terms of the joint adaptation model, these socio-cognitive factors may influence how the adaptation rates of the two partners are stabilised. For example, it is possible that a person with a dominant personality may be less likely to change his/her movement profiles. Thus, it may be shows as a low adaptation rate, which in effect increases the adaptation rate of a less dominant partner. Thus, in future research it will be interesting how this joint adaptation model behaves in the presence of socio-cognitive factors.

6.5.5. Application of joint adaptation model

The joint adaptation model may contribute to a more comprehensive understanding of the mechanisms underlying cooperative action and algorithms for developing adaptive robot assistants to support various human activities. In industry, for example, robotic systems have been introduced in order to maximise production levels, to cut the cost and to perform tasks in hazardous environments in place of people. One of the challenges for developing an interactive robotic system is that each user has different movement characteristics, which may not be stable across time. Thus, implementing adaptive characteristics of each user in interactive robots may vastly improve the performance outcome. Nevertheless, current robotic systems are largely used as a tool for humans wherein the users unidirectionally adapt to characteristics of the robot. This relationship sets a limit to what they can achieve and richness of experience that the user has in cooperation. This study aims to facilitate the scientific understanding of social interaction among people that can be applied to develop a more competent and biologically-inspired robotic system as well as for setting a safety guideline for industries by monitoring how the humans are interacting with the robots. Furthermore, an application of robotic systems has been actively introduced to medical (e.g., Narazaki, Oleynikov, & Stergiou, 2006) and clinical (e.g., Johnson, 2006) settings. Currently, the majority of the systems available are pre-programmed to assist healthcare professionals for their specific needs, and developing adaptive systems could further improve their performance. In addition, the socially intelligent system may be commercially attractive since it could help in designing more elaborate household robots and computer-simulated virtual avatars including for gaming with more human-like characteristics.

6.6. Conclusions

Previous studies have shown that the CNS processes and represents actions of others and self in a largely overlapping fashion. Nevertheless, there has been little understanding of the form in which people control their movements for interpersonal interaction. This study demonstrated that people process the adaptive characteristics of a cooperation partner, adjust their own adaptation rate according to the perceived motor error, and so manage their individual contributions to maintain a net level of adaptation during rhythmic interpersonal motor coordination. This error correction was a gradual process such that the motor parameters were adjusted over the course of several cycles, the time characteristics of which adjustment were relatively unaffected by changes in the adaptation rate of the robot partner.

This modulation of adaptation rate may crucially underlie social interaction, which enables people to respond flexibly to other people’s actions in a wide variety of social interactions and thus facilitate goal-directed behavior in joint actions. In conclusion, the present study described motor coordination between a person and an adaptive robot in a cooperative task, and it provides strong evidence for interpersonal interaction at adaptation rates during an interpersonal continuous motor task. The study therefore suggests that the joint adaptation model developed in Chapter 5 can be extended to a task in which two people coordinate continuous movement.

Chapter 7

Epilogue: Multi-Person Motor Coordination

7.1 Brief summaries of the experimental chapters

The fundamental objective of this thesis was to understand and demonstrate how implicit, nonverbal cues support the coordinated movements of two people working towards a shared goal. While researchers have generally tackled the challenge of understanding the human brain by focusing on a single actor interacting with a controlled environment, there is a growing appetite in neuroscience for investigating how the CNS operates at a social level. In particular, much attention is being paid to those studies of 'joint action' which are laying foundations for an understanding of how people represent conspecifics in the CNS (Sebanz et al., 2006). However, there have been very few studies specifically focusing on the sensory-motor interactions between people; this thesis aims to contribute to social neuroscience by providing analysis of movement coordination in joint action.

Through a series of studies, it describes how the CNS learns and controls movement with respect to concurrent movement executed by another person using a cooperative object-lifting paradigm. In this paradigm, a participant lifted (and, in one case, lowered) a bar with a task partner to a target height as synchronously as possible so that the bar was kept level throughout the movement. Good performance, in terms of keeping the bar level, depended on matching a task partner's movement characteristics, such as onset time, velocity and acceleration.

In **Chapter 2**, motor learning, through haptic interaction, by the lift task partners was addressed. In the study, paired participants jointly lifted two types of bar. One was a rigid object whereas the other rotated freely around the grasp points (when, for instance, the lifting speeds of the participants differed). This free rotation of the object resulted in a reduction of the rotational information available at the finger tips. Initially, the participants produced notably jerky lifting trajectories, which indicated that control over the movement coordination with their task partner was predominantly based on feedback. When the participants repeatedly lifted the same bar, a quick reduction in jerk cost over trials was observed. This improvement was lost when the dynamics of the bar (i.e. the mass distribution) changed, indicating that the participants learned partner dynamics rather than kinematics. Consistent with this, a further disruption in learning was observed when the participants used the bar with freely rotating grasp points. Therefore, this chapter highlights the role of haptic feedback in interpreting and learning the dynamics of a task in order to successfully coordinate movements with a task partner.

Chapter 3 addressed the contributions of feedforward and feedback control by varying the predictability of the lifting trajectory produced by the task partner. In this study a humanoid robot played the role of the task partner to allow manipulation of the movement trajectory with which participants were required to coordinate their movement. The results revealed evidence for cross-trial learning as shown by a reduction in unnecessary force exchange between the partners. In addition, there was a reduction in kinematic errors including the maximum difference in the vertical positions and velocities of the bar handles held by the participant and robot. When the robot behaved unpredictably in the middle of the lifting motion, the participants amended the error within the same trial with a response delay of approximately 150 ms. Therefore, this chapter highlights feedforward and feedback control in the cooperative object-lifting paradigm.

In **Chapter 4,** dynamic evolution of movement parameters during a human-human cooperative task was modelled in terms of an error-based learning scheme. This study compared a range of kinematic and kinetic parameters in order to investigate how interpersonal differences in these parameters affected the progress of subsequent movements. The analyses indicated that a first-order linear error correction model provides a good account of cooperative interaction, and that kinematic parameters are particularly well-suited for model-fitting. This may appear to be in disagreement with the findings in Chapter 2, which documented the importance of kinetic interaction for successful cooperation. The primary task of the pair in these two studies was to reduce their kinematic difference, as expressed through the dynamics of the object. Thus, it is comprehensible that the interaction process at the kinetic level plays a key role for information exchange, yet the evolution of the kinetic parameters would not need to conform to error-based learning. This study also demonstrated that the task instruction (i.e., assignment of Leader and Follower in the task) influenced how the paired participants adapted their movements to each other. Therefore, the study presents evidence that the degree to which a person adapts to the error may be influenced by cognitive factors such as task knowledge. In conclusion, this chapter proposed a cooperative model in which action is moderated by an adaptation rate that regresses behavioural outcome with regard to interpersonal errors from previous trials.

Chapter 5 investigated whether adaptation to a task partner is optimised at an individual or a cooperative level. During two-person interaction, both partners are, in principle, adaptive agents. This can lead to a risk of “over-adaptation” since both partners are adapting to correct the same error. Therefore, to optimise motor performance at a cooperative level, the pair must take account of the statistics of adaptation by their partner when adapting their own motor plan. Using a computer-simulated partner whose movements adapted to the participants at various rates, this study provided clear evidence that the people can implicitly and flexibly adjust their adaptation rates with regard to the adaptation rate of their partner in order to optimise the performance at a cooperative level.

Chapter 6 extended the joint adaptation model observed in Chapter 5 to a continuous movement task. In this study, participants cooperated with a robot to move an object rhythmically up and down. In an equivalent form to the experimental manipulation in Chapter 5, the adaptation law was applied to the robot such that it (the robot) changed its movement frequency in order to reduce the difference with the participants; it did this at various rates.

The results confirmed the presence of joint adaptation in a continuous movement task such that the adaptation rate of the participants decreased when that of the robot was high, and vice versa. Detailed kinematic analyses of the rhythmic movements are provided which indicate that feedback and feedforward forms of control are engaged for interpersonal error correction, yet the degree of feedback correction was not affected by the adaptive characteristics of the robotic partner.

7.2 Impact of Research

The fundamental purpose of the CNS is to allow an actor to successfully interact with the environment, and the ability to learn is critical in coping with a complex and often slowly, yet constantly, changing relationship between oneself and that environment. Much evidence has suggested that the CNS can flexibly learn environmental constraints, such as the dynamics of a novel object or workspace (Wolpert et al., 2000) or novel kinematics induced by prismatic displacement of the visual field (Redding et al., 1996). In parallel, studies of social neuroscience have reported strong evidence that the CNS processes and represents the actions of others and self in a largely overlapping fashion (Sebanz et al., 2003). Nevertheless, there is little understanding of the form in which people control their movements during interpersonal interaction.

This thesis advances our understanding of human motor control within social settings by demonstrating that people process adaptive statistics of a task partner, adjust their own adaptation rate to a motor error, and realise optimal movement at a cooperative level.

Methodologically, this thesis has achieved a multidisciplinary approach by forging bridges between experimental psychology, computer science, and cognitive robotics. These studies not only reveal novel aspects of human brain function for a cooperative task, but also illustrate methodological difficulties and possible solutions for those who wish to study behavioural interaction of multiple persons using quantitative methods. In addition, these studies may also provide useful information concerning the design of interactive assistance robots that are socially intelligent

7.3 Qualifications and future directions

7.3.1 Task Specificity

The present thesis focused on cooperative object-lifting as a target task to investigate the control processes underlying interpersonal interaction. However, this is just one of countless ways in which people may interact with each other. Some components of these other ways may be captured by the joint adaptation model described in this thesis, but significant modifications may be required to account for others. For example, the simple handing of an object from one person to another also requires a level of cooperation. By having two people translate the object, the two partners can cover a wide range of task space using only upper body movements, coverage that one person acting alone could only achieve using locomotion. Moreover, lifting an object with another person, rather than alone, reduces the individual load on each partner. In order to achieve a smooth and fast transition of the object, the movements of the partners need to be coordinated with each other. Certain movement parameters of the handover, such as timing or spatial location, can be predicted and refined by repetitive practice in the same manner that people learn to lift an object with a task partner. If the two actors aiming to hand an object over to one another find themselves at spatially different positions, for instance, the location can be adjusted in the next trial given a prediction about the partner's correction. In contrast, the moment of the handover may instead require a different motor strategy. When the dyad physically makes contact to pass the object over, there is haptic interaction wherein one actor releases the object as the other person starts supporting its weight.

Because the current joint adaptation model was derived for a task wherein the primary goal of the task was to produce a symmetric movement with the partner, it fails to explain how paired participants purposely produce asymmetric yet compatible sets of movements. Recent brain imaging studies have suggested that the planning of asymmetric cooperative movement involves the mirror neuron system (Kokal et al., 2009; Newman-Norlund et al., 2007), neural systems that commonly code actions performed by another person as well as those of one's own (Rizzolatti et al., 2010). Thus, these asymmetric actions may be derived from a "single" motor plan of the partners being delegated into two effectors, in a similar form to the way asymmetric movements are controlled in bimanual coordination (Guiard, 1987; Sainburg, 2002). One suggested modification of the model may be that it requires an intermediate level of representation wherein the planned movements of the partner and self are represented independently. Joint adaptation then could be formed on the basis of the prediction error about the partner's trajectory, rather than the absolute difference between the partners in the performance as implemented in this thesis.

While the current model captures the coordination of symmetric movements between individuals, it can be extended to understand the coordination dynamics of more than two people. For example, motor interaction between more than one, say four, partner(s) may be required to lift a larger and heavier object. The four partners concurrently adjust their motor outputs to each other in order to improve the accuracy. In effect, three interpersonal errors (one against each of the others) can be defined. When multiple sources of errors are present, a combination of these errors should lead to a change of behaviour. In a simple form, this relationship can be expressed by adding error terms as follows:

$$Y_{p1\,n+1} = Y_{p1\,n} + \alpha_{p1}\,(Y_{p2\,n} - Y_{p1\,n}) + \beta_{p1}\,(Y_{p3\,n} - Y_{p1\,n}) + \gamma_{p1}\,(Y_{p4\,n} - Y_{p1\,n}) \qquad \text{eq. 7.1}$$

where $Y_{p1\,n}$ is a current response for Partner 1. The next response is determined by the correction factors, α_{p1}, β_{p1}, γ_{p1}, for asynchronies against Partner 2 ($Y_{p2\,n}–Y_{p1\,n}$), Partner 3 ($Y_{p3\,n}–Y_{p1\,n}$), and Partner 4 ($Y_{p4\,n}–Y_{p1\,n}$), respectively.

Thus, the adaptation rate in the joint adaptation model can be conceptualised as an index of “dependence” on one or more partners, expressing the degree to which the partner corrects the movement to the timing of the partner(s). When there are four people interacting to lift an object, the spatial configuration of each partner’s stance may influence this dependence, for example, by adapting movement to the closest partner. In this way, this “dependence” can be quantitatively expressed using an extension of the joint adaptation model. Although a mathematical solution to such an equation requires greater complexity, it will provide a unique perspective into the understanding of group dynamic.

7.3.2 Deterministic vs. Probabilistic model

An important issue to be considered is the biological plausibility of the joint adaptation model since the current joint adaptation model is theoretical. Interpersonal interaction has previously been modelled in terms of a dynamical system which describes the dependence of two oscillating systems (Oullier et al., 2008). With respect to individual action, probabilistic models (e.g. Bayesian based models) are reported to outperform deterministic models (Todorov et al., 2002; Sarkar et al., 2002). In Chapter 3, it was also shown that an increased number of predictors may slightly improve the prediction of the partner’s behaviour. While these models may be more successful in describing the evolution of movement parameters, they commonly require prior knowledge about the system such as the mass and the spring system of the arm for upper-body movement. A primary purpose of the present research was to demonstrate the existence of joint adaptation during cooperative interaction; to this end, a simple linear model had a practical advantage due to the simplicity of its theoretical interpretations and modifications. Therefore, a simple deterministic model developed in this thesis is believed to serve as a valuable foundation for developing more sophisticated models of motor control in the future, for instance, to examine how the optimal gain of a pair might be realised in terms of probabilistic theory.

7.3.3 Determinants of an adaptation rate

This thesis demonstrated that people can effectively accommodate contribution of an adaptive partner in a cooperative task so that the summed adaptation rates of the partners are sustained at a certain level. However, it remains unclear how a dyad delegates the adaptation rates between its respective partners. Recently, Braun and colleagues (2009) have described cooperative behaviour in terms of efficient decision making. In their study, two participants jointly moved a handle to a target, but the force required to move the handle in space varied. When they chose a “cooperative” path, the participants both received resistance force of 3 N/m as they moved the handle to its target. When they both chose a “defective” path, they received 7 N/m. When one person selected the “cooperative” path but the other one did not, the former received 10 N/s and the latter received no stiffness (0 N/s). Under such circumstances, the participants preferentially chose the “defective” part whereby their partner would never be at an advantage. When they performed the same task bimanually, in contrast, the participants actively achieved the cooperative solution. Thus it seems that people are estimating costs of relying on their partner when they make a decision about how they should perform the task. Although this study showed a tendency for people to optimise their individual action over cooperation, there is evidence suggesting that people do not simply discount the performance of others, but rather track the probability of their partner’s reliability in making a decision. In a study by Behrens and colleagues (2008), participants performed a decision-making task wherein a correct response could be predicted by the pattern of previous correct responses as well as by a clue provided by a confederate. The reliabilities of the reward-based learning and confederate advice were independently varied to study how the participants' decision-making was influenced by the statistical properties of the reward prediction error and confederate prediction error. The results revealed that the participants could learn both reward and social value in a similar fashion but independently. This study provides strong evidence that the optimal response in decision-making is in consideration of both probability of the correct response and the probability of the correct advice by the confederate. Thus, the degree and type of joint adaptation may depend on the cost and gain of the cooperation outcomes as well as on other task-relevant information such as motor noise. These issues are particularly relevant to extending the joint adaptation model to a stochastic (i.e. probabilistic) model, and to understanding how the statistics about a task partner are established through the course of interaction.

How people interact with others can change significantly in relation to the physical and social environment. Given that the nature of the task itself is social, in that it requires cooperation with and accommodation of, another person, it is predicted that the modulation of the task partner may be strongly linked with the social attributes of the task partners, their relationship and the interaction setting. There is much evidence that interpersonal interaction is strongly linked with cognitive processes. Research has shown that the way people interact with others, such as whether they are cooperating or competing with each other, can change significantly with context of interaction (Georgiou, Becchio, Glover, & Castiello, 2007). In addition, the way one person interacts with another person varies significantly depending on attributes such as emotional state (Grammer, Kruck, Juette, & Fink, 2000; Janovic, Ivkovic, Nazor, Grammer, & Jovanovic, 2003), perceived physical capability of their partner (Isenhower, Marsh, Carello, Baron, & Richardson, 2005), as well as any previous interaction history with this partner (Oullier et al., 2008). Also, studies have shown that mimicry of a person tends to induce more generous behaviour by he/she who is mimicked (van Baaren, Holland, Kawakami, & van Knippenberg, 2004). In all, decisions concerning the way in which an actor would be involved in the cooperative process may be partly determined by social dimensions such as partners' attitude, social group, personality, and the relationship among cooperators. Thus, it would be interesting to investigate how the adaptation rate of the partners in the joint adaptation model might be stabilised on the basis of these socio-cognitive factors. Moreover, the present paradigm provides tangible quantitative hypotheses regarding sensitivity to the statistics of the social partner. This paradigm may thus provide a useful framework for understanding the neural mechanisms which are known to affect social skills in disorders such as autism (Hamilton, 2009) and schizophrenia (Sprong, Schothorst, Vos, Hox, & Van Engeland, 2007). Such follow-up studies should provide further important insights into how the CNS processes interpersonal interaction.

7.4 Final Remarks

Lack of knowledge about the future action or reaction of a partner might lead to an unstable outcome. One of the problems in understanding the behaviour of two persons is that they are responsive to each other and their task solutions are dynamically defined. The present thesis, for the first time, examined the cooperative framework in which this dynamic process is modulated by the error corrective behaviour of the two people. Through a series of studies, mechanisms which support cooperative interaction through the control and learning of behavioural statistics about a task partner were demonstrated. Importantly, these control systems regulate adaptive behaviour in order to optimise cooperative processes.

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Appendices

Appendix I

Error-Based Learning vs. Mimicry

This section contrasts adaptation rates in terms of error-based learning of interpersonal action error and behavioural mimicry of a task partner using simulation. The error-based learning viewed in terms of evolution of a movement parameter to adjust one's own motor command and minimise movement error with the partner. In contrast, mimicry is a direct reflection of the partner's action. Thus, mimicry can be expressed as follows.

$$P_{A(n+1)} = \beta_A * P_{B(n)}$$

eq. S1.1

where β_A is a mimicry rate which determines the rate at which the next own action, $P_{A(n+1)}$, is a mimicry product of the current action performed by a task partner, $P_{B(n)}$.

Time-series data of mimicry and error-based learning models were simulated using this equation and the error-based equation as presented in Chapter 5 (Equation 5.1), respectively. An adaptive partner evolved its action for 80 responses in terms of the error-based equation. A factorial combinations of one's own adaptation (or mimicry) rate and partner's adaptation rates was scaled between 0.0 – 1.0 incremented at 0.01 steps. 100 iterations were preformed for each combination to re-estimate the adaptation rates of one's own action due to the error-based learning and mimicry. For simplicity, the initial value $P_{A(1)}$ and $P_{B(1)}$ were set to 0 with a small Gaussian noise (SD = 5) since the mimicry model would immediately attenuate the parameter to 0 at β_A = 0 in the next iteration, which would strongly bias the statistical estimate of adaptation rate. Subsequently, these adaptation rates for all combinations were contrasted with the originally prescribed adaptation (or mimicry) rates (see Figure S1.1).

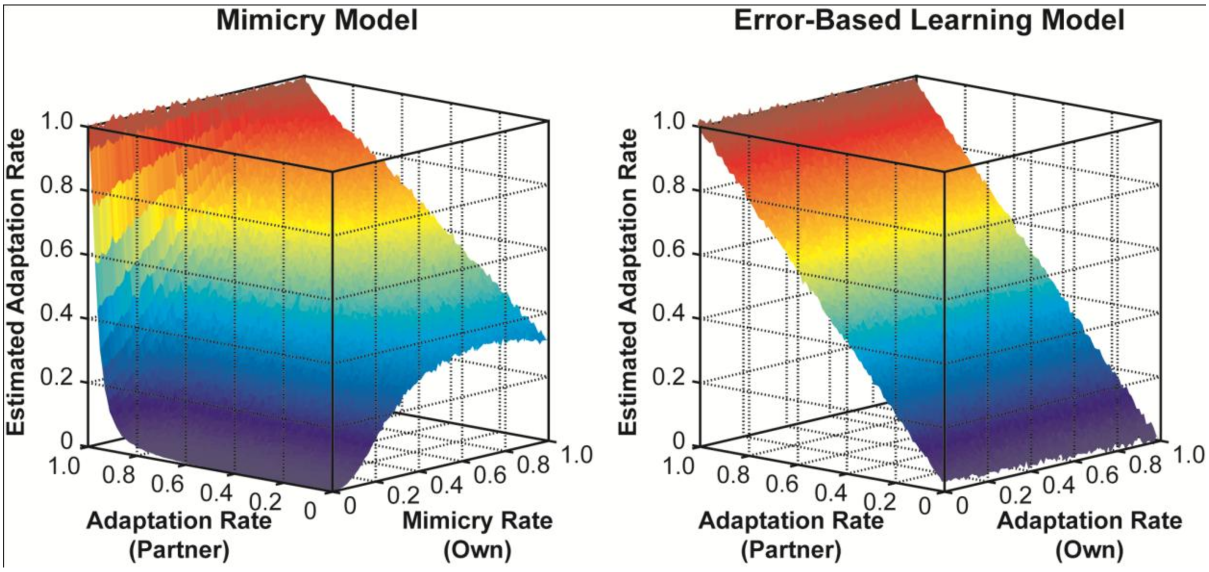

Figure S1.1. Dependences of one’s own adaptation/mimicry rate on the adaptation rate of the task partner in the error-based learning and mimicry models (n = 100).

The main difference between the error-based model and mimicry model was that the mimicry model resulted in a positive bias in the re-estimated adaptation rate due to an increase of partner’s adaptation rate. This is likely to be caused by the fact that the mimicry model emulated the error-based learning of the task partner. In contrast, independence of one’s own and partner’s adaptation rates were preserved for the error-based learning model. Thus, the negative relationship of the adaptation rates between the two partners reported in Chapter 5 and Chapter 6 were likely to be due to an active modulation of adaptation rates by the participants, and not statistical artefacts and/or a result of unidirectional behavioural mimicry.

Appendix II

Optimal variation of learning rate

Here, we describe changes in the optimal adaptation rate, given a known adaptation rate of the partner. Under our model, a participant at any trial holds a current estimate of when to execute the action in relation to the pacing tone (z_n). In the absence of feedback, this estimate would evolve over time as a random walk, simulated by the addition of a small state noise term on every time step (η_n). The actual time of the action (y_n) is then the sum of z_n and motor output noise (ε_n). To predict the time of action on the next trial (z_{n+1}), each participant learns with adaptation rate (α), based on the perceived discrepancy between their own and the partner's action ($y_{on} - y_n$). We also assume that each participant does not perceive the true discrepancy, but corrupted by perceptual noise (φ_n). In sum, our model is described as follows:

$$
\begin{gathered}
y_n = \ z_n + \varepsilon_n \\
y_{on} + z_{on} + \varepsilon_{on} \\
z_{n+1} = z_n + \alpha(y_{on} - y_n + \varphi_n) + \eta_n \\
z_{on+1} = z_{on} + \alpha_o(y_{on} - y_n + \varphi_{on}) + \eta_{on}
\end{gathered}
$$

eq. S2.1

where the subscript *o* refers to the processes of the partner ('other'). The noise terms $\varepsilon, \eta,$ and φ are assumed to have a mean of zero and a variance of $\sigma_\varepsilon^2\ , \sigma_\eta^2, \sigma_\varphi^2$. Given these variances, we can estimate how the optimal adaptation rate (α_{opt}) changes when the adaptation rates of the partner (α_o) varies between no adaptation (α_o = 0) to a full adaptation (α_o = 1). The adaptation rate is assumed to be at optimal when the overall discrepancy of the two partners (i.e., mean square of $y_o - y$) average over a long time span is minimum. For a non-reactive environment (α_o = 0), the relationship between the noise sources and the optimal adaptation rate is defined by the steady-state solution for the Kalman gain (Equation. S2.2). In the case of two independent actors, the total drift of the system (*S*) is defined by the sum of σ_η^2 and $\sigma_{\eta o}^2$. The total random noise (*R*) would be the sum of the two motor noise components (σ_ε^2 + $\sigma_{\varepsilon o}^2$) and the perceptual noise (σ_φ^2 + $\sigma_{\varphi o}^2$) in the adaptation process. Given these variances, the steady state solution of the estimation uncertainty (*P*) is:

$$P = \sigma_\eta^2 + \frac{\sqrt{\sigma_\eta^4 + 4\sigma_\eta^2 R}}{2}$$

eq. S2.2

which then yields the optimal adaptation rate:

$$\alpha_{opt} = \frac{P}{P+R}$$

eq. S2.3

Since we do not know the exact distribution of the noise terms, we first assume that the observed adaptation rate of 0.15 for a computer adaptation rate of α_o= 0 in the main study is optimal. Using this assumption we can then estimate the distribution of the noise terms and then calculate the optimal adaptation as $\alpha_o$change. We also assume that the partner (computer) has no perceptual, motor, or state noise for simplicity.

In essence, the Kalman gain describes that it is more effective to be conservative and not to adapt to the current internal estimate of action when there is large perceptual/motor noises environment (Equation S2.3). Since the observed adaptation signal $(y_n - y_{on} + \varphi_n)$ $y$consists of their own perceptual processes as well as their own and the partner's motor processes, an increase in any of these noise terms would lead to a decrease of α_{opt}. In contrast, if we perceive that the environment is changing rapidly (i.e., a larger σ_η^2 or $\sigma_{\eta o}^2$ with respect to perceptual/motor noises), α_{opt} should increase (Behrens et al., 2008; Burge et al., 2008). From Equation S2.3 we can derive that setting R = 4 and σ_η^2 = 0.42 results in α_{opt} = 0.15, which roughly matches our empirically determined adaptation rate (the scaling between R and σ_η^2 is arbitrarily defined).

Given these values, we can now predict α_{opt} for an arbitrarily defined α_o. For a reactive (adaptive) environment, the Kalman filter cannot provide a closed-form solution for the optimal adaptation rate. We therefore determine the optimal value by simulating data (100 trials) for a given adaptation rate of the partner by varying adaptation rates between -1 to 1 in steps of 0.05. We then determined the average mean square error (MSE) and sporadically detected α_o which yield the smallest MSE (Figures S3.1 and S3.2). It is important to note that, in contrast to the Kalman filter model for α_o= 0, it now makes difference whether the noise on the error signal arises from motor or perceptual processes: Motor noise (ε_n) can be perceived by both partners and would lead to adaptive changes in partner's estimate of the current state (z_{on+1}), whereas perceptual noise (φ_n) is only accessible to the one person.

We first simulated α_{opt} under the assumption that the variance was purely due to the motor noise. Figure S2.1 shows the expected MSE of the two partners when α_o was set to 0, 0.6 or 0.9. As expected for α_o = 0, the smallest error was observed at around 0.15. For the higher adaptation rates, the model predicts that α_{opt} should become negative in order to cancel out the excessively strong response to the motor noise by the partner. In principle, the model indicates that the adaptation rates of the two partners should be inversely correlated. It is important to note that, however, negative adaptation rates had not been observed in our study.

The ability to undo the partner's adaptation to lower the overall adaptation rate to the optimal level, assumes that the actor would have had a perfect knowledge of the adaptation signal that the partner learned from ($y_{on} - y_n + \varphi_{on}y$). However, this is clearly not the case in the presence of perceptual noise. To illustrate this, we repeated the simulation by assuming that all noise is derived from the perceptual noise (Figure S2.2). Now, a negative adaptation rate could not undo the excessively high adaptation rate of the partner, as the participant does not have access to the error signal from which the partner learned. Therefore α_{opt} reduces non-linearly towards zero, as α_o increases though it never goes negative.

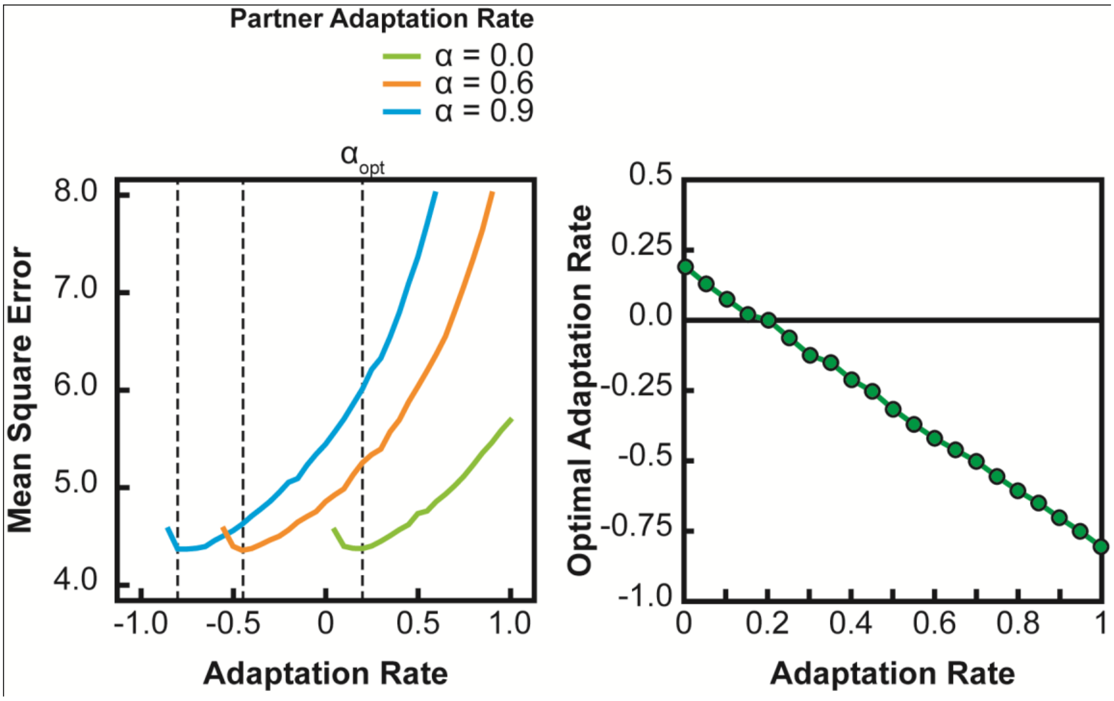

Figure S2.1. Changes in the optimal adaptation rate due to motor noise. **Left.** The changes in MSE of two partners ($\sum(\boldsymbol{y} - \boldsymbol{y_o})^2$) across the associated adaptation rates (varied between -0.5 to 0.5 at 0.05 steps) with the adaptation rates of 0, 0.6 and 0.9. 500 data points were generated using Equation S.2.1 for 100 trials and the MSE were averaged for each combination of the rates. The point at which the error is the smallest indicates that the given adaptation rate is optimal. **Right.** The optimal adaptation rate was obtained across associated partner's adaptation rates of 0 to 1 (0.05 steps). Note that the optimal rate is about 0.15 when the partner's adaptation rate is 0 and steadily decreases to negative values as the partner's adaptation rate increases.

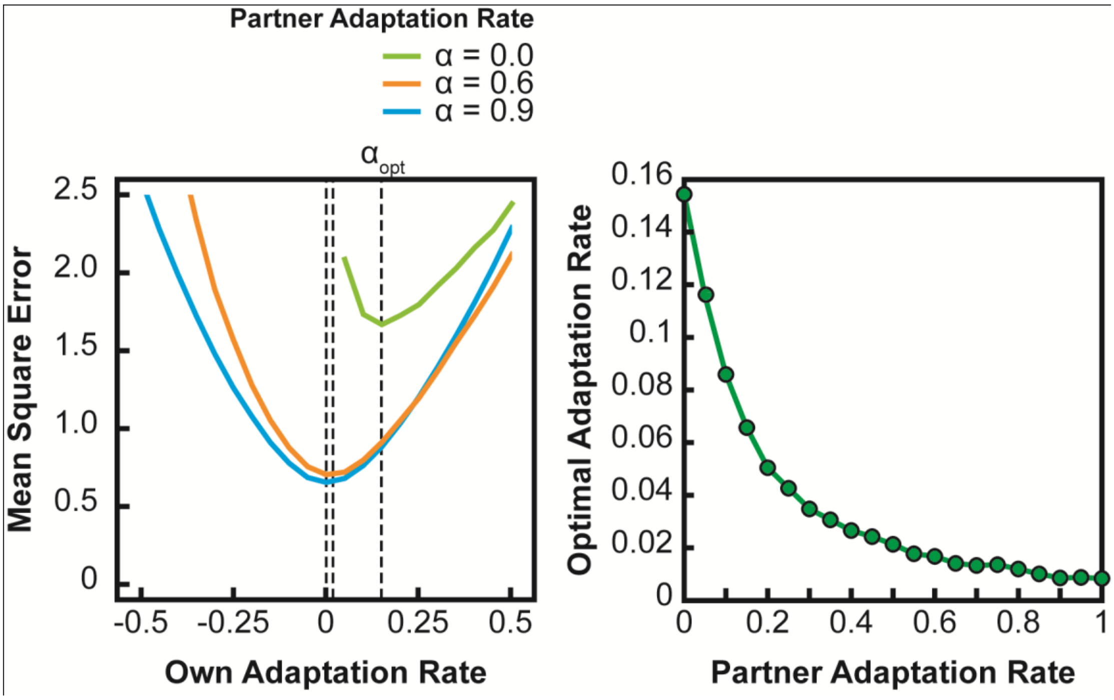

Figure S2.2. Changes in the optimal adaptation rate due to perceptual noise. **Left.** Changes in mean square error of two partners. **Right.** Changes in the optimal adaptation rates due to changes in the partner's adaptation rate. The optimal adaptation rate decreased as the partner's adaptation rate increased. Nevertheless, unlike with the presence of only motor noise, the optimal adaptation rate saturates around zero and never became negative.

Appendix III

Estimation of adaptation rates in presence of online corrections

Here we show that estimates of the adaptation rate of a participant can be valid and independent of the adaptation rate of the computer simulated partner. We also allow for the online corrections, which was evident in the empirical data to understand its effect on the estimated adaptation rate. Data were simulated as follows:

$$p_n = z_n + \varepsilon_n \qquad \text{eq. S3.1}$$

where p_n is the originally planned own Time of Action (ToA) at trial n with a motor noise ε. z is the current state of the ToA. Subsequently, the deviation from the partner's ToA (y_{on}) is reduced at the online adaptation rate β_A, which results in the end result of the ToA (y_n).

$$y_n = p_n - \beta_A (p_n - y_{on}) \qquad \text{eq. S3.2}$$

The state of the internal model is updated in order to reduce the ToAs between the partners at an adaptation rate α. Furthermore, a forgetting factor, g limits the drifting of the ToA to around the initial value, y_1.

$$z_{n+1} = g(z_n - y_1) - \alpha (y_{on} - y_n) + y_1 \qquad \text{eq. S3.3}$$

For simulation, the true adaptation and correction rates for the participants were set close to the main study at 0.2 and 0.1, respectively. The motor noise was normally distributed with a standard deviation of 40 ms. A forgetting factor was set at 0.8, which eliminated an excessive drift in the simulation. The partner's adaptation rates (α_o) was either 0.0 (Sim0%), 0.6 (Sim60%), 0.9 (Sim90%). The data were simulated for 20 participants for each rate. For statistical analyses, the participant's adaptation rates were re-estimated using linear regression. These results indicated that the rates were underestimated for all three types of partners (Figure S3.1); the adaptation rates were 0.169 (SD = 0.025) for Sim0%, 0.158 (SD = 0.032) for Sim60% and 0.167 (SD = 0.027) for Sim90%. One-sample t-test (target value = 0.2) confirmed the small underestimation of the adaptation rates, t (59) = -9.846, p < .0005. A one-way between groups ANOVA indicated there was no group mean difference (p = .436), suggesting that our model estimation has a tendency to underestimate the adaptation rate, but there was no bias due to the size of the computer's adaptation rate.

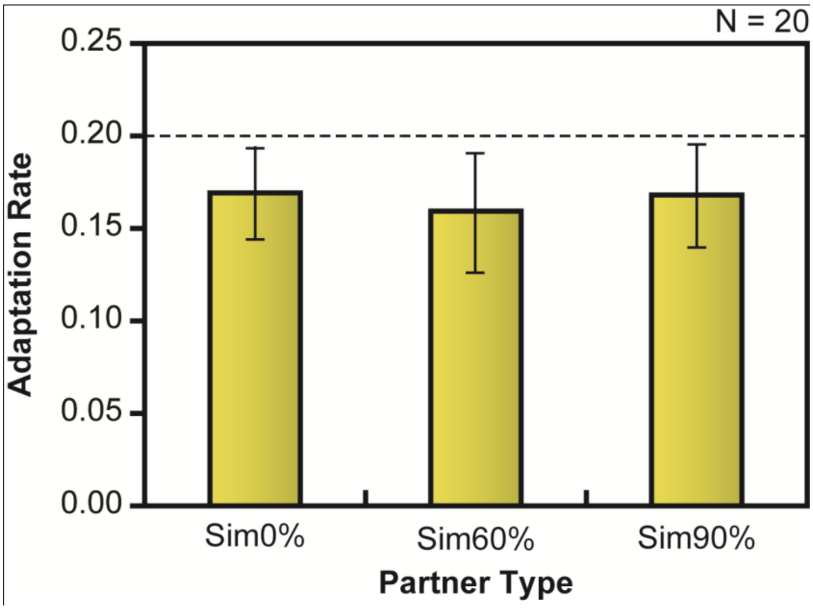

Figure S3.1. Simulated adaptation rates with presence of online correction. The data were generated using our adaptive model with the online adaptation rate of 0.1 and the adaptation rate of 0.2 (dotted line). Our model estimation method successfully re-estimated the adaptation rate for all three simulation type despite that the estimated rates were slightly smaller than the prescribed rate (= 0.2).

Appendix IV

Joint Action and Reaction: Adaptive Control in Cooperative Object Lifting

Presented at Society for Neuroscience 2009 in collaboration with Prof. Abderrahmane Kheddar[1] and Dr. Paul Evrard[1]

[1]CNRS-UM2 LIRMM, France and CNRS-AIST Joint Robotic Laboratory, UMI3218/CRT, Japan

When two people perform a cooperative action, departures from the desired trajectory may be corrected by either or both persons. A significant issue in such joint action task is how a dyad avoids over-correction in case the correction is initiated by both persons. The present study investigated the adaptive behaviour of dyads (one human participant, one robot) in a cooperative task that involved lifting a bar while keeping it level. We were interested to observe how human participants would adaptively modulate the degree to which they correct movement errors (i.e., adaptation rate) as a function of adaptation rate applied by the robot. We expected that the participants would increase the adaptation rate when that of the robot is reduced, and vice versa if the central nervous system (CNS) is capable of optimising the performance as a dyad. A humanoid robot, HRP2 (Kawada Industry, Japan) was employed as a task partner which operated to reduce a kinematic difference (i.e., peak velocity difference) with a human partner at a predefined adaptation rate over trials (Figure S4.1). In the task, the human participant and HRP2 grasped handles attached to each end of a long flat bar. At the end of fixed-paced auditory signals provided to a human participant, HRP2 started lifting the bar with a minimum-jerk trajectory defined over a fixed start and end movement points at varying speeds. The objective of the participant was to lift the bar simultaneously so the bar orientation remained horizontal. The movement of HRP2 and human participants were tracked using a motion tracking system. The difference in the peak velocities between them was registered as error to HRP2 and used to modify movement speed in the subsequent trial at a predefined rate. For analysis, the adaptation rate of the human participants was approximated using the slope coefficient of a linear regression, entered the peak velocity difference and a subsequent change in the velocity as covariates. The results revealed clear evidence of modulation of the adaptation rate in response to that implemented in HRP2. Furthermore, the summed rate of the human and HPR2 remained approximately constant and optimal across different rates set by HRP2. In conclusion, the present study suggests that humans can incorporate behavioural characteristics of a task partner to optimise the outcome of a shared goal as a dyad in a cooperative task.

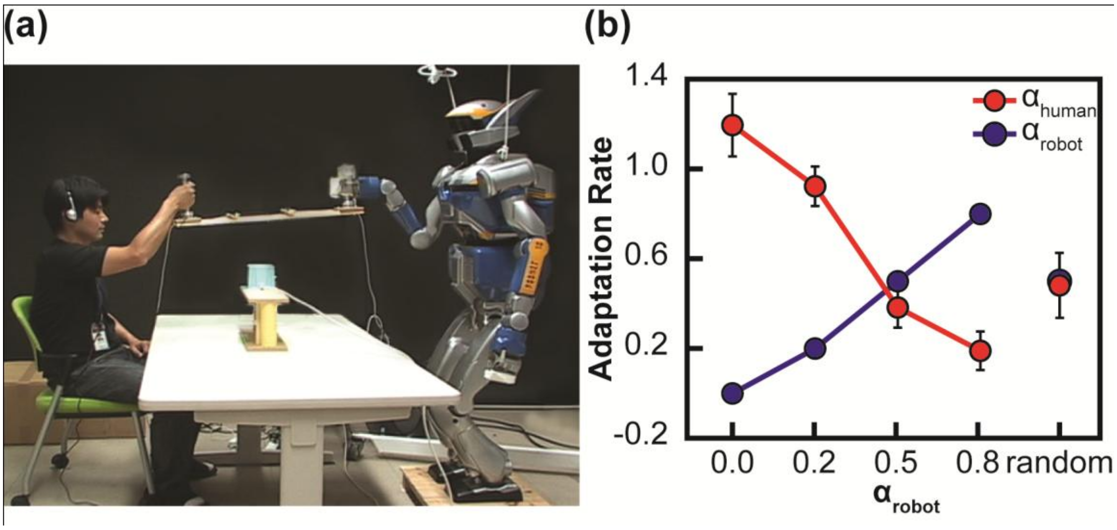

Figure S.4.1. (a) The experimental set-up. The robot (Kawada Industries, Japan) is a full-sized humanoid robot with 30 degree of freedom (DoF), of which 6DoF of the right arm were programmed to follow a predetermined trajectory. A soft cushion inserted between the handle and the gripper allowed the bar to rotate as far as 30 degrees in the sagittal plane. The bar, which weighed approximately 1kg, was designed so that the shape and mass distribution of the bar was symmetric in the participant's sagittal and frontal planes. A two-sensor mini-bird motion tracking system (Ascension Technology Corporation) recorded the position and orientation of the bar at 100Hz. The position and velocity of each handle was then calculated to control the robot's action in the next trial. **(b)** The adaptation rates of human participants across different rates set by the robot. Simple linear regression analysis confirmed a reciprocal relationship between adaptation rate of the participants ($\alpha_{human)}$ and robots (α_{robot}) such that an increase of α_{robot} led to a decrease of α_{human} ($\alpha_{human} = -1.154 \times \alpha_{robot} + 1.048$, $r^2 = .796$). The error bars represent one standard error.