

École polytechnique de Louvain

Adaptive feedback control in bimanual cooperative tasks

Author : Anthony **SAVOCCO**

Supervisor : **Frederic CREVECOEUR**

Readers : **James MATHEW, Philippe LEFEVRE, David CORDOVA
BULENS**

Academic year 2020–2021

Master [120] in Biomedical Engineering

Abstract

This study explores the question of adaptation in bimanual cooperative tasks. Previous studies of Crevecoeur et al. (2020a [1] and 2020b [2]) hypothesized the presence of online corrections within the movement in unimanual reaching movement experiments. These online corrections gradually improved even when the external disturbances applied were unexpected. They extracted from muscles recordings the latency of this feedback adaptation, which was approximately 250 ms after the reach onset. This master thesis is part of a larger study aiming to investigate the feedback adaption in the specific case of bimanual coordination. Both limbs may display this within movement feedback adaptation and, the latency could be similar or distinct compared to the unimanual case. Therefore, we conducted a bimanual cooperative reaching movement experiment to search some insights to these questions. A first objective of our work was to reproduce previous findings from Diedrichsen et al. (2007 [3]) suggesting that both limbs adapted to a force field perturbation even if one limb remained unperturbed when the goal task was shared between them. Our analysis corroborated their conclusion and strengthened it by the examination of muscles recordings. We also searched for the presence of online corrections during catch trials where the perturbation was unexpectedly removed. We found a reduced terminal peak end force across catch trials for the perturbed hand that could explain the decreasing path length observed. The muscles recordings did not highlight a potential feedback adaptation latency. We also extended the adaptive control model proposed by Crevecoeur et al. (2020a [1]) to the bimanual case with two different controllers: the linear-quadratic-Gaussian (LQG) and the robust controllers.

Keywords Bimanual coordination · Feedback adaptation · Motor learning · Force field · Reaching movements

Contents

1	Introduction	4
1.1	Motor control	4
1.2	Bimanual coordination	5
1.3	Learning during bimanual coordination tasks	6
1.4	Context of the work	7
1.5	Aim of the work	9
2	Materials and Methods	11
2.1	Participants	11
2.2	General procedure	11
2.3	Data acquisition	12
2.4	Data analysis	12
2.5	Mathematical modelling	13
3	Results	17
3.1	Simulation results	17
3.1.1	LQG controller: dual-goal tasks	17
3.1.2	LQG controller: common-goal tasks	17
3.1.3	Robust controller: dual-goal tasks	18
3.1.4	Robust controller: common-goal tasks	19
3.1.5	LQG (Right) and Robust (Left) controllers	20
3.1.6	LQG (Left) and Robust (Right) controllers	21
3.2	Experimental results	22
4	Discussion	32

1 Introduction

In this section, a brief insight into motor control will be first brought by addressing the complex relationship between the nervous system control and the mechanical properties of our body, and, by describing a theory of motor coordination: the optimal feedback control theory. Then, the bimanual coordination will be explored from the neural control to the constraints that such a configuration can lead to. Next, a short overview of learning during bimanual tasks when dynamical disturbances are applied will be provided. In the last part of this introduction, I will finally introduce the aim of my master's thesis.

1.1 Motor control

The complexity behind animal and human movement, at the basis of their interaction with their environment, is particularly noticeable when we suffer from neuromuscular conditions. Our ability to fine tune our movements reflects the complex interaction between the control of the nervous system and the mechanical properties of our limbs.

The motor function results from the connection between three layers of the motor system: the mechanics of our limbs, the neural control, and the motor behavior. The mechanics of our limbs and muscles define how muscle activity is translated into the required movements. The neural control is managed by the central nervous system organized into three hierarchical levels: the spinal cord, the brainstem, and the cortex. The motor behavior illustrates how the body will act facing a specific motor task reflecting the interaction between the two previous layers of the motor system (Scott, 2004 [4]).

A theoretical framework that captures the complexity of motor control and that could explain the interaction between the three layers of the motor system is the optimal feedback control theory. The optimal feedback control theory proposes that biological systems learn to generate motor commands that optimize their behavior in accordance with the goal task (Diedrichsen et al., 2010 [5]).

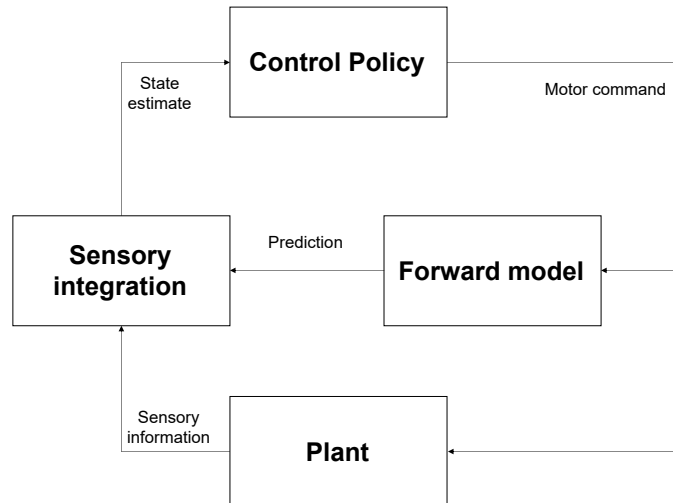


Figure 1: The architecture of optimal feedback control adapted from [5]

The optimal feedback control theory architecture is composed of the control policy, the forward model, the sensory integration, and the plant (Fig. 1). The control policy is adjusted by the motor task and its goal. The plant describes the system and its environment. The plant receives a motor command and generates a delayed and noisy sensory information about the

current plant state. The forward model acquires a copy of the efferent motor command and provides an estimate of the plant state. This estimate is then completed by the integration of the sensory information. Finally, the control policy translates the current state estimate into a new motor command (Diedrichsen et al., 2010 [5]).

1.2 Bimanual coordination

The ability to combine movements between limbs is crucial in daily life. Interacting with objects, dressing, cooking, or playing the piano and many other tasks require coordination between the limbs. Sometimes limbs can be directed to produce a symmetrical action (e.g. when we clap our hands). On other occasions, the task may require the limbs to work asymmetrically. For instance, tying one's shoes. Other more complex coordination patterns can be performed. For example, playing the piano requires complex and distinct movements between the two hands (Kennedy et al., 2016 [6]).

Regarding the mechanics of the upper limbs, they are anatomically symmetrical. Nevertheless, there is an individual preference for the use of one hand compared to the other, a phenomenon referred to as handedness. This latter hand is known as the dominant hand and the other, the non-dominant hand. The handedness impacts the bimanual coordination in different ways. Notably, the management of sensory information, the difference of variability in motor output between both hands, or even the attribution of errors between both limbs for instance. Therefore, the inequalities in motor performance observed between hands do not come from physiological differences but rather from their neural control. Although handedness influences bimanual coordination, it will not be further developed in this work. For more information, see "*Using Robust and Optimal Control theory to understand handedness and bimanual coordination*" (Córdova Bulens, 2017 [7]).

Regarding neural control, a traditional viewpoint was to consider that a single brain locus was responsible for bimanual coordination. However, several studies have instead pointed out the presence of a distributed network that coordinates the neural processes underlying many coordinated functions. The network's distributed nature may explain the perturbations of inter-limb behavior in various coordinated movement disorders (Swinnen, 2002 [8]). The importance of the corpus callosum in bimanual coordination is highlighted in numerous studies. The corpus callosum is the largest collection of white matter tissue in the brain that connects both hemispheres. It coordinates the two sides of the body (Gooijers et al., 2014 [9]).

About the motor behavior, there are two cases: the uncoupled case where both hands work independently and the coupled one, the opposite. Liao et al. highlighted a distinct neural motor control between these two scenarios (uncoupled and coupled) using paired-pulse transcranial magnetic stimulation to monitor the intracortical inhibitory modulation. Regarding the common goal tasks, they observed that both arms worked in a "give and take pattern" and the presence of an impact of the non-dominant arm control on the stability of the bimanual force. By contrast, in the dual-goal tasks, both hands were positively paired with each other. Moreover, neither arms did not affect the bimanual force stabilization (Liao et al, 2018 [10]).

All of this underlines the fact that the concepts of bimanual coordination diverge from the unimanual one. The bimanual configuration implies supplementary restrictions affecting the behavior of both limbs during movements. For instance, in some situations, the same goal can be completed with different contributions of the two arms. These coupled scenarios features redundancy. It can a problem when an error is produced during the task. The nervous system must attribute this error to one of the two limbs. Reichenbach et al. demonstrated that the motor

system imputes the correction to the most probable source of the error to elicit learning and increase future performances (Reichenbach et al., 2013 [11]). However, the redundancy can be also exploited by the nervous system. O’Sullivan et al. exhibited that the nervous system uses this multi-effector redundancy to minimize the motor output variability and effort by studying the shared force production between two fingers (O’Sullivan et al., 2009 [12]).

Temporal constraints influence the coordination of bimanual coordination. A first example is temporal preferences. The production of mirror-symmetrical movements (in-phase mode) are preferred over the asymmetrical ones (anti-phase). The latter are less stable and requires more attention and supervision. The movements that diverge from the in-phase or the anti-phase modes are more complex to coordinate. Another example is when two hands had to reach separate goals located at different distances. They will move at asymmetrical speeds to reach the goal at the same time (Wiesendanger et al., 2004 [13]). Some studies suggested that the better stability and ease to produce the in-phase bimanual coordination patterns compared to the anti-phase ones is due to several constraints including the neural crosstalk. The neural crosstalk is defined as a mirror copy dispatched to the homologous muscles of the contralateral limbs. The neural crosstalk framework explains that each limb has its own motor plan, and the force command of one limb is partially diverted to the other limb, potentially leading to interference for asymmetrical movements (Kennedy et al., 2016 [6]).

Spatial constraints are also involved. For instance, when subjects are asked to draw lines of different amplitudes, a tendency to draw lines of the same amplitudes emerges (Swinnen, 2002 [8]). Drawing lines in the same directions is less complex to execute than drawing perpendicular lines in front of you (Jirsa et al., 1998 [14]). The spatial constraint has also been investigated during a bimanual force field adaption task by Casadio and coworkers. The idea was to couple both dynamically and spatially the upper limbs. The experiment consisted of center-out reaching movements where both limbs begin their movement from the same position. The common final targets were equally located on a circle and the sequence of presentation of the peripheral targets was randomized. The results showed that there is a protective mechanism that prevents movements that can lead to crossing hands. This protective mechanism could influence the learning of force fields when they may give rise to crossing the hands. The results also exposed the fact that the movement is led by the hand located at the same side as the final target (Casadio et al., 2010 [15]).

1.3 Learning during bimanual coordination tasks

Shadmehr et al. have established the use of force fields as a standard model for the experimental study of sensorimotor adaptation to dynamic perturbations. Confronted to a force field perturbation, the subjects may initially co-contract to reduce the impact of the disturbance, and then they will potentially learn to anticipate and compensate the external force (Shadmehr et al., 1994 [16]). This paradigm has been extended to the study of bimanual coordination. As written previously, two scenarios can be depicted in bimanual coordination tasks: the uncoupled and coupled scenarios. Some researchers investigated the differences and the transfer of learning between the two scenarios and even the unimanual case.

In the uncoupled scenario, Tcheang et al. investigated learning upon the application of a force field to one arm, while the other was also perturbed by a force field or remained unperturbed. There was no differences between the dominant and non-dominant arm concerning motor performance over the exposure period whether the other arm was perturbed or unperturbed. Their results underlined the fact that, in an uncoupled scenario, there is no interference or facilitation in the simultaneous learning of dynamical disturbances between the limbs (Tcheang et al., 2007

[17]). Nozaki et al. questioned the presence of transfer of learning of dynamical disturbance between the unimanual and uncoupled bimanual cases. They concluded that there is a transfer of learning, but it remains limited. They suggested an incomplete overlap between the learning mechanisms of unimanual and bimanual adaptation (Nozaki et al., 2006 [18]).

Regarding the coupled scenario, Diedrichsen et al. have probed the difference in adaption when the goal was common or separate for both limbs. In the common goal, one common cursor was displayed at an equal distance of both hands and had to be moved to a final target. In the dual-goal task, each hand had its proper cursors and final targets. Their results showed that when the goal was common, the unperturbed hand presented signs of adaptation contrasting with the dual-goal task and showed a stronger presence of bimanual correction highlighting the task-dependency of adaptation. They also investigated the role of visual feedback on the presence of bimanual corrections. They randomly withdrew the visual feedback during some of the perturbed trials and observed that the prior instruction on the task given to the participants was sufficient to elicit bimanual corrections (Diedrichsen et al., 2007 [3]). Jackson et al. discussed the adaptation of the left upper limb to a velocity-dependent force field matching the moving right upper limb. The disturbance was applied either with a delay (250 or 500 ms) or without a delay to the static left hand when the right hand had to move. Their results demonstrated that the subjects were gradually capable to predict the disturbance but also to counteract it with increasing accuracy (Jackson et al., 2008 [19]). Howard et al. suggested that the motor system can use partially separate representations for the dynamics of both upper-limbs in uncoupled and coupled fashion (Howard et al., 2008 [20]).

1.4 Context of the work

This work explores the bimanual cooperative adaptation in the light of the work of "*Optimal Task-Dependent Changes of Bimanual Feedback Control and Adaptation*" from Diedrichsen et al. (Diedrichsen et al., 2007 [3]), "*A Very Fast Time Scale of Human Motor Adaptation: Within Movement Adjustments of Internal Representations during Reaching*" and "*Feedback Adaptation to Unpredictable Force Fields in 250 ms*" both from Crevecœur et al. (Crevecœur et al., 2020a [1] and 2020b [2]).

As stated earlier, Diedrichsen et al. studied bimanual coordination from the perspective of optimal control. They found that adaptation depends on the task (cooperative or not) influencing the response produced as well as the adaptation of both arms to a perturbation. Notably, they highlighted the adaptation of the unperturbed hand during a bimanual cooperative task upon the application of a force field to other arm. In his paper, two experiments were carried out.

The first experiment consisted in reaching movements with force field disturbances. Two identical sessions were set up with either one- or two-cursors conditions. The participants began with unperturbed trials. Then, for the next eight blocks of trials, a leftward or rightward force field was applied on one of the hand. And, for the last six blocks, Diedrichsen and coworkers randomly withdrew the visual feedback. They defined a correction rate within (individual to each hand) and between hands. They exposed, during the one-cursor condition, a growing correction rate between hands at the cost of a decreased correction rate within hands. In the contrary, in the dual goal tasks, the correction rate was mainly within hands. They also showed, for the common cursor condition, that the lateral velocity profile of the unperturbed hand became significantly affected by the direction of the force exerted on the other hand around 190 ms after the start (approx. the force field peak). Additionally, they investigated the correlation between the lateral coordinate of both limbs. As they explained, the optimal control theory claims that the coordination of movements is linked to the task goals. In the common cursor condition, the

optimal control theory predicts a growing negative correlation between the lateral coordinate of both limbs leading to a highly negative correlation for the endpoints, which was confirmed both by their computational and experimental results.

In the second experiment, participants performed eight adaptation runs including 20 unperturbed trials, 80 perturbed trials, and again 20 trials. The perturbation was applied to the same direction and the same hand within the adaptation run. Catch trials had been also included in the perturbed trials for which they did not apply the perturbation. In both conditions, they observed that the perturbed hand exhibited a quick adaptation to large errors produced by the disturbance. This adaptation was also apparent during catch trials where the force field was unexpectedly switched off. Regarding the unperturbed hand, its initial direction also changed in the one-cursor condition across perturbed trials contrasting with the observation made in the two-cursors configuration.

The adaption of bimanual coordination has been investigated on trial-by-trial or longer scale. Crevecoeur and his coworkers suggested the presence of smaller scale adaptation occurring within the ongoing movement in a unimanual case and a latency of motor control corresponding to ~ 250 ms (Crevecoeur et al., 2020a [1] and 2020b [2])

The question of adaptation to perturbation in the case where the same movement cannot be repeated several times has been investigated. They proposed the presence of an online correction within the movement that could adapt to an external disturbance. They set up two experiments to question their hypothesis (Crevecoeur et al., 2020a [1]).

The first experiment consisted in unperturbed reaching movements with random perturbed catch trials. Orthogonal velocity-dependent force field ($F_x = \pm L\dot{y}$) in clockwise and counter-clockwise directions have been used as perturbation. To outline the online control during the perturbed catch trials, they extracted the maximal lateral deviation and the maximal target overshoot (i.e. maximal lateral deviation near the movement end). They observed no significant changes of maximal lateral deviation suggesting no clear perturbation anticipation, while the maximum target overshoot presented a significant exponential decay. To understand what strategies have been used to reduce the overshoot, they monitored the force profiles produced by the participants. Although the force field perturbation remained the same across perturbed trials, a decrease of the force at the end of the movement has been observed, which suggests the application by the subjects of a reduced lateral force to counter the disturbance. Moreover, the correlation between the force applied and the force field showed a significant increase across trials, characterizing a motor adaptation.

These results could be linked to a change of controller during the movement. During a catch trial, the subjects used a controller adapted to unperturbed trials and then, switched to another controller to correct their trajectory. This controller being partially adapted to the force field applied during the ongoing catch trials. As the subjects encountered the same force field perturbation, the corresponding controller was updated explaining the better motor performance across catch trials. Furthermore, the fact that catch trials were randomly distributed and thus, not anticipated implied that the switch of controllers is due to the sensory information collected within the movement. They also observed that unperturbed trials following the catch trials showed an after-effect indicating a link between these control changes within the movement (feedback adaptation) and trial-by-trial learning (feedforward adaptation).

The second experiment was designed to obtain a more direct connection between the perturbation and the online correction. It was necessary to investigate whether subjects learn

specifically the force field. Indeed, the subjects may simply change their limb's impedance or modify their movement kinematics to produce the corrections during their reaching movement. They used a via point located at two-thirds of the path between the initial and the final target. The participants received the instruction to stop at the via point, and then, to continue their movement. The stop at the via point was necessary for two reasons. First, to withdraw the force field without the participants noticing it. Secondly, to avoid that the after effect observed after the via point came from momentum following their previous correction. The monitoring of hand trajectories after the via point suggests that the existence of a force field before the via point produces an after effect. From these results and the previous one, they proposed the hypothesis that the nervous system monitored model parameters online.

In "*Feedback Adaptation to Unpredictable Force Fields in 250 ms*" (Crevecoeur et al., 2020 [2]), Starting from the previous hypothesis, Crevecoeur and coworkers looked at the feedback adaptation latency from muscle recordings. They worked with reaching movements and estimated that the latency of the feedback was approximately 250 ms after the home target exit.

They replicated the first experiment of the previous paper (Crevecoeur et al., 2020 [1]). Moreover, they measured the onset of changes in muscle recordings corresponding to the feedback adaptation moment. They obtained the same results from the maximal lateral displacement and target overshoot. The target overshoot decay was associated with a more decreasing force value near the movement end across trials as demonstrated in the previous paper. This decay of terminal end force was linked with a decrease of muscle activity between early and late perturbed trials. By comparing the EMG from early and late trials, they found that the onset of changes for the agonist's muscle was 237 ± 15 ms after the reach onset (exit of the home target), while for the antagonist's muscle, 400 ± 15 ms have been obtained.

The second experiment was similar to the first one except that in addition to the orthogonal force fields, they added also curl force fields (i.e. $F_x = \pm L\dot{y}$ and $F_y = \pm L\dot{x}$). Their results showed that participants were able to produce adapted feedback responses to the different kinds of perturbations. They observed a similar time for the onset of changes regardless of the perturbation type (curl or orthogonal) for the agonist and antagonist muscles.

1.5 Aim of the work

In this work, we will first reproduce the findings of Diedrichsen and his team with the novelty of EMG correlate. Then, the very fast time scale adaptation will be investigated in the specific case of bimanual cooperative tasks with perturbation of one limb. This master thesis is part of a larger work that aims to answer the following questions:

- (1) Do both limbs display this within-trial feedback adaptation?
- (2) Is the latency of this feedback similar to the unimanual case?

Nevertheless, we keep in mind the difference in the experiment design with the work of Crevecoeur and coworkers. Indeed, in their work, Crevecoeur et al. worked with unperturbed trials and unexpected force field catch trials. In our case, we used perturbed trials with unperturbed catch trials. As a result, we are not sure that the same conclusion could be made based notably on the analysis of maximum target overshoot or the terminal peak end force.

The second part of my thesis focus on the expansion of the adaptive control model proposed in "*A Very Fast Time Scale of Human Motor Adaptation: Within Movement Adjustments of Internal Representations during Reaching*" (Crevecoeur et al., 2020 [1]) to the bimanual case

with two distinct controllers: the linear–quadratic–Gaussian (LQG) and the robust controllers.

2 Materials and Methods

2.1 Participants

17 right-handed participants (nine males and eight females, age: 24 ± 1.5) took part in the experiment. They all signed a consent form and completed Edinburgh Handedness Inventory to assess their handedness. There were all healthy subjects (no known neuromuscular diseases) and naïve to the task. The experimental paradigm was approved by the Ethics Committee of the host institution (UCLouvain, Belgium) and complied with the Declaration of Helsinki. Participants were compensated for their participation.

2.2 General procedure

The experiment corresponded to a bimanual common goal task. Participants worked with the Kinarm End-Point robot (KINARM, Kingston, ON, Canada). They seated in front of the robot and their foreheads rested on a stable resting cushion to minimize head movements. They grasped the handles of each robotic arm and were instructed to make visually-guided forward reaching movements towards a virtual target. Their hands, as well as the robotic handles, were below the workspace in a way they were not able to see them. Nevertheless, the position of their hands was given on the screen in the form of a cursor (one for each hand). A middle cursor, at an equal distance of both hands, was also displayed. The workspace contained also three home targets and one final target placed at 15 cm forward the home target (Fig.2).

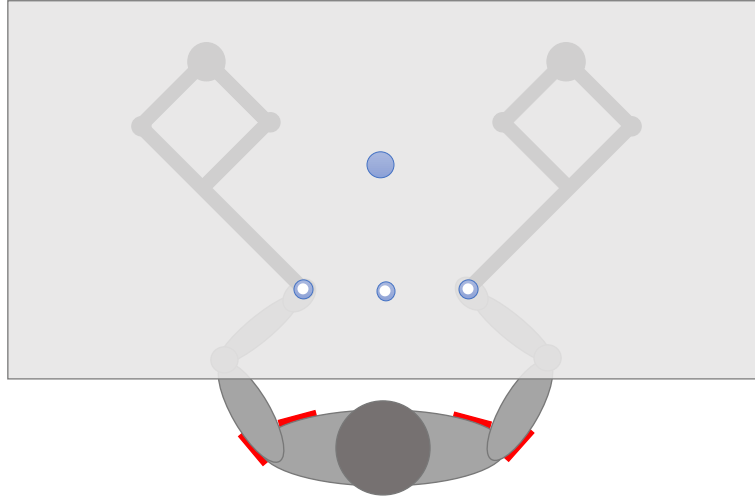


Figure 2: Experimental setup

The first step of the experiment consisted in placing the three cursors in home targets. After a random time between [2,4] s, the final target became full red corresponding to the start signal. The goal was to reach with the middle cursor the final target in a specific time window and to stabilize there. To help participants to find the correct speed, three different outputs were given at the end. If the participants were too slow, the final target remained full red. If they were too fast, the final target became empty red. And finally, if their movement was between [600,800] ms, the final target turned full green. In this case, the score was incremented and was displayed during the current block of trials to provide some feedback to the participants (Fig.3).

The experiments are arranged in seven blocks named in order: Baseline, CW (stands for clock-wise) Learning, Washout 1, CW Relearning, Washout 2, CCW (stands for counter-clockwise) Transfer 1, and CW Learning. The Baseline block included 15 unperturbed trials. The CW learn-

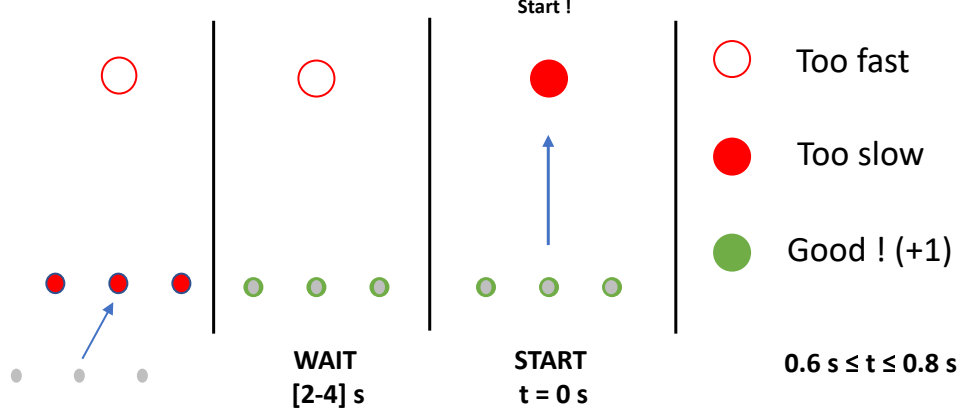


Figure 3: Time course of events

ing and CCW Transfer 1 blocks consisted of 150 trials subdivided, in practice, into 3 smaller blocks of 50 trials. These 50 trials included 45 perturbed trials and 5 unperturbed trials randomly distributed. The perturbation was a curl velocity-dependent force field (i.e. $F_x = \pm 15\dot{y}$ and $F_y = \pm 15\dot{x}$). The perturbation was only applied on the right hand. Washout 1 and 2 were both 40 unperturbed trials block. Finally, the CW Learning block was composed of 15 clockwise perturbed trials. In the following analyses, only the three first blocks will be used.

2.3 Data acquisition

The positions and velocities of the cursors and the forces between the handle and the hands of the subjects are sampled at 1 kHz and were digitally low-pass filtered (2nd order dual-pass Butterworth filter with a cutoff frequency of 50 Hz). The velocity profiles were computed offline from numerical differentiation of the positions (second-order finite-difference algorithm). During the experiment, the muscle activity of the right and left pectoralis major (shoulder flexor) and posterior deltoids (shoulder extensor) were recorded with surface electrodes. The EMG signals were acquired at 1 kHz. Then, the EMG signals were digitally bandpass filtered (fourth-order dual-pass [10, 400] Hz). Some EMG signals displayed noise at 50 Hz, therefore all EMG signals were also band-stop filtered (50 Hz Notch filter).

2.4 Data analysis

Two markers were defined as time references. The first marker, reach onset, corresponds to the moment when the cursors exit the home targets. It is used to align the force profiles across all trials and participants. The second marker, named pert on, occurs approximately at one third of the distance between the middle home target and the final target. At this time reference, the forward velocities reached approximately their peak. In the same way as the force profiles, the EMG signals were aligned from the pert on across trials and participants. The alignments of these different signals were performed to decrease the trial-to-trial variability.

To measure potential adaptation of the perturbation to the perturbation, exponential fits on several measurements were used. The 99.5% confidence interval corresponding to the parameter responsible for the curvature was performed to detect if the parameter included or not the value of 0 ($p < 0.005$). If the parameter includes 0, then the exponential fit is reducing to a linear fit. From the positions of cursors, the maximal lateral deviation, the maximum target overshoot (or simply called overshoot), the path length, and the aiming angle were extracted. The aiming angle corresponds to the angle between the vector joining the cursor positions at reach onset and pert on, and, the forward vector starting at the reach onset cursor position. The lateral velocity profiles of both limbs were monitored at an early and late stage of the perturbed trials. From the

force profiles, the correlation between the measured force (i.e. the force at the junction between the robot’s handle and the participant’s hand) and the commanded force (i.e. the perturbation computed offline from the velocities profiles) as well as the terminal peak end force were also investigated. The terminal peak end force corresponds to a force peak at the end of the movement. For the left hand (unperturbed), the correlation was performed between the right hand produced force and its produced force.

To analyze the strategy adopted by the participants during the movements, the variability and the time course of the correlation between the lateral displacement of both hands were computed. The variability is defined as the area of the 95% confidence ellipse around points corresponding to the cursor positions taken across several trials at a certain time. To understand the evolution of the variability during the movement of each cursors individually, the area of the 95% confidence ellipse fitting their positions included in a 30 ms moving time-window across the last 30 perturbed trials has been performed. The trajectories are aligned on reach onset beforehand.

To analyze the change of dynamics of the unperturbed hand due to the catch trials, the last 10 catch trials have been observed. These 10 catch trials lied in the asymptote of the learning of behavioral parameters. The behavioral parameters have been also inspected for the trials before and after catch trials. Another analysis consisted to take all catch trials spaced at least five trials from another catch trials as well as the previous trial and the five trials following these catch trials. Then, the average across all participants has been realized for their aiming angle, maximum lateral displacement, and maximum target overshoot.

To measure the onset of changes in EMG between early and late perturbed and catch trials, EMG were averaged across the first four trials and the last four trials to contrast the participants’ behavior at an early and late stage of the block. Next, the signals were averaged into a 30 ms centered sliding window. Paired t-tests between the two means values (one for the early and one for the late trials by participant) were performed across time. The sliding comparisons produced a time series of p-values. To find the onset time of change in EMG, the time with the highest statistical difference ($p < 10^{-4}$) across the population is located. The onset of changes is defined as the moment where the p-value surpasses for the first time the value of 0.05 after pert on, and, before the time corresponding to the highest statistical difference ($p < 10^{-4}$) across the population. The onset of changes is then defined from the reach onset time index. Since there is some variability between the reach onset and the pert on indexes across trials and subjects, the cumulative individual distribution of the delay between the two indexes was computed, and the mean and standard deviation of the medians were extracted. These mean and standard deviation are used to define the delay. The delay is therefore of the form: (pdrop time + the mean of the reach onset medians) $\pm$ the standard deviation of reach onset medians.

2.5 Mathematical modelling

This section describes the extension of the adaptive control model for the bimanual case (Crevecoeur et al., 2020 [1]). The uncoupled and coupled scenarios were both developed with two different controllers: (1) the linear quadratic-Gaussian and (2) the robust controllers. In the uncoupled scenarios, the two limbs realize a reaching movement towards their individual final target (Fig.4: A). Regarding the coupled scenario, both limbs must work together to reach a final target with a common cursor placed at a mid-position between both limbs (Fig.4: B).

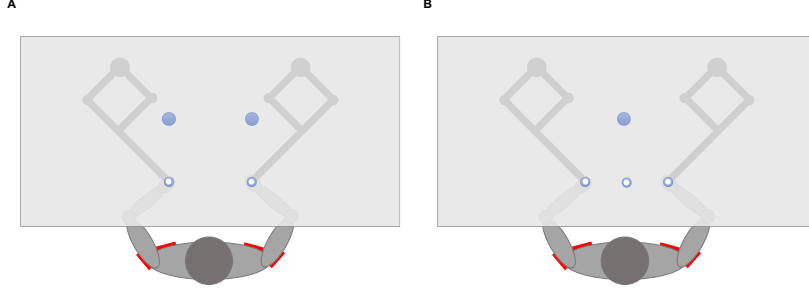


Figure 4: **A**, two-cursors condition (uncoupled case). **B**, one-cursor condition (coupled case).

The state-space representation and the model equations developed with the LQG controller come from "*A very fast time scale of human motor adaptation: Within movement adjustments of internal representations during reaching*" (Crevecœur et al., 2020 [1]). For the robust controller, the state space representation is similar to the previous one and the model equations are described in "*Robust Control in Human Reaching Movements: A Model- Free Strategy to Compensate for Unpredictable Disturbances*" (Crevecœur et al., 2019 [21]).

The system described the translation of a point mass (2.5 kg) comparable to the mass of an arm in the horizontal plane. The state vector is $\mathbf{z} = [x, y, \dot{x}, \dot{y}, f_x, f_y]^T$. The state space representation is the following:

$$\begin{aligned} m\ddot{x} &= -k\dot{x} + f_x + f_{ENV_x} \\ m\ddot{y} &= -k\dot{y} + f_y + f_{ENV_y} \\ \tau\dot{f}_x &= u_x - f_x \\ \tau\dot{f}_y &= u_y - f_y \end{aligned}$$

where k is the dissipative constant (0.1 Nsm^{-1}), f_{ENV_x} and f_{ENV_y} are respectively the x and y components of the unknown perturbation $\vec{f}_{ENV} = \pm L\dot{y}\vec{\hat{x}} + \pm L\dot{x}\vec{\hat{y}}$.

The first step to extend the adaptive control model was the modification of the state space representation to include the second limb. To do so, the state space representation has been duplicated, and hence, the different matrices of the model expanded. The new state vector was $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}]^T$

and, for example, the system matrix $A_{6 \times 6}$ became

$$A_{ext} = \begin{pmatrix} A_{6 \times 6} & 0_{6 \times 6} \\ 0_{6 \times 6} & A_{6 \times 6} \end{pmatrix}$$

The two limbs remained independent at this point. The coupling of the two limbs was set by the definition of the cost function as proposed by Diedrichsen et al. (Diedrichsen et al., 2007 [3]). The following cost function for the uncoupled case was proposed:

$$J = \sum_{t=1}^T \alpha_t [w_p(\|p_{L,t} - g_L\|^2 + \|p_{R,t} - g_R\|^2) + w_v(v_{L,t}^2 + v_{R,t}^2)] + \sum_{t=1}^{T-1} w_u(\|u_{L,t}^2\| + \|u_{R,t}^2\|)$$

while for the coupled case, the cost function was:

$$J = \sum_{t=1}^T \alpha_t [w_p (\| \frac{p_{L,t} + p_{R,t}}{2} - g \|^2) + w_v (v_{L,t}^2 + v_{R,t}^2)] + \sum_{t=1}^{T-1} w_u (\| u_{L,t} \|^2 + \| u_{R,t} \|^2)$$

In the two-cursors condition, the cost function penalizes the distance between the limbs and their individual target, their velocities and the total sum of the squared motor commands of each limb. In the one-cursor condition, the penalties on the positions are replaced by a term that penalizes the common cursor position in respect to the final target. The parameter α corresponds to a polynomial buildup that scales the terminal cost to obtain a smooth buildup of the terminal cost.

The implementation of the robust controller on the adaptive control model required additional modification. The cost matrix Q must be reversible, therefore the cost function proposed by Diedrichsen et al (Diedrichsen et al, 2007 [3]) for the common cursor condition must be adapted. Two elements have been added to the state vector: the horizontal and vertical positions of the common cursor. The state vector was hence $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}, x_{MID}, y_{MID}]^T$ and the cost function became:

$$J = \sum_{t=1}^T \alpha_t [w_{MID,p} (\| \frac{p_{L,t} + p_{R,t}}{2} - g \|^2) + w_v (v_{L,t}^2 + v_{R,t}^2) + w_{LR,p} (\| p_{L,t} - g_L \|^2 + \| p_{R,t} - g_R \|^2)] \\ + \sum_{t=1}^{T-1} w_u (\| u_{L,t} \|^2 + \| u_{R,t} \|^2)$$

where the cost $w_{LR,p}$ corresponding to the positions of the limbs was kept low to minimize their impact. The addition of the common cursor in the state vector representation could be discussed. Adding the common cursor would imply that subjects take account to the common cursor during the trial. Nevertheless, Diedrichsen et al. showed experimentally that the display of the common cursor was not required to elicit bimanual corrections.

Another possibility to couple the two limbs could be explored. Notably, the dynamic pattern theory and the neural crosstalk depicted among others (Swinnen et al., 2002 [8]). The key ideas of dynamic pattern theory are the determination of collective variables (such the relative phase $\Phi := \theta_{Limb,1} - \theta_{Limb,2}$) for behavioral patterns and the determination of their dynamics obtained by studying the stability (and loss of stability) of these patterns. The system dynamics is defined by an equation of motion of the collective variable. The neural crosstalk underlines the presence of pathways that facilitate neural interactions between control streams, leading to mutual patterns of interference in the motions of the limbs.

Concerning the update of the model estimate, the rule used to update the value of the estimate of the parameter L from f_{ENV} was given by:

$$L_{t+1} = \hat{L}_t + \gamma \frac{\partial z_{t+1}}{\partial L} e_{t+1}$$

where γ is the coefficient of learning and $e_t := z_t - \hat{z}_t$ the prediction error. In the following simulations, only the coefficient of learning was similar for both hands. Both limbs used their corresponding state vector elements for the prediction error and the partial derivative, therefore they updated individually their corresponding part in the estimated system matrix.

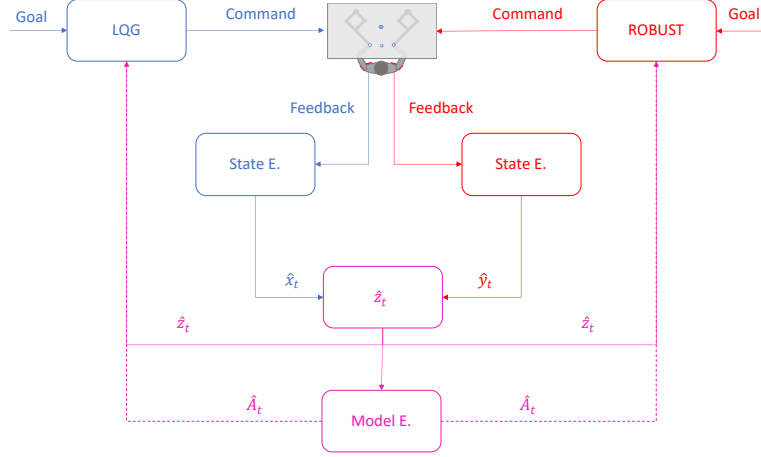


Figure 5: Adaptive control model: LQG and robust controllers (adapted from Crevecœur et al. (2019))

The adaptive control model with each limb regulated by a different controller was the last implementation. Let's consider, for example, that the left limb is controlled by the LQG controller and the right one by the robust controller. At each time step, the model with the LQG controller computed one full state vector $\hat{x}_t$ (Fig.5, blue) and another by the robust controller $\hat{y}_t$ (Fig.5, red). Then, a new state vector $\hat{z}_t$ (Fig.5, magenta) is formed by joining the right limb state elements from $\hat{x}_t$ and the one corresponding to the left limbs from $\hat{y}_t$. This new state vector $\hat{z}_t$ is used to update the estimated matrix $\hat{A}_t$ and to compute $\hat{x}_{t+1}$ and $\hat{y}_{t+1}$ respectively with the LQG and the robust controllers.

The mixed model goal is to investigate the fact that each arm present a specialized behavior. Indeed, Yadav et al. proposed that the dominant arm control is more based on predictive control, while the non-dominant arm is more based on a impedance control (Yadav et al., 2014 [22]). The robust controller tends to minimize the worst-case scenario produced by the introduction of a perturbation leading to trajectories less impacted by the disturbance compared to the LQG controller (Cordova Bulens, 2017 [7]). This asymmetry in performance comes from on different assumptions about potential disturbances made by the two controllers (Crevecœur et al., 2019 [21]). Therefore, this divergence between these two controllers have been exploited to simulate a distinct behavior between the limbs.

3 Results

3.1 Simulation results

All codes have been implemented to simulate a clockwise and counterclockwise curl velocity-dependent force field on either one limb or both limbs with the presence or not of catch trials. However, for the sake of simplicity, the simulation has been only made with a clockwise curl velocity-dependent force field applied on the right hand. The following simulations consist of 40 trials with 6 catch trials. Delay have been added either with a Kalman filter (for the LQG controller) or by the system augmentation (for the robust controller). No delay has been implemented for the mixed model.

3.1.1 LQG controller: dual-goal tasks

The simulation parameters were:

- Simulation time = 600 ms
- Time step = 1 ms
- Delay = 50 ms (Kalman filter)
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(10^5, 10^5, 20, 20, 0, 0, 10^5, 10^5, 20, 20, 0, 0)$
- Polynomial buildup $\alpha = (\frac{t}{N})^{25}$
- Learning rate = 0.1

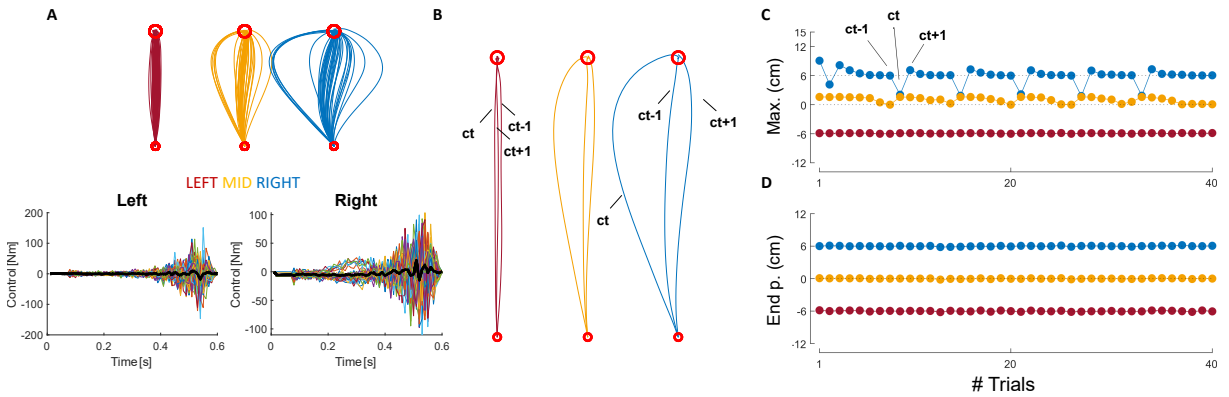


Figure 6: ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

3.1.2 LQG controller: common-goal tasks

The simulation parameters were:

- Simulation time = 600 ms
- Time step = 1 ms
- Delay = 50 ms (Kalman filter)

- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(10^5, 10^5, 20, 20, 0, 0, 10^5, 10^5, 20, 20, 0, 0)$
- Polynomial buildup $\alpha = (\frac{t}{N})^{10}$
- Learning rate = 0.1

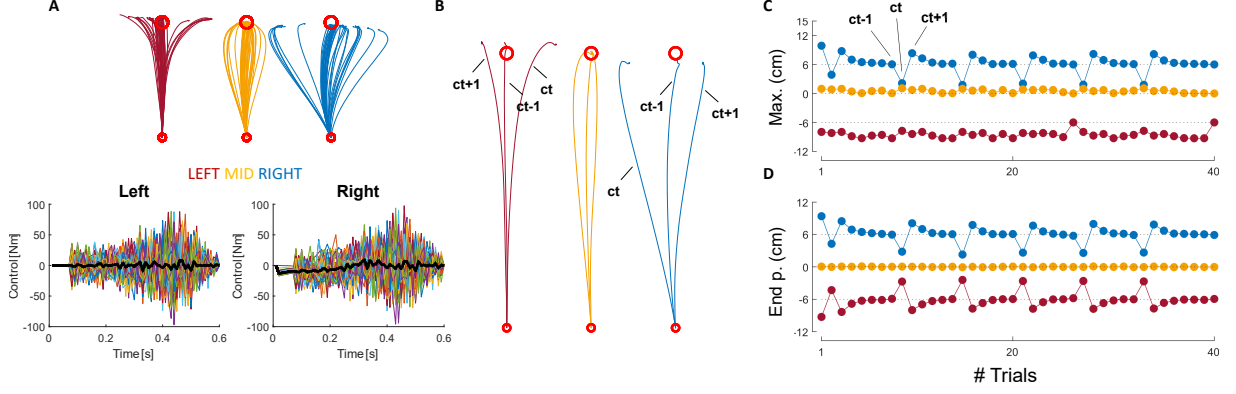


Figure 7: ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

3.1.3 Robust controller: dual-goal tasks

The simulation parameters were:

- Simulation time = 600 ms
- Time step = 1 ms
- Delay = 50 ms (System augmentation)
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}, x_{MID}, y_{MID}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(10^6, 10^6, 10^4, 10^4, 1, 1, 10^6, 10^6, 10^4, 10^4, 1, 1)$. The costs corresponding to the forces are kept low to minimize their impacts.
- Polynomial buildup $\alpha = (\frac{t}{N})^3$
- Learning rate = 0.1

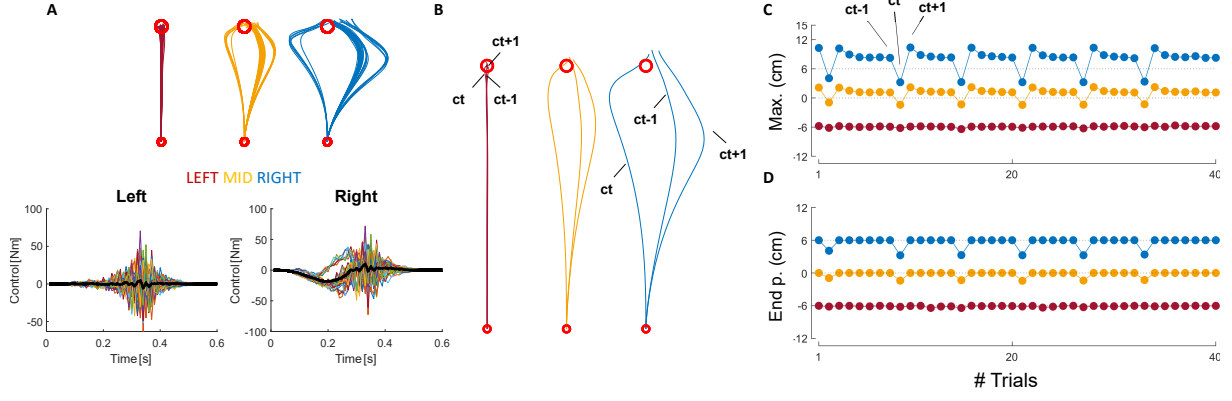


Figure 8: ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

3.1.4 Robust controller: common-goal tasks

The simulation parameters were:

- Simulation time = 600 ms
- Time step = 1 ms
- Delay = 50 ms (System augmentation)
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}, x_{MID}, y_{MID}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(1, 1, 10^4, 10^4, 1, 1, 1, 1, 10^4, 10^4, 1, 1, 10^8, 10^8)$. The costs corresponding to the forces and the positions of both limbs are kept low to minimize their impacts.
- Polynomial buildup $\alpha = (\frac{t}{N})^3$
- Learning rate = 0.1

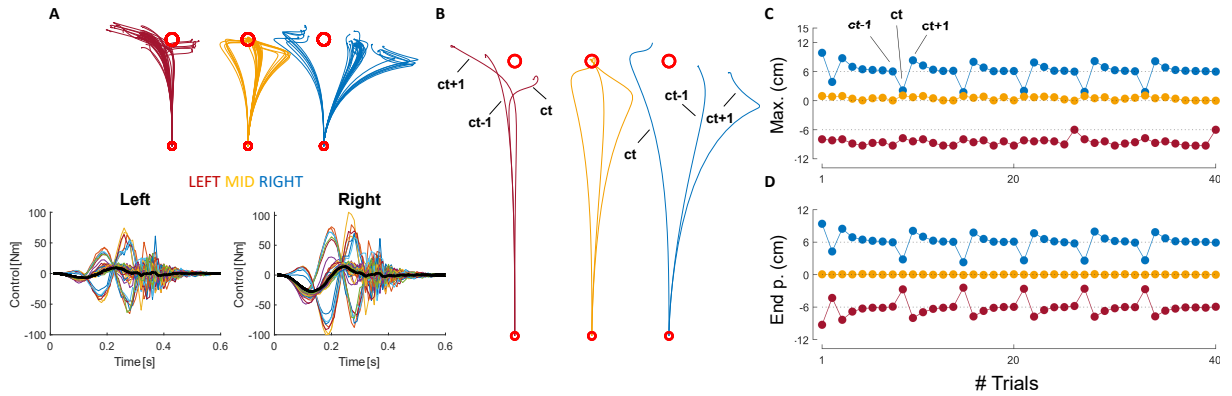


Figure 9: ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

3.1.5 LQG (Right) and Robust (Left) controllers

The simulation parameters for the LQG controller were:

- Simulation time = 600 ms
- Time step = 1 ms
- No delay
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(1000, 1000, 20, 20, 0, 0, 1000, 1000, 20, 20, 0, 0)$
- Polynomial buildup $\alpha = (\frac{t}{N})^{25}$
- Learning rate = 0.1

The simulation parameters for the robust controller were:

- Simulation time = 600 ms
- Time step = 1 ms
- No delay
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{R_x}, f_{R_y}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{L_x}, f_{L_y}, x_{MID}, y_{MID}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(10^6, 10^6, 10^4, 10^4, 1, 1, 10^6, 10^6, 10^4, 10^4, 1, 1)$. The costs corresponding to the forces are kept low to minimize their impacts.
- Polynomial buildup $\alpha = (\frac{t}{N})^6$
- Learning rate = 0.1

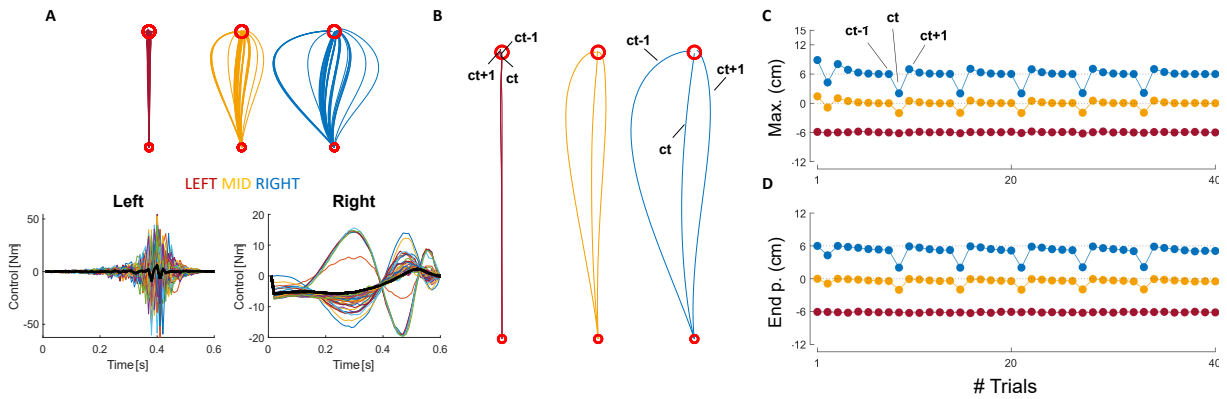


Figure 10: Two-cursors condition. ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

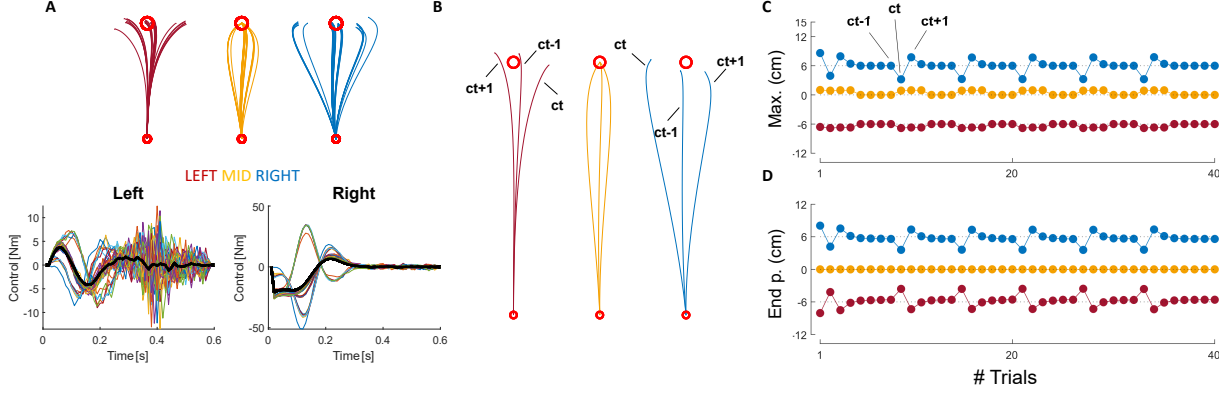


Figure 11: One-cursor condition. ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

3.1.6 LQG (Left) and Robust (Right) controllers

The simulation parameters for the LQG controller were:

- Simulation time = 600 ms
- Time step = 1 ms
- No delay
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{x,R}, f_{y,R}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{x,L}, f_{y,L}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(1000, 1000, 20, 20, 0, 0, 1000, 1000, 20, 20, 0, 0)$
- Polynomial buildup $\alpha = (\frac{t}{N})^3$
- Learning rate = 0.1

The simulation parameters for the robust controller were:

- Simulation time = 600 ms
- Time step = 1 ms
- No delay
- State vector $\mathbf{z} = [x_R, y_R, \dot{x}_R, \dot{y}_R, f_{x,R}, f_{y,R}, x_L, y_L, \dot{x}_L, \dot{y}_L, f_{x,L}, f_{y,L}, x_{MID}, y_{MID}]^T$
- Cost matrix $\mathbf{Q} = \text{diag}(1, 1, 10^4, 10^4, 1, 1, 1, 1, 10^4, 10^4, 1, 1, 10^8, 10^8)$. The costs corresponding to the forces and the positions of both limbs are kept low to minimize their impacts.
- Polynomial buildup $\alpha = (\frac{t}{N})^{3.5}$
- Learning rate = 0.1

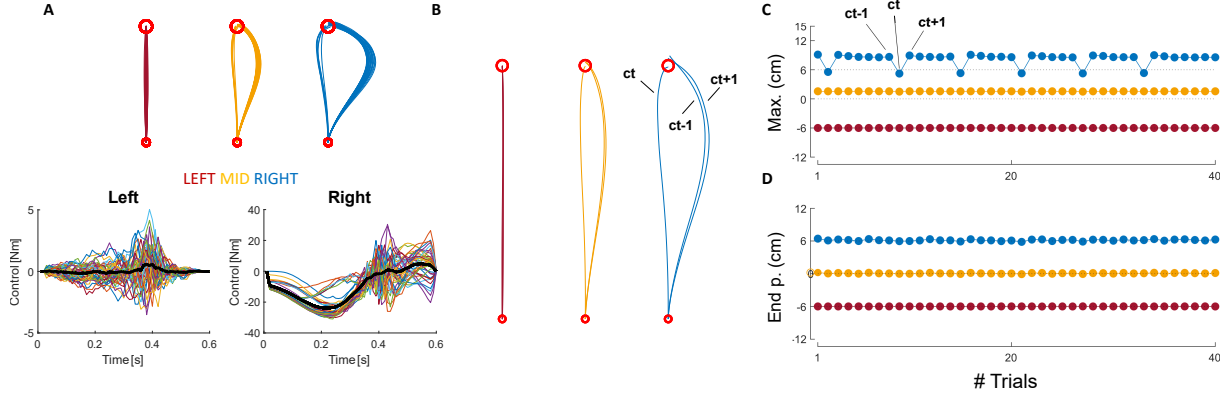


Figure 12: Two-cursors condition. ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

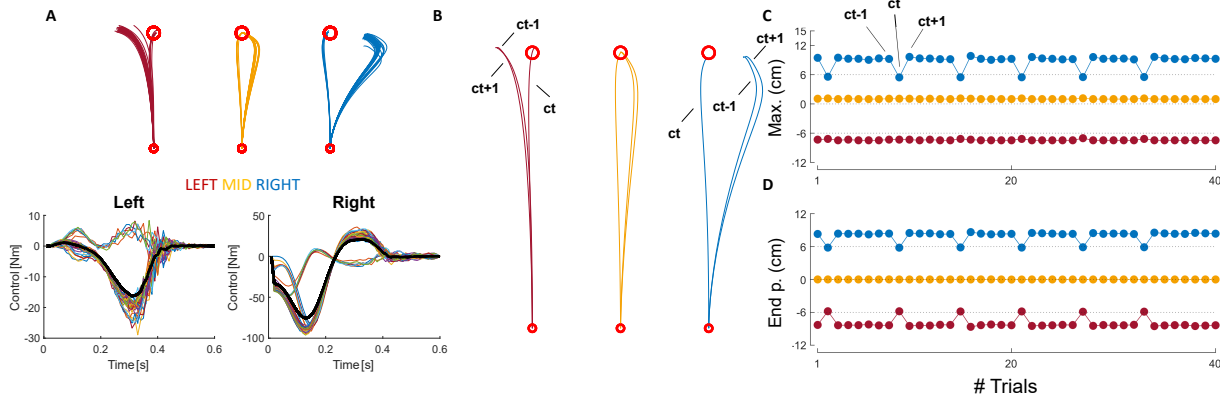


Figure 13: One-cursor condition. ct, Max. and End p. stand respectively for catch trials, maximum lateral deviation and end point position. **A**, top, Hand traces; bottom left, Control vector (mean in black) for the left limb; bottom right, Control vector (mean in black) for the right limb. **B**, Effect of the catch trials on the learning process. **C**, Maximum lateral deviation. **D**, Maximum target overshoot.

3.2 Experimental results

The experiment goal was to reproduce previous findings from Diedrichsen et al. to assess standard adaptation in the mid cursor condition (Diedrichsen et al., 2007 [3]). The novelty lies in the use of the force profiles and EMG analysis between the early and late stages of the perturbed trials.

Concerning the catch trials, they have been analyzed in the same ways as in Crevecoeur et al. (Crevecoeur et al., 2020 [2]) The analysis aim at:

- (1) investigating the presence of feedback response adaptation to the unpredictable catch trials and,
- (2) measuring the potential moment when muscle activity starts to manifest a feedback tuning corresponding to the unexpected switch-off of the force field.

We should keep in mind that in our experiment the catch trials did not correspond to an unexpected force field as in Crevecœur et al. (Crevecœur et al., 2020a [1] and 2020b [2]).

The cursor traces (Fig.14) show the participants' cursor paths during the three-block for the first and last trials (except for the Baseline). Subjects tended to produce a curved inner reaching movement rather than a straight path with both hands in unperturbed trials (Baseline). Following the introduction of the perturbation, a clear deviation of the right hand and the mid cursor was visible in the direction of the disturbance. Then, at the end of the block, these two traces were less deviated reflecting an adaptation to the force field. An after-effect was observable on the first trial of the Washout block. The after-effect vanished as the participants went through the Washout block. For the unperturbed hand (i.e. the left cursor), the impact of the disturbance was less perceivable. Nevertheless, the left-hand path became more straight at the end of the perturbed block and slightly directed to the opposite direction of the perturbation.

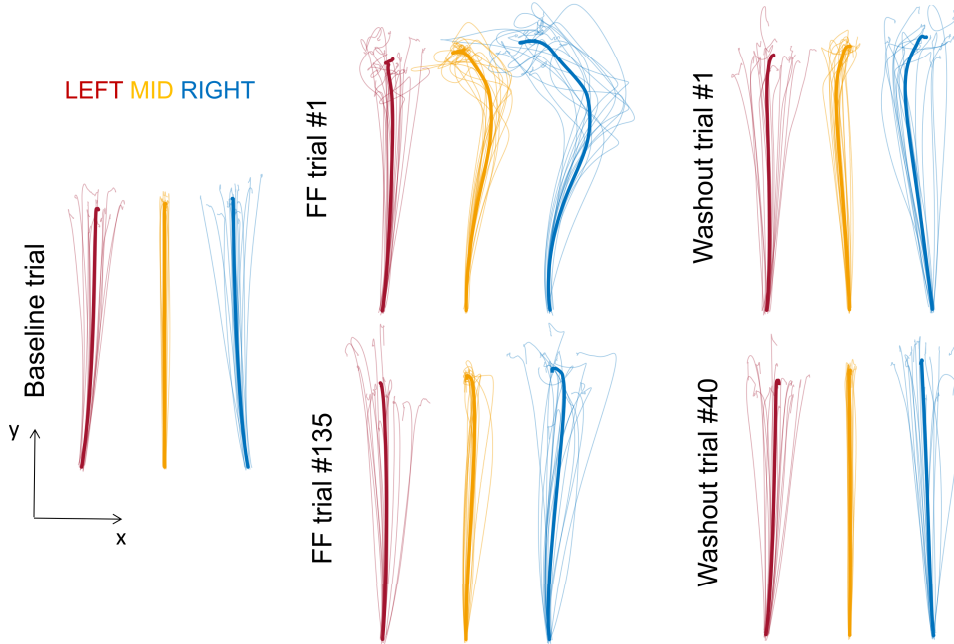


Figure 14: Hand paths from all participants (light color traces) and mean across participants (dark color traces) for Baseline (top left), the first and last perturbed trials (resp. top and bottom center) and the first and last trials of Washout (resp. top and bottom right). FF stands for force field and corresponds to the trials from the CW Learning block.

The behavior parameters for the Baseline reaffirm what has been observed on the hand traces. The right and left hands both started with a slight angle turned toward the center, resulting in a curved path and thus, a lateral deviation. The mid cursor rather adopted a straight path from the home target to the final one with no maximal lateral deviation and a very low aiming angle (Fig.15: A and D, 1-15).

Regarding the perturbed trials, the disturbance caused a lateral deviation in the direction of the force field as well as a target overshoot (Fig.15: A and B, 16-150). Moreover, the path length was highly increased for the first trials (Fig.15: C, 16-150). The left hand, although being unperturbed, was also impacted but at a smaller scale. These three behavior parameters declined across trials for all cursor before reaching a plateau. This plateau will be referred as the asymptote. The exponential fits of all cursors described a significant curvature for the maximum lateral deviation, the maximum target overshoot and the path length. The aiming angle

displayed a decreasing value across trials for both hands (Fig.15: D, 16-150). This suggests that movements initially directed toward the center became more and more straight over the trials to minimize the disturbance's impact. The exponential fits highlighted a significant exponential decay for the aiming angle across trials for both hands in contrast to the mid cursor.

The first Washout trials illustrated the after-effect resulting in the adaptation of the force field. All four behavior parameters demonstrated a comeback to their Baseline values across the unperturbed trials. The exponential fits of the maximum lateral deviation and the target overshoot only highlighted a significant curvature for the mid cursor, while only the right and mid cursors displayed the same results for the path length. Regarding the aiming angle, the right cursor was the only one to get a significant exponential fit.

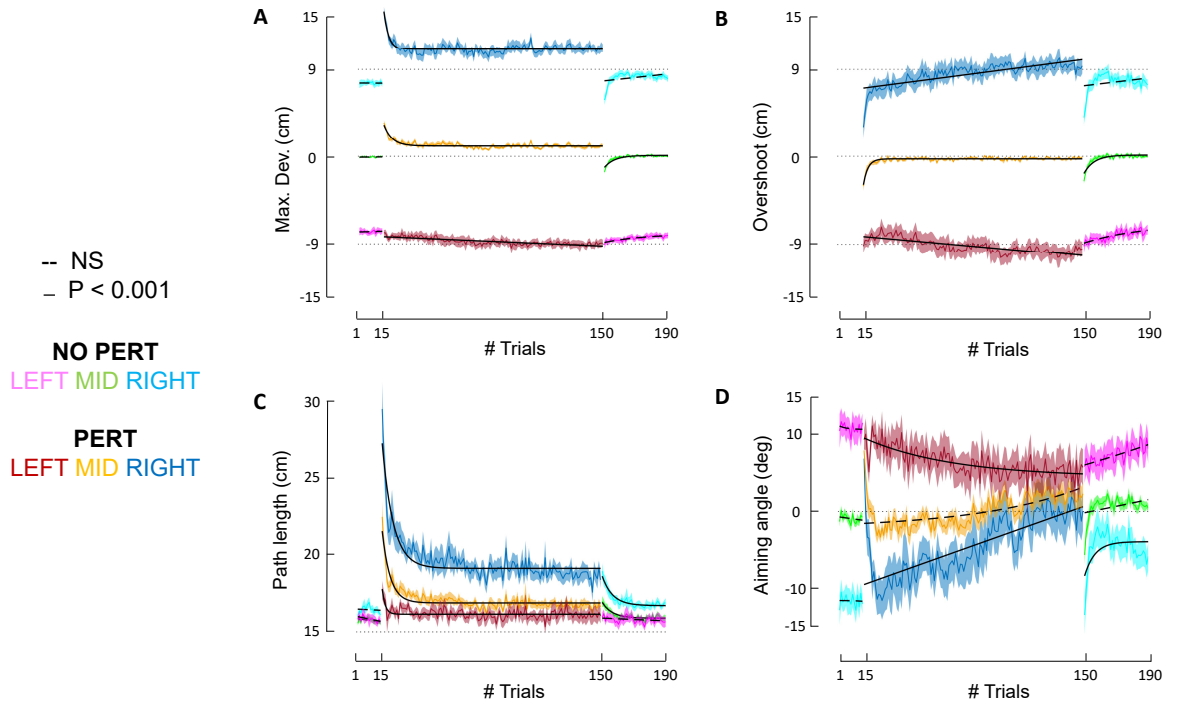


Figure 15: The shaded traces (mean $\pm$ SEM across participants) represent behavior parameters across trials (catch trials not displayed). The solid black lines correspond to the exponential fits while the dashed one, the non-significant exponential fits. **A**, Maximum hand path deviation. **B**, Maximum target overshoot (none for Baseline). **C**, Path length. **D**, Aiming angle.

From the lateral velocity profile of the first perturbed trial, we observed that the lateral velocity of the unperturbed hand (Fig.16: bottom right) showed a peak in the direction of the force field applied to the other hand (Fig.16: top right). For the last perturbed trial, both limbs presented a reduced lateral velocity profile across the movement (Fig.16: top and bottom left). Moreover, the left lateral velocity profiles seemed to begin to depend significantly on the direction of the force field (Fig.16: bottom left).

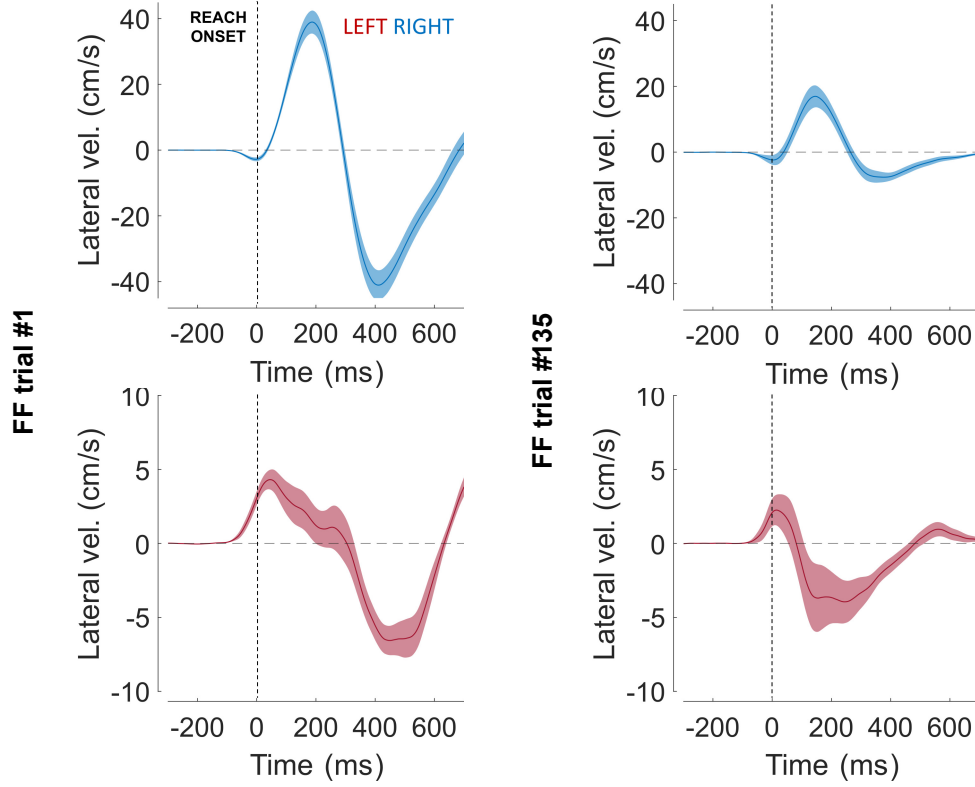


Figure 16: The shaded traces (mean $\pm$ SEM across participants) represent lateral velocity profiles across the movement of the first and last perturbed trials. **FF trial 1**, Right (top) and left (bottom) lateral velocity profiles for the first perturbed trial. **FF trial 135**, Right (top) and left (bottom) lateral velocity profiles for the last perturbed trial.

The evolution of the variability (see Fig.17: A and D) underlined a peak around the right lateral velocity peak and remained high for the end of the movement for both limbs. Even so, the mid cursor showed a smaller variability across the movement and displayed a decreasing variability after the peak. The unperturbed and perturbed trials revealed a distinct evolution of variability (Fig.17: A and D). Firstly, the peak of the right hand and mid cursor happened before the left one. Secondly, the left hand manifested a stronger variability in the perturbed trials.

The time course of unperturbed trials (Fig.17: B) exhibited a strong negative correlation between the lateral displacement of both limbs. In the perturbed trials (Fig.17: E), the correlation remained low and exposed a high variability between the participants. However, the correlation seemed to become more negative in the last part of the movement. In fact, some participants demonstrated a growing negative correlation ($\text{corr} < -0.7$) across the perturbed trials. The correlation of the endpoints' lateral coordinate between both limbs were highly negative during the unperturbed and the 30 last perturbed trials for all participants.

The relationship between the previous correlation and the scores for the corresponding perturbed trials was low ($\text{corr} = 0.1444$). As said previously, subjects had a stronger correlation between the lateral displacement of both limbs in the unperturbed trials ($\text{corr} (\text{mean} \pm \text{std}) = -0.8885 \pm 0.1539$ instead of -0.5175 ± 0.3069 for the 30 last perturbed trials). However, a high correlation was not linked with the success rate for unperturbed trials ($\text{corr} = 0.3804$).

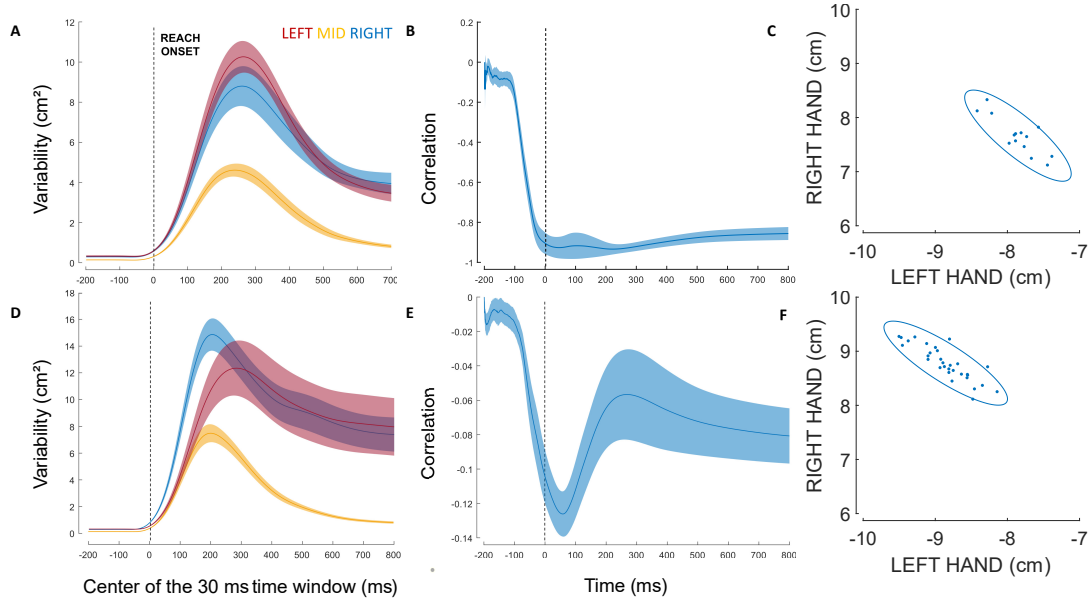


Figure 17: **A**, The evolution of variability for the 15 unperturbed trials (Baseline). **B**, The time course of the correlation between the lateral displacement of both hands with the individual subjects score for the 15 unperturbed trials (Baseline). **C**, Correlation of the endpoints' lateral coordinate between both limbs of one participant for the 15 unperturbed trials. **D**, The evolution of variability for the last 30 last trials. **E**, The time course of the correlation between the lateral displacement of both hands with the individual subjects score for the last 30 last trials. **F**, Correlation of the endpoints' lateral coordinate between both limbs of one participant for the last 30 perturbed trials.

During the Baseline trials, two phenomena were observed from force profiles (Fig.18). First, a peak at an early stage of the movement resulting in a slight aiming angle and, hence the curved path previously observed. Secondly, the left and right hands displayed a reversed force profile leading to the high negative correlation of their lateral coordinate.

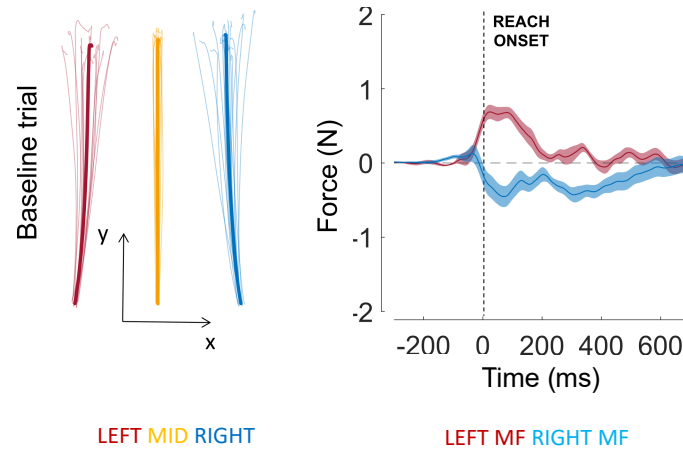


Figure 18: All force profiles (mean $\pm$ SEM across participants) displayed concerns the lateral component. **Left panel:** Cursor trajectories for the last Baseline trials. **Right panel:** Right and left measured force profiles for the last Baseline trials.

In the perturbed trials, the right-hand force counteracted the perturbation and its reaction to the disturbance fitted it more and more across trials (Fig.19). By comparing the first and last trials left-hand force profiles, the left hand seemed to produce an attenuated force during its

movement despite being unperturbed (Fig.19).

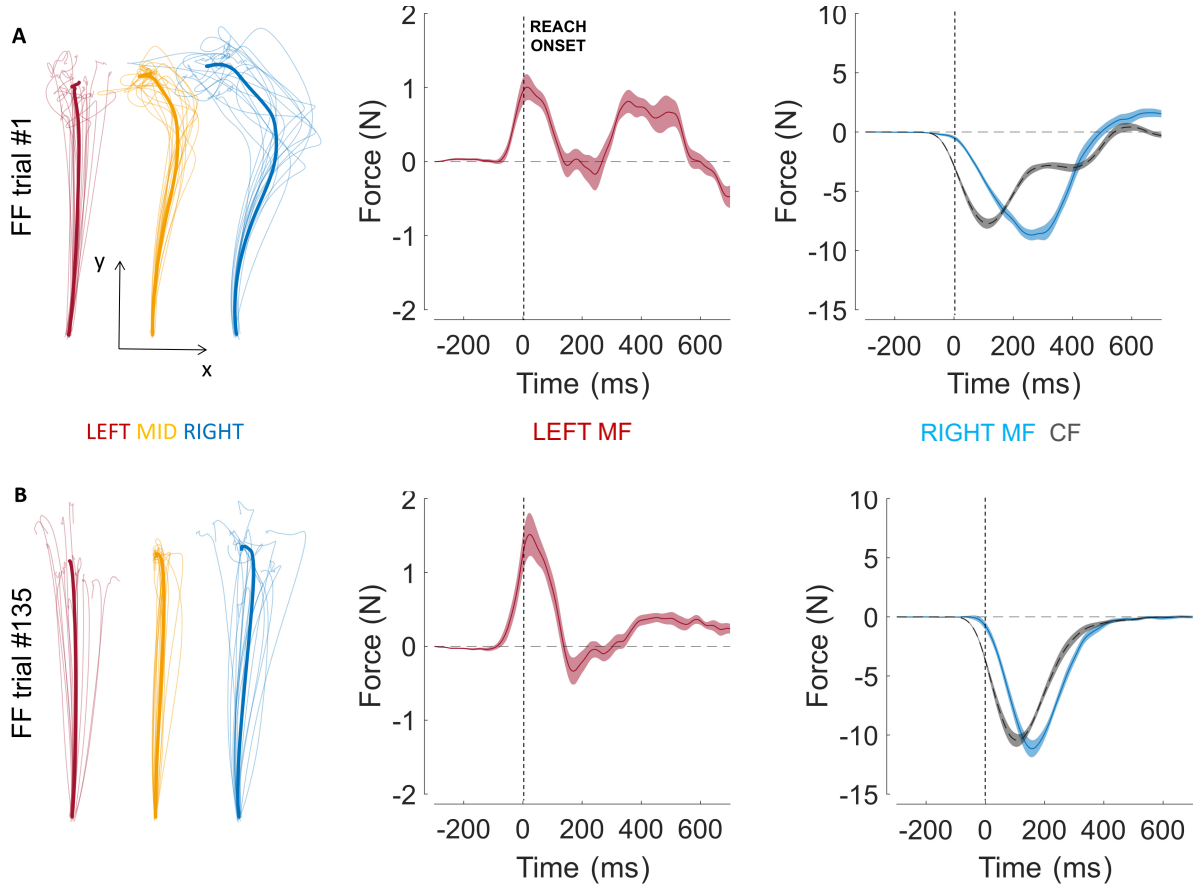


Figure 19: All force profiles (mean $\pm$ SEM across participants) displayed concern the lateral component and are normalized. The commanded force profiles are inverted for an illustration purpose. **A**, Left panel: Hand traces for the first perturbed trial; Middle panel: Left measured force profile (red shaded trace, mean $\pm$ SEM) and the sum of the right measured and commanded forces (grey shaded trace, mean $\pm$ SEM); Right panel: Right measured (blue shaded trace, mean $\pm$ SEM) and commanded (grey shaded trace, mean $\pm$ SEM) force profiles. **B**, The same graphs for the last perturbed trial.

As observed on the force profiles, the correlation between the commanded and the right measured force increased across trials. The terminal peak-end force decreased in value across trials. The decrease may be explained by better control of the force required to counteract the perturbation and therefore, a reduced maximal target overshoot. The exponential fits featured a significant curvature for the correlation and the terminal peak end force. The correlation between the right and left measured forces dropped for the early trials and then, stayed stable across perturbed trials. The left terminal peak showed a slight increase for the early perturbed trials up to an asymptote.

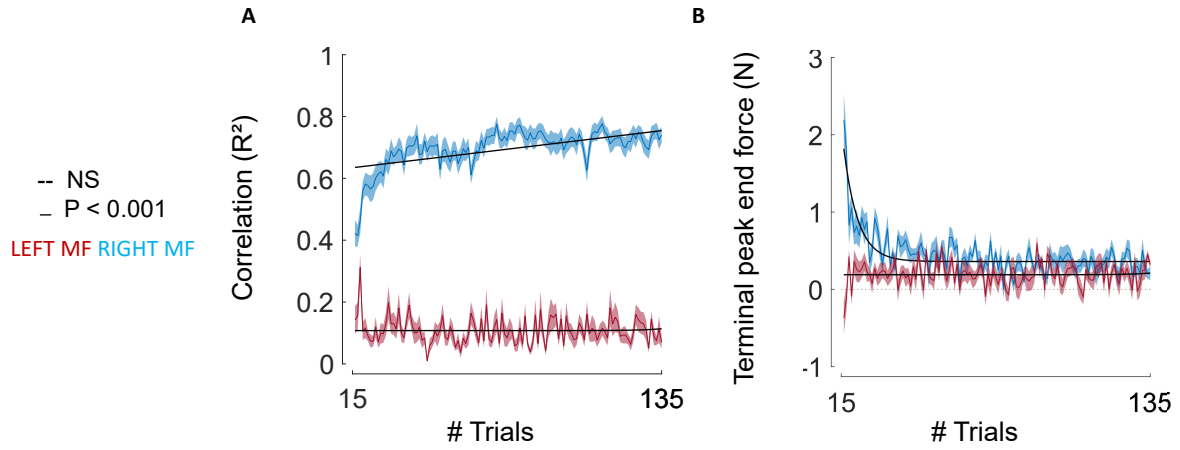


Figure 20: **A**, In blue, the correlation between the commanded force and the right measured force. In red, the correlation between the left and the right measured forces. **B**, The right (blue) and left (red) terminal peak end force.

Regarding the perturbed limb, the agonist muscle (Fig.21: B) featured a translated and an attenuated peak of activity in last trials compared to the early ones. That suggested that the participants anticipated and adapted their force to counter the perturbation. After the drop of activity of the agonist's muscle, the antagonist one (Fig.21: A) displayed an increasing activity. Similarly, the antagonist muscle exhibited a translated and attenuated peak of activity in last trials. For the unperturbed limb, both muscles exhibited a reduced activity across trials. The left posterior deltoid (Fig.21: C) highlighted a translated activity for the last four trials suggesting that the left limbs produced an anticipate and improved reaction to the perturbation of the other arm. Unfortunately, it was less noticeable for the left pectoralis major (Fig.21: D).

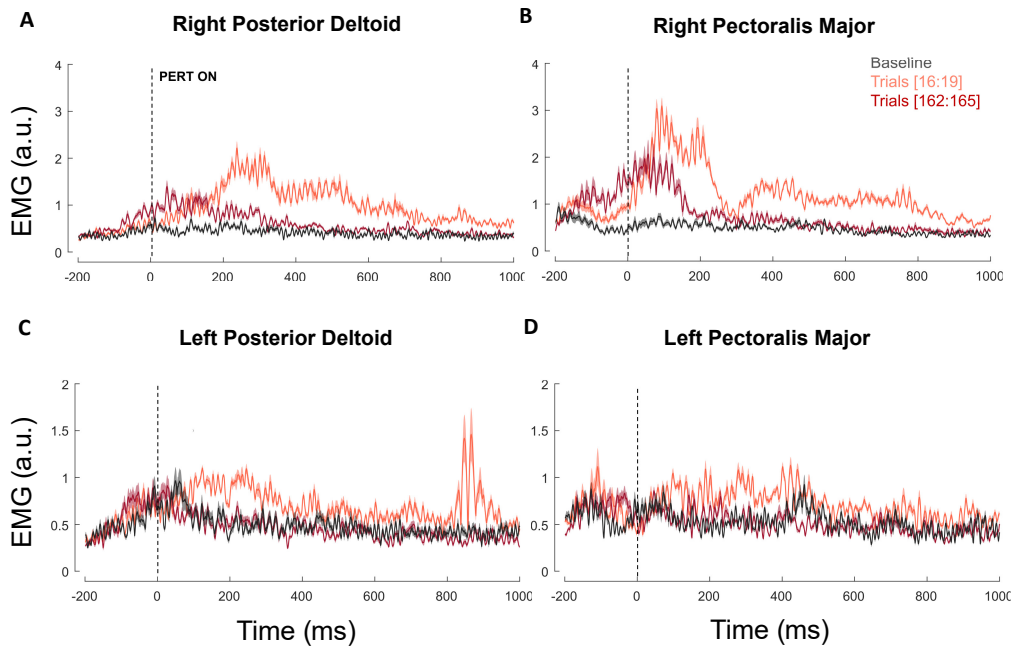


Figure 21: The mean and the SEM are both respectively represented with a solid trace and with a shaded area. **A**, Activity of the right posterior deltoid (antagonist). **B**, Activity of the right pectoralis major. **C**, Activity of the left posterior deltoid. **D**, Activity of the left pectoralis major.

The next point probed was the change of dynamics of both limbs produced by the unexpected

catch trials. A greater interest was given to the undisturbed arm. Looking at the simulations in mid cursor condition, the unperturbed hand demonstrated a fluctuation of maximum lateral deviation and end-point position due to the catch trials. Following this fluctuation, the system came back to the value obtained before the catch trials.

To observe this phenomenon from the experimental data, the aiming angle, the maximum lateral deviation and the maximum target overshoot have been computed for trials occurring before a catch trial (Fig. 22: cyan square), then for catch trials (Fig. 22: green circles), and finally, for trials succeeding a catch trial (Fig. 22: red stars). The perturbed and unperturbed hands presented both a variation due to the introduction of a catch trials.

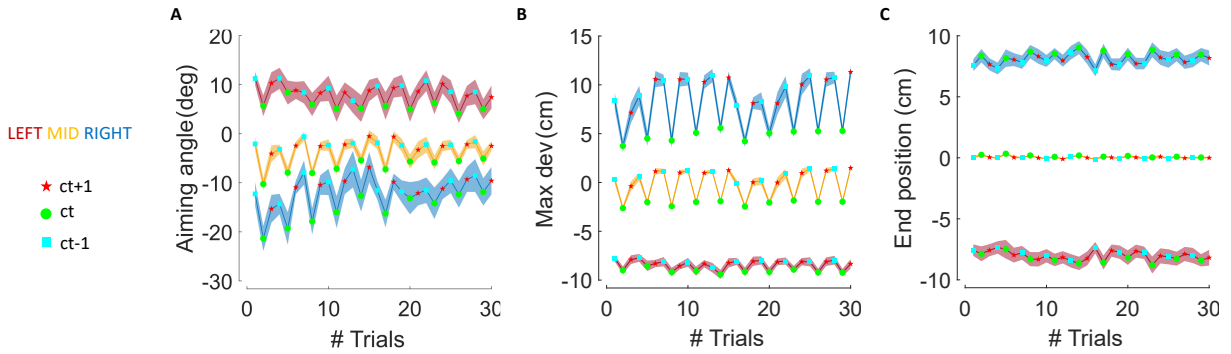


Figure 22: The three following metrics have been displayed the following way: a trial previous to a catch trial (cyan square), then a catch trial (green circle), and finally, a trial succeeding a catch trial (red star). The shaded traces (mean $\pm$ SEM across participants) represent the behavior parameters across these trials. **A**, The aiming angle. **B**, The maximum lateral deviation. **C**, The end position of cursors.

Focusing on the unperturbed hand, the average made on catch trials (and the previous trials as well as the five following ones) and across participants demonstrated a return to the former value (i.e. before the catch trials) in a similar way observed in simulations (Fig. 23).

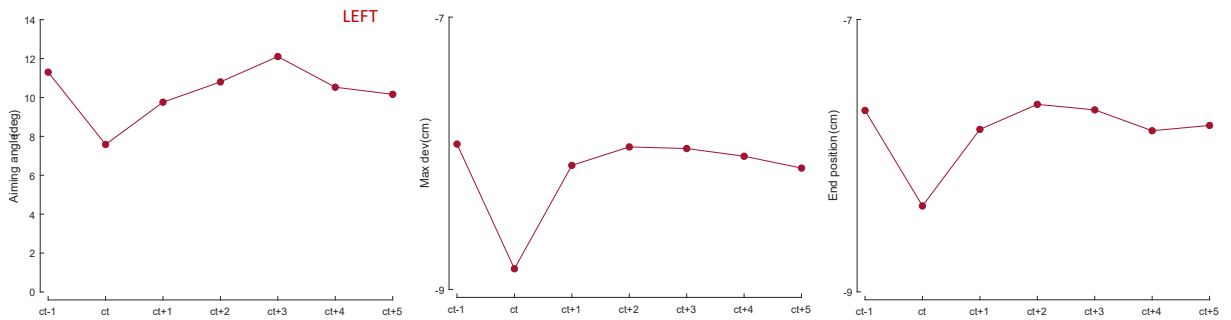


Figure 23: The three following metrics have been displayed the following way: a trial previous to a catch trial (cyan square), then a catch trial (green circle), and finally, 5 trials succeeding a catch trial (red star). The values are the average across participants and catch trials respecting the condition (2). **A**, The aiming angle. **B**, The maximum lateral deviation. **C**, The end position of cursors.

A last point investigated was the feedback analysis of catch trials. During the perturbed block, 15 unperturbed trials have been placed. Only the last ten trials were investigated. Indeed, the first five trials were outside the asymptote of learning and hence, we can consider that participants were adapted to the disturbance for these trials. Except for the correlations and

the aiming angle that seemed to continuously evolves in the asymptotic part (Fig.20), the other metrics remained stable across perturbed trials located in the asymptote part. If, there was a presence of controller change as proposed by Crevecoeur et al. (Crevecoeur et al., 2020a [1]), the first controller corresponding to the perturbation should present similar motor performance across the catch trials, while the second corresponding to the force field switch-off should become more efficient. In their work, they demonstrated a similar maximum lateral deviation and a decreasing maximum target overshoot across their catch trials. As stated previously, since we did not work with force field catch trials, the identification of this phenomenon could not be observed.

Hand traces from catch trials displayed a slight difference between the first and last catch trials. Notably, the right hand seemed to feature a more curved trajectory at a later stage of the movement. The differences were not perceivable from the force profiles.

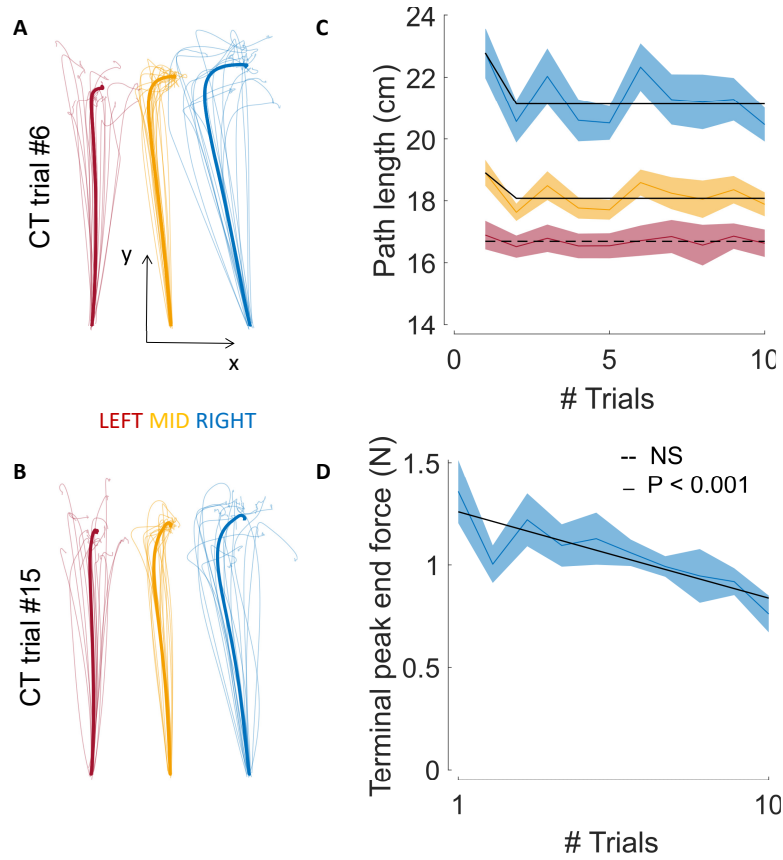


Figure 24: **A**, Hand traces for the sixth catch trials (first in the learning asymptote). **B**, Hand traces for the last catch trials. The mean and the SEM are both represented respectively with a solid trace and with a shaded area. **C** Maximum lateral deviation. **D**, Aiming angle. **E**, Force profiles of both limbs for the 6th catch trials. **F** Force profiles of both limbs for the last catch trials. **G**, The terminal peak end force.

The aiming angle featured a slight increase in absolute value from both limbs but did not display any significant exponential fits. The maximum lateral deviation as well as the maximum target overshoot of cursors remained stable across the catch trials. However, concerning the right limb, the terminal peak-end force demonstrated a decrease and had a significant curvature for its exponential fits. As a result, subjects may apply a decreasing force at the end of the movement. The path length of the right hand and the mid cursor also exhibited a decrease across the catch trials and a significant curvature of their exponential fits. Regarding the EMG, the differences between the muscle activities of both limbs were hardly detectable. The onset of changes has

been investigated between the early and late catch trials. Nevertheless, in the search of a potential drop in p-values, no moment of high statistical difference across populations of EMG data has been found.

4 Discussion

The first objective of my master’s thesis was the analysis of motor performances from participants in a full predictable standard trial-by-trial learning paradigm to reproduce the findings of "*Optimal task-dependent Changes of Bimanual Feedback Control and Adaptation*" (Diedrichsen et al., 2007 [3]) with, in addition, the uses of force profiles and muscles activities. In "*Optimal task-dependent Changes of Bimanual Feedback Control and Adaptation*" from Diedrichsen et al. (Diedrichsen et al., 2007 [3]), it has been showed that both hands demonstrate adaptation to a dynamical perturbation event applied to a single hand when the goal is shared. Two experiments have been performed in two distinct conditions: the two-cursors and the one-cursor condition. The first experiment corresponded to a bimanual reaching movement task in a random learning paradigm, while the second one was in a standard trial-by-trial learning paradigm.

The second objective was the investigation of feedback adaptation during catch trials in the light of previous papers from Crevecoeur and coworkers (Crevecoeur et al., 2020a [1] and 2020b [2]). On the one hand, simulations based on the adaptive control model framework using two distinct control strategies: the linear-quadratic-Gaussian (LQG) and robust controllers. Again, two configurations have been tested: the two-cursors and the common cursor conditions. On the other hand, from experimental data in one-cursor condition, by the analysis of catch trials where the force field was unexpected turned off.

The analysis performed in this work supports the finding that the unperturbed hand demonstrates an adaptation to a perturbation in a common goal configuration as advanced by Diedrichsen et al. (Diedrichsen et al., 2007 [3]). Indeed, despite being unperturbed, the left hand exhibited a decreased path length with a reduced maximum lateral deviation and maximum target overshoot corresponding to a straighter path across perturbed trials. The value of the aiming angle (the initial error for Diedrichsen’s paper) in our experiment is distinct from the results of the second experiment performed by Diedrichsen et al. (Diedrichsen et al., 2007 [3]). That difference may be explained by the fact that the experimental condition is distinct. Indeed, the movements of participants were restricted in contrast with our experiment. Furthermore, they averaged its value across the two directions of the force field (leftward and rightward) and the two hands. However, the same conclusion can be deduced from our experiment. The evolution of the aiming angle indicates that the unperturbed hand corrects its initial direction to oppose the force field perturbation.

From the lateral velocity profiles, Diedrichsen et al. demonstrated that, starting at 190 ms (approx. the force field peak), the unperturbed hand displayed a lateral velocity significantly dependent on the direction of the force imposed on the other hand in its first experiment (the random trial-by-trial learning paradigm). In our case, these findings have been also observed except for early perturbed trials.

Next, Diedrichsen and his team analyzed the correlation between the lateral displacement of both limbs. In common cursor condition, he stated that the optimal control policy infers that endpoints of both hands should become negatively correlated. This effect results from the bilateral corrections of the motor noise and should increase progressively over the course of the movement. In our case, both in unperturbed and perturbed trials, the endpoints of both hands were negatively correlated. The time course of the correlation between the lateral displacement of both hands showed quickly a high negative correlation in the unperturbed trials. That contrasts with the growing evolution displayed in their paper. About the last 30 perturbed trials (not investigated by Diedrichsen et al.), participants demonstrated a low negative correlation during the movement. However, an increase has been noticed late in the movement. We hypothesise that both limbs would become more negatively correlated at the end of the movement to assure

the common cursor to reach and stabilize in the final target. The evolution of variability in unperturbed and perturbed trials, both hands show a high variability at the end of the movement leading to a minimized variability for the common cursor. This result highlights the fact that bilateral correction are present in a common cursor configuration.

As said previously, the novelty of the study was to investigate the adaptation of both limbs during the experiment by monitoring force profiles and the activity of the muscles. EMG data illustrate that the perturbed hand exhibited a reduced and left-shifted muscle activity from agonist and antagonist muscles. Regarding the unperturbed hand, this effect was only detectable in posterior deltoid recordings. This decrease suggest that participants learn to anticipate and adapt their movement to counteract the perturbation impact in both limbs (perturbed or not). This finding emphasizes the presence of bilateral correction during the bimanual cooperative tasks.

The results of the simulation approach we developed converge toward the same conclusion. In a common goal task, both limbs contribute to the diminution of error generated by the common cursor. Moreover, the introduction of a catch trial generated a change of dynamics in the unperturbed hand, which was gradually abolished in the next trials. By comparing the experimental results, similar observations were made.

In conclusion, this current study contributed to further investigate the bilateral correction during a common goal task, strated by Diedrichsen and his team. The same conclusions have been deduced with EMG correlates. Nevertheless, in their paper, Diedrichsen et al. quantify the amount of correction made between and within hands. He demonstrated that the within hands correction rate increased, while the between hands correction rate dropped in the common goal configuration compared to the dual-goal one. The quantification of the correction rate between and within the hand as well as its evolution across trials was not investigated in our study. The comparison with the two-cursors condition has also not been developed. Another distinction with Diedrichsen comes from the design of its task. In their standard trial-by-trial learning experiment, participants realized several sessions where the direction of the perturbation (leftward or rightward) and the hand on which he applied the perturbation was changed. They also check the impact of the visual feedback on the emergence of bimanual corrections to verify whether the view of the common cursor was sufficient to generate bimanual corrections. In our work, the different findings were based on data where only the right hand was perturbed with a clockwise force field disturbance. Besides, the influence of visual information has not been taken into account.

Concerning the feedback adaptation, although the maximum target overshoot remained unaltered across catch trials, a reduced terminal peak led to a shorter path length for the perturbed hand. Regarding the unperturbed hand, no relevant evidence of feedback adaption has been established. The muscle activity remained too similar and therefore, no suggestion of a clear change of behavior has been found. The analysis was initially made with force field catch trials in papers from Crevecoeur et al.. So, there was no guarantee that the same observation about the maximum target overshoot and hence, a reduced terminal peak could be made. Lastly, the reduced path length observed in the perturbed hand could be an insight of a within-trial feedback adaptation presence. Nevertheless, there was no possibility to determine the latency of this feedback from the right muscles recordings.

Finally, future researches on feedback adaptation could focus primarily on analogous experiments made by Crevecoeur et al. in the two previously cited papers. For instance, by setting unperturbed trials with force field catch trials, we could directly directly make the comparison

with their results, and maybe identify similar evidence of feedback adaptation in bimanual cooperative tasks. The two main questions underlying previously need more investigation:

- (1) Do both limbs display this within-trial feedback adaptation?
- (2) Is the latency of this feedback similar to the unimanual case?

The utilization of via point to potentially observe near-instantaneous after-effects or even the effect of alternating different kinds of force fields (i.e. orthogonal and curl force fields in different directions) as it has been performed by Crevecoeur et al. could be explored.

Another investigation could be the comparison of the feedback latency between unimanual and bimanual (cooperative or not) tasks. Could be possible a transfer of learning between unimanual and bimanual cooperative tasks? Is this change of configuration could impact this feedback adaption?

References

- [1] Frédéric Crevecoeur, Jean Louis Thonnard, and Philippe Lefèvre. A very fast time scale of human motor adaptation: Within movement adjustments of internal representations during reaching. *eNeuro*, 7(1):1–16, 2020.
- [2] Frédéric Crevecoeur, James Mathew, Marie Bastin, and Philippe Lefevre. Feedback adaptation to unpredictable force fields in 250ms. *Eneuro*, 7(April):1–13, 2020.
- [3] Jörn Diedrichsen. Optimal Task-Dependent Changes of Bimanual Feedback Control and Adaptation. *Current Biology*, 17(19):1675–1679, 2007.
- [4] Stephen H. Scott. Optimal feedback control and the neural basis of volitional motor control. *Nature Reviews Neuroscience*, 5(7):532–544, 2004.
- [5] Jörn Diedrichsen, Reza Shadmehr, and Richard B. Ivry. The coordination of movement: optimal feedback control and beyond. *Trends in Cognitive Sciences*, 14(1):31–39, 2010.
- [6] Jason B. Wang Chaoyi Shea Charles H. Kennedy, Deanna M. Boyle. Bimanual force control: cooperation and interference? *Psychological Research*, 80(1):34–54, 2016.
- [7] David Córdova Bulens. *Using Robust and Optimal Control theory to understand handedness and bimanual coordination*. PhD thesis, 2017. Prom. : Lefèvre, Philippe; Crevecoeur, Frédéric.
- [8] Stephan P. Swinnen. Intermanual coordination: From behavioural principles to neural-network interactions. *Nature Reviews Neuroscience*, 3(5):350–361, 2002.
- [9] J. Gooijers and S. P. Swinnen. Interactions between brain structure and behavior: The corpus callosum and bimanual coordination. *Neuroscience and Biobehavioral Reviews*, 43:1–19, 2014.
- [10] Wan wen Liao, Jill Whittall, Joseph E. Barton, and Sandy McCombe Waller. Neural motor control differs between bimanual common-goal vs. bimanual dual-goal tasks. *Experimental Brain Research*, 236(6):1789–1800, 2018.
- [11] Alexandra Reichenbach, Angela Costello, Peter Zatzka-Haas, and Jörn Diedrichsen. Mechanisms of responsibility assignment during redundant reaching movements. *Journal of Neurophysiology*, 109(8):2021–2028, 2013.
- [12] Ian O’Sullivan, Etienne Burdet, and Jörn Diedrichsen. Dissociating Variability and Effort as Determinants of Coordination. *PLoS Computational Biology*, 5(4), 2009.
- [13] Mario Wiesendanger and Deborah J. Serrien. The quest to understand bimanual coordination. *Progress in Brain Research*, 143(03):491–505, 2004.
- [14] VK Jirsa, A Fuchs, and JA Kelso. Connecting cortical and behavioral dynamics: bimanual coordination. *Neural computation*, 10(8):2019–2045, November 1998.
- [15] Maura Casadio, Vittorio Sanguineti, Valentina Squeri, Lorenzo Masia, and Pietro Morasso. Inter-limb interference during bimanual adaptation to dynamic environments. *Experimental Brain Research*, 202(3):693–707, 2010.
- [16] Reza Shadmehr and Ferdinando A. Mussa-ivaldi. Adaptive Task of Dynamics during Learning of a Motor. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 14(5):3208–3224, 1994.

- [17] Lili Tcheang, Paul M. Bays, James N. Ingram, and Daniel M. Wolpert. Simultaneous bimanual dynamics are learned without interference. *Experimental Brain Research*, 183(1):17–25, 2007.
- [18] Daichi Nozaki, Isaac Kurtzer, and Stephen H. Scott. Limited transfer of learning between unimanual and bimanual skills within the same limb. *Nature Neuroscience*, 9(11):1364–1366, 2006.
- [19] Carl P T Jackson and R Chris Miall. Contralateral manual compensation for velocity-dependent force perturbations. pages 261–267, 2008.
- [20] Ian S. Howard, James N. Ingram, and Daniel M. Wolpert. Composition and decomposition in bimanual dynamic learning. *Journal of Neuroscience*, 28(42):10531–10540, 2008.
- [21] Frédéric Crevecoeur, Stephen H. Scott, and Tyler Cluff. Robust Control in Human Reaching Movements: A Model-Free Strategy to Compensate for Unpredictable Disturbances. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 39(41):8135–8148, 2019.
- [22] V. Yadav and R. L. Sainburg. Handedness can be explained by a serial hybrid control scheme. *Neuroscience*, 278:385–396, 2014.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
École polytechnique de Louvain

Rue Archimède, 1 bte L6.11.01, 1348 Louvain-la-Neuve, Belgique | www.uclouvain.be/epl