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Differences between right and left arms in human reaching adaptation

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Abstract

This master's thesis expands research on differences between left and right arm for reaching movements with perturbations. Experiments with curl force fields were conducted on right-handed subjects. Their results are analyzed and discussed in this thesis. The current model used for handedness in reaching movements, the hybrid control scheme of Yadav and Sainburg, is questioned. It combines anticipation and impedance control, which assumes the increase in stiffness and viscosity of the arm to counter disturbances. Instead, we suggest the use of a robust control strategy. It is specialized in countering unexpected perturbations, by having high control gains. The analyzes include results from catch trials with null fields, to see the anticipation of the subjects. The EMG signals of the Pectoralis Major and Posterior Deltoid were also analyzed. General differences between left and right arm seem to be more subtle than described in previous research. The thesis ends with a inter-subjects analysis, suggesting a correlation between control gains and the ability to learn. Our results show that subjects/arms with lower control gains would tend to be better learners.

Contents

Chapter 1

Introduction

Handedness is a feature of the human body that we encounter every day. The differences between both arms can vary a lot between different people. Most of them have a dominant and a non-dominant arm. They have preferences for one arm for all tasks. The dominant arm is used in the daily life for activities like writing, brushing one's teeth or playing sports. Some people are very left handed or very right handed. Others are more comfortable performing certain tasks with their left hand and others with their right hand. These people are more ambidextrous. We can also observe differences between people, some are much better learners than others (for both arms). The best example of that is tennis superstar Rafael Nadal. He is arguably considered the greatest left handed tennis player of all time. Yet, Nadal does everything of his daily life with his right hand. He is uncapable of writing with his left hand, for example. Isn't it surprising that the greatest left handed player is not fully left handed ? It shows that general differences between left and right arm are quite subtle and should be analyzed carefully.

These differences evolved through habits, but lateralization in the brain also plays a big role. The left hemisphere of the brain controls the right arm, while the right hemisphere controls the left arm. Each hemisphere has a specialization, which has a direct impact on how each arm is controlled.

This motor lateralization and the influence it has on learning is what is analyzed in this thesis. There has already been a lot of research on handedness. The left hemishphere of the brain (for right-handers) is believed to be specialized in language, routine behaviour in general, and the dexterity of the right hand [1]. However, it is not fully understood where this difference lies in terms of control strategies for each arm. My research focuses on reaching movements with perturbations. So far, a model was developed by Yadav and Sainburg to characterize motor lateralization in reaching movements. It is called the "hybrid control scheme" [2], [3]. This model combines anticipation (predictive control) and impedance control, which is the ability of the limb to counter disturbances due to intrinsic properties such as stiffness and viscosity. The hybrid control scheme was widely accepted in the literature, but recent results seem to question it. They suggested that the actual values of the stiffness and viscosity are likely much lower than what has been published, and used by Yadav and Sainburg in their model. Furthermore, the trials that were used to develop the hybrid control scheme used a within subject design. One arm performed all of its trials before the other arm started [2], [3]. By doing so, the second arm will possibly have learned from the first arm. It was suggested in previous research that this interlimb learning is asymmetrical: one arm would inherit more from adaptation in the other arm due to lateralization in the brain [4]. Therefore, it can bias the results. This can be solved by randomizing the trials of both arms.

To bring new results and analyses to this, experiments were conducted on right-handed subjects.

The analyses of these experiments are the main topic of this thesis. The experiments were randomized bi-manual trials with perturbations. This way, we can check the validity of the hybrid control scheme.

Furthermore, new results from Crevecoeur, Cluff and Scott [5] describe the differences in control strategies for expected and unexpected perturbations. They suggest the use of a more ”robust” controller in certain situations when the dynamics are not well known. It is best to counter unexpected perturbations. The robust controller assumes that better stabilization can be achieved through higher neural feedback gains or reflexes. It has not yet been used in the literature to describe handedness, but it is quite promising. The results are analyzed in these frameworks. No simulation was performed. The same authors analyzed the differences in control gains between good and partial learners [6]. They suggested that partial learners tended to have higher control gains, thus more robust controllers.

The main goal of this thesis is to show that general differences between left and right arm are more subtle than expected and that the robust controller would be a good alternative to the hybrid control scheme. Furthermore, the correlation between control gains and learning is analyzed.

Chapter 2

State of the art

This chapter describes the relevant findings, models and controllers from previous research that are needed to understand this thesis. The results are interpreted in the framework of these models. They are used here conceptually as no simulation was performed.

2.1 Motor lateralization

Let us start by going through the main findings on motor lateralization. In 2009, it was discovered that specialization of the brain's two hemisphere already existed in vertebrates 500 millions years ago [1]. These specializations have evolved throughout the years and are still present today. The left hemisphere of the brain (for right-handers) is believed to be specialized in language, the dexterity of the right hand, and routine behaviour in general. On the other hand, the right hemisphere would be more specialized in reacting to emergencies, organizing items spatially, recognizing faces and processing emotions. However, this research didn't explain the differences in motor lateralization specifically.

More on this came from other studies, also in the beginning of the 21st century. Various results and findings were observed that can explain handedness. The left hemisphere of the brain is said to be more "predictive". It is specialized in optimizing the dynamics of the movement, the trajectories tend to be more straight and smooth. They are optimal in terms of energetic costs. It is also specialized in controlling limb segment inertial dynamics [7]. It was shown that the brain uses an internal model to know the dynamics of our movements and the objects we are in contact with [8]. Adaptation to new intersegmental dynamics requires the development of a new dynamic model. We explain in the next section its role in reaching movements. The development of a new internal model should be more effective for the dominant arm [9]. It is coherent with the observations that the dominant arm is more skillful for writing, drawing or throwing a ball.

In contrast, the right hemisphere of the brain is more "impedant", better to stabilize around an equilibrium position or to obtain a better precision. It also appears to be more effective for load compensation. This supports a specialized role of the non-dominant arm in sensory feedback error correction [10]. One example that reflects these differences is when eating meat: the left hand holds the fork in the meat, and keeps it steady, while the dominant hand holds the knife and performs the more delicate movement.

2.2 Feedback control model

Our approach to understand how the CNS (central neural system) controls the arms to perform reaching movements uses linear control. The framework that we present here is called: the feedback control model. This is important to understand the concept of controller, and how it is used in this case. It represents how a system can be controlled to obtain a desired state, while having feedback. In this case, we want to analyze how the CNS controls the arms during reaching movements, while having a visual feedback from the eyes. The model is the following:

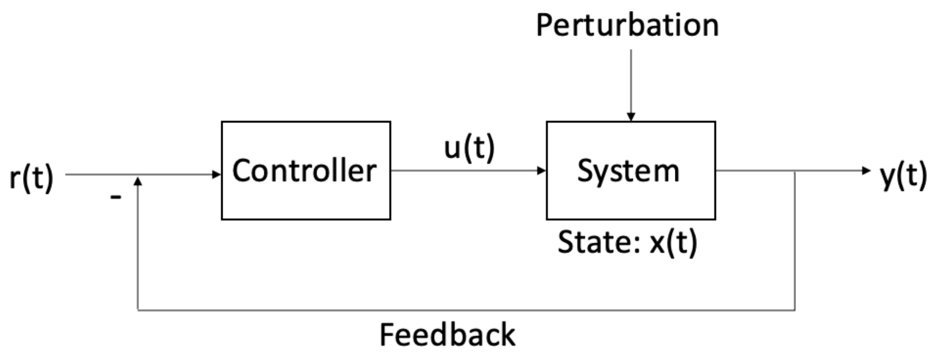


Figure 2.1: Feedback control model

Where:

- The system we want to command is the arms. They are used to reach the target and counter the perturbation. The state vector of the system is $x(t)$.
- The controller is the strategy used by the CNS, knowing the observation, to obtain the desired position
- $r(t)$ is the desired position, where we want our hand/cursor to be
- $y(t)$ is the observation, what our eyes see. The error on the position of the hand, which is $r(t) - y(t)$ is used by the controller to define the appropriate command signal
- $u(t)$ is the command signal, sent by the CNS to the muscles
- The perturbations are disturbances that have an influence on the state of system. They perturb the reaching movements during the trials.

The concept of control gains is very important here. Some controllers will be compared by their differences in control gains. It is a proportional value, which represents the relationship between the magnitude of the command signal and the magnitude of the error $r(t) - y(t)$. If the control gains are high, even a small error will have a big impact on the command signal from the controller. Therefore, the response from the system will also change a lot.

In this thesis, we try to understand more about the control strategies of our brain and how they differ from one hemisphere to the other. Our brain uses an internal model, which is used to define the motor command that should be sent to the arms. This model is known from experience, it represents the dynamics of the system. If someone handles a very familiar object, for example its phone, it has a good idea of the dynamics of this object. Therefore, when carrying this object, the internal model will be quite accurate. When performing reaching movements with perturbations, the disturbances are learned. They become part of the internal model, which becomes more and more accurate. Therefore, as the subjects learn, they anticipate the perturbations more. By doing so, they have more chance to reach the desired position and they can do it in a more efficient way.

When a motor command is sent to the arm, the corresponding muscle fibers react to it by depolarizing. A small part of this electric signal is present on the skin. This can captured by an electromyogram (EMG). It is often used in research to measure the muscular activity of the participants during trials.

2.3 Origins of impedance control

The first controller that we will discuss is the impedance controller. At the moment, it is one of the most popular models used to explain handedness. It is important for the reader to understand how this models works, but also how and why the scientists came to this result.

In 1984, it was suggested in a paper of Hogan [11] that the CNS would co-activate antagonist muscles to modulate musculoskeletal impedance. An example of co-activation of antagonist muscles, is when the biceps and the triceps are activated at the same time. It costs metabolic energy, without performing any useful work. The rationale for co-contraction is the hypothesis that it increases the intrinsic mechanical impedance of the joints, which makes them mechanically rigid. For example, when someone is carrying an object, the gravity will tend to destabilize its posture. The total joint stiffness must then increase to preserve postural stability.

Later, in 1994, Shadmehr and Mussa-Ivaldi [12], [13] tried to characterize the joint stiffness and viscosity (or damping) of a human arm. Intuitively, stiffness can be understood as the torque required to move the shoulder/elbow by 1 radian. Viscosity is the torque that needs to be applied to set the shoulder/elbow in movement with an angular speed of 1 rad/s. Of course, this depends on whether or not you voluntarily contract your biceps or triceps. Neural feedback also has an influence, for example if you have a reflex or if you have learned to anticipate the perturbation. As we will see later, this was not taken into account when taking these measures. Joint stiffness and viscosity are characterized by the following equations:

$$\text{Stiffness:} \quad \begin{bmatrix} T_1 \\ T_2 \end{bmatrix} = \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix} * \begin{bmatrix} d\theta_1 \\ d\theta_2 \end{bmatrix}$$

$$\text{Viscosity:} \quad \begin{bmatrix} T_1 \\ T_2 \end{bmatrix} = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} * \begin{bmatrix} d\dot{\theta}_1 \\ d\dot{\theta}_2 \end{bmatrix}$$

Where :

- $T_{1,2}$ is the torque on the shoulder or elbow $[N * m]$
- $\theta_{1,2}$ represents the angular displacement of the shoulder or elbow $[rad]$
- $\dot{\theta}_{1,2}$ represents the angular velocity of the shoulder or elbow $[rad/s]$
- K_{ij} represent the joint stiffness between the parts of the arm $[Nm/rad]$
- B_{ij} represent the joint viscosity between the parts of the arm $[Nm * s/rad]$

The values that they used were the following:

$$K = \begin{bmatrix} -15 & -6 \\ -6 & -16 \end{bmatrix} \text{ and } B = \begin{bmatrix} -2.3 & -0.9 \\ -0.9 & -2.4 \end{bmatrix}$$

Burdet et al. published in 2001 [14] results that would confirm the theory of Hogan. Their experiments showed that the CNS can voluntarily control the stiffness or viscosity at the end of a movement to stabilize around the equilibrium position. A new framework is based on this principle, it is called: impedance control. At this point, we do not speak of handedness or differences in control between left and right arm.

2.4 The hybrid control scheme

In 2011, Yadav and Sainburg added to this idea, when they came up with a new hypothesis for motor lateralization that involved impedance control [2], [3]. This model was developed to support the various results and findings that have been observed in the beginning of the 21st century in [9], [15],[7], [10]. Their model is still accepted in the literature today and considered as the main explanation for handedness. It is a hybrid control scheme, in which both arms use two controllers: a predictive controller in the beginning of the movement and an impedance controller at the end. The predictive controller is used in the beginning of the trial to anticipate. The impedance controller increases stiffness and damping to stabilize around an equilibrium. The interlimb difference would be in the switch time between these controllers: the dominant arm would switch to the impedance controller later than the non-dominant arm.

The full description of the hybrid control scheme is thoroughly explained in [2], [3]. Without going in the details of fitting procedure, we describe here the key parameters. This is the mathematical equation of the hybrid control scheme:

$$T = (1 - w)T_{work} + w(-K(\Theta - \Theta_f) - B(\dot{\Theta} - \dot{\Theta}_f))$$

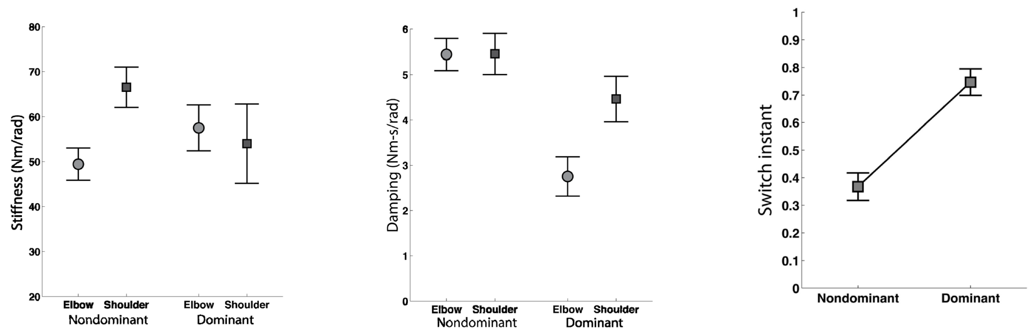
Where:

- T is the torque applied on the handle
- T_{work} is the torque that minimizes a cost function combining the error from the desired final position, and energetic costs. It is the contribution of the predictive controller.
- K is the stiffness of the arm
- B is the viscosity of the arm
- w is the weight of each controller, depending on s, the switch instant between the two controllers. If $s = 0$, $w = 1$ and the control is purely impedant. On the other hand, if $s = 1$, $w = 0$, the control is purely predictive.
- Θ is the state vector of the position, Θ_f corresponds to the desired final position
- $\dot{\Theta}$ is the state vector of the velocities, $\dot{\Theta}_f$ is the desired final speed (in most cases: 0)
- The terms $K(\Theta_f - \Theta)$ and $B(\dot{\Theta}_f - \dot{\Theta})$ are based on the framework of the feedback control model.

The parameters were computed using particle swarm optimization to have the best possible fit on the observed experimental data. Their experiment was to make 150 reaching movements towards 3 different targets, located at 20 centimeters from the start position at angles of 50°, 90°, and 130°, relative to the frontal plane. There were no force fields to disturb the reaching movement. On the other hand, no visual feedback was provided to the subject until the end of the trial. Half of the subjects performed the first 75 trials with their non-dominant arm, and the rest with their dominant arm. The other half of the subjects did it the other way around.

Wang and Sainburg [4] suggested the existence of asymmetrical interlimb transfer. The non-dominant arm shows better performances at a task after initial training with the dominant arm. The opposite is not true. Initial training with the non-dominant arm had no effect on subsequent performance with the dominant arm. This interlimb transfer has an influence in the trials conducted by Yadav and Sainburg. The half of the subjects that started with the dominant arm, should reveal better performances when starting to use the non-dominant arm. On the other hand, the subjects who started with the dominant arm will not have any prior learning when starting to use the non-dominant arm. This is the first flaw in the model of Yadav and Sainburg, to which this thesis can bring an improvement. By randomizing the trials between the dominant and non-dominant arm, it shouldn't happen that one arm has learned more than the other and can provide useful interlimb transfer.

All the results of their model fitting are not presented here, but only the key parameters that will be used later. They are shown on Figure 2.2. The trajectories corresponding to different switch instants are shown on Figure 2.3.



(a) Values of the parameter of stiffness K (Source: [3])

(b) Values of the parameter of viscous damping B (Source: [3])

(c) Switch instants obtained by the hybrid control scheme (Source: [3])

Figure 2.2: Results of the fitting of Yadav and Sainburg's hybrid control scheme on the average trajectory of their data (Source: [3])

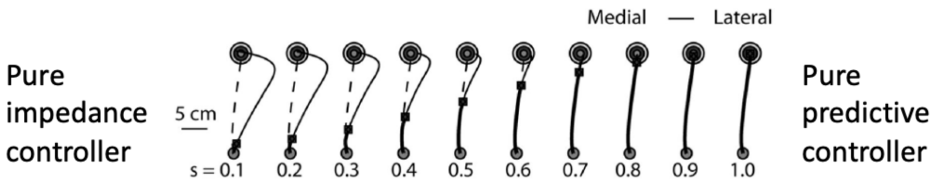


Figure 2.3: Trajectories predicted by the hybrid control scheme for different switch instants s (Source: [3])

Looking at Figure 2.2a, we can see that the values of the parameter of stiffness vary between 45 and 70 $[Nm/rad]$. As a reminder, Shadmehr and Mussa-Ivaldi's values [12] were $K = 16Nm/rad$ and $B = 2.4Nm * s/rad$. Thus, the values of stiffness obtained are up to 4 times more than used in [12]. Same observation about Figure 2.2b, the values of viscous damping are 2 to 3 times higher than published by Shadmehr and Mussa-Ivaldi. We know the concept of the impedance controller is that it increases the stiffness and viscosity of the arm around an equilibrium position. This can explain why the values of Yadav and Sainburg are so high compared to [12]. However, the values published by Shadmehr and Mussa-Ivaldi [12] come from 1994 and have barely been checked until then. Twenty years later, in 2014, Crevecoeur and Scott questioned these values and performed new experiments to estimate them [16]. According to them, the values from 1994 are biased because they are based on reflexes following a perturbation, which does not represent the intrinsic stiffness and viscosity of the joint. Also, they do not consider any contribution from neural feedback and didn't check their results with EMG. Neither did Burdet et al. in 2001 [14]. The results obtained by Crevecoeur and Scott are 10 times smaller than the values from 1994. They estimate muscle's stiffness to be $K = 1.61Nm/rad$ and their viscosity to be $B = 0.14Nm * s/rad$. On the one hand, measurements based on physiological properties have produced values that are 10 times less than values proposed previously in the literature. On the other hand, the model by Yadav and Sanburg suggest values that are 4 times bigger. Thus one may question whether these parameter are compatible with the physiology. This is the second flaw of their model that is presented here. It questions the credibility of the impedance controller.

Let us now have a look at the trajectories of the reaching movements. It is important to note that their trials were null fields, without any force field. We can observe that the left arm is expected to have a bigger deviation from a straight path. The same result is obtained in various other articles. According to Yadav and Sainburg [2], [3], the switch time to the impedance controller would be around 0.35 for the non-dominant arm. Thus, for more than half of the trajectory, an impedance controller would be used. Its purpose is to keep the arm stable around an equilibrium position. This is not the case here, as it is not near an equilibrium position. Furthermore, it is not clear why the impedance controller would deviate the trajectory. This is the third flaw of their model. They are the reason why our experiments make sense and can bring useful contributions to their assumptions.

Yadav and Sainburg conducted other experiments in 2014 [17]. They involved velocity dependant force fields. Half of them were consistent, the force fields were always the same. The other half was inconsistent, the factor between the speed and the commanded force varied randomly between the trials. This time, the results were not used for curve-fitting or simulation. They seemed to validate the hybrid control scheme. The left arm performed better than the right arm for the inconsistent field. This makes sense from the perspective of impedance control. It would make the arm mechanically rigid, which can be useful to counter inconsistent perturbations. On the other hand, the right arm was better for the consistent field. Since it is believed to be more predictive, it makes sense. Anticipation is useful when the dynamics are well known, which is the case in a consistent field. Therefore, it seems to validate its specialization for predictive control. We will come back later on this result and show that it can be explained from another perspective.

2.5 LQG controller

The next models that will be discussed have not yet been used for describing handedness or motor lateralization. Instead, they were the subject of a recent article from Crevecoeur, Scott and Cluff in 2019 [5]. This article suggests that LQG and robust controller (H_∞) could describe different control strategies of the brain to counter expected and unexpected perturbations in reaching movements. Their results showed similarities with those of Yadav and Sainburg for bi-manual trials with consistent and inconsistent fields [17]. Therefore, it makes sense to look at motor lateralization from the perspective of LQG and robust controllers.

The linear-quadratic-Gaussian (LQG) controller is very famous in linear control. It is used to control a linear dynamic system, with a quadratic cost function and where the observation is

impacted by an additive white Gaussian noise.
The dynamic model that we will use is slightly different from the usual LQG-framework. It contains multiplicative noise on the motor commands, as in the paper of Todorov and Jordan from 2002. [18]

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + \sum_{i=1}^{k} C_i \epsilon_i(t) u(t) + v(t) \\ y(t) = Hx(t) + \omega(t) \end{cases}$$

In the context of our experiments, this is what the parameters and variables represent:

- $x(t)$ is the state vector, it contains the positions and speeds of the hand
- $y(t)$ is the observation, what our eyes see and the position of the cursors. It is influenced by the Gaussian white noise $\omega(t) \sim N(0, \Omega)$
- $v(t)$ is the perturbation, the forces applied by the handles
- $u(t)$ is the motor command sent by the brain
- $\epsilon_i(t)$ are standard random variables ($\sim N(0, 1)$), representing the multiplicative noise on the motor commands
- A, B, C_i, H are matrices that characterize the system

When conducting the experiments, the goal of the subjects is to send the appropriate motor commands to the muscles. It needs to counter the perturbation and arrive at the desired final position, while having a minimal energetic cost. To do so, we must define the cost function that characterizes the energetic cost of the movement, and find the optimal motor commands $u(t)$ that minimize it.
The cost function is the following:

$$J(u, x) = x^T(t)Qx(t) + u^T(t)Ru(t)$$

This leads us to the following optimization problem:

$$u(t) = argmin_u(\int_0^{t_f} x^T(t)Qx(t) + u^T(t)Ru(t)dt)$$

Where Q and R are positive definite matrices, used to weight the importance of energetic cost versus the error on the position. t_f is the final time of the trial. The solution can be found using a modified Kalman filter, which takes into account the multiplicative noise[18].

Let us now dicuss the properties of an LQG controller: It minimizes the expected cost of movement, making the trajectories straighter and smoother. It handles sensorimotor (Gaussian) noise efficiently [19]. On the other hand, it doesn't take non-Gaussian disturbances, nor model errors into account. Thus, it is less robust and more sensible to model errors. This is the main limitation of the LQG. As you can probably guess, this controller is similar to the predictive controller described by Yadav and Sainburg [2], [3]. It can be associated with the specialization of the dominant hemisphere, and shows good results when the movement is well known and with expected perturbations.

2.6 Robust controller (H_∞)

What would happen in case of non-Gaussian perturbation or errors in the model? In real life, our brain doesn't know the exact dynamics of all the objects we are in contact with. We can still use LQG, but since we partially violate the assumptions of the model, it is expected that it does not perform well. A complementary strategy would be to use a robust controller. The idea behind this controller is explained in detail in a book of Basar and Bernard in 1991 [20]. It uses a "mini-max" or "worst-case" strategy, often seen in game theory. The notation H_∞ comes from the infinite norm of the error, which is minimized by this controller. This strategy maximizes the minimal payoff that can be obtained in a game. In our context, it will be impacted as little as possible by unexpected, non-Gaussian perturbations. This also implies that the controller uses a model-free control design, less sensitive to model errors, more robust.

In our biomechanical model, larger feedback control gains were observed from the robust controller. Thus, in a reaching movement, it tends to have a higher speed towards the target and a stronger response to perturbations. This was shown in the results of Crevecoeur, Scott and Cuff in 2019 [5]. As we can expect, the robust controller showed better results in the case of unexpected disturbances.

Mathematically, it can be seen as a modified LQG, where we try to minimize the energetic cost function in the worst case scenario. The noise $\epsilon(x, \omega)$ here represents the unknown disturbance. We have that:

$$\epsilon(x, \omega) = \Delta Axdt + Cd\omega$$

Where dt and dw are the instantaneous differences of the time and the noise. The first term corresponds to the model error and the second term to the Gaussian process noise. The new cost function will be:

$$\tilde{J}(u, x, \epsilon) = J(u, x) - \gamma^2 \epsilon(x, \omega)^T \epsilon(x, \omega)$$

The parameter γ also needs to be optimized in order for the solution to exist and to correspond to the H_∞ solution. The full development is available in [5].

The LQG and robust controller are complementary, but not exclusive. Most situations require a trade-off between sensitivity to model errors and efficiency. For this purpose, it is possible to weight the contribution of both controllers, to find the adequate trade-off.

2.7 Control strategy and learning

In 2019, Cluff, Crevecoeur and Scott conducted experiments to understand the difference in control strategies used by different people. The subjects were divided in two groups, based on how well they adapted to perturbations during a single session of reaching movements. One group was the partial adapters and the other was the good learners.

Simulations showed that the strategy of the good adapters corresponded to an LQG controller. On the other hand, the partial learners used a more robust controller. A second experiment confirmed this. This time, the perturbations varied over a short period of time, making it difficult to adapt. It was shown that the group of the good learners adapted to this situation by using a more robust controller, closer to the control strategies of the partial adapters [6]. This shows the differences in ability to learn and in control gains between different people. It suggests that there could be a correlation between the control gains and the ability to learn. This hypothesis will be verified by doing an inter-subjects analysis of the results of our experiments.

Chapter 3

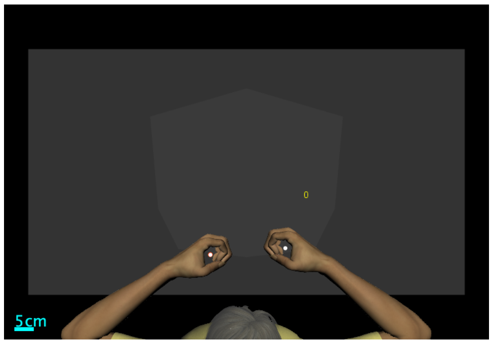
Experiments and methods

The first step of the research was to conduct the experiments and collect the data. Twelve young, healthy and right-handed volunteers (between 20 and 23 years old) were gathered for this. Similar researches often use 18 subjects. It is enough to get significant results from a statistic point of view, and makes it more convenient to compare results between different experiments. The goal was to have 18 participants as well, but the measures for the pandemic forced me to stop after 12 tests. This is still a good number and is sufficient to have significant results. Since all the subjects were right-handed, the differences are analyzed between the right and left arm. Generalizing them to dominant and non-dominant would require data from left-handed participants, which are not available here.

3.1 Set-up

The experiments took place at the Institute of NeuroScience of UCLouvain, Belgium. The instrument used is called KINARM, short for Kinesiological Instrument for Normal and Altered Reaching Movements (BKIN Technologies Ltd, Kingston, Canada). This machine contains two robots connected to mechanic handles. They applied forces on the hands of the subject during the trials. The KINARM is connected to a real-time computer, that measures the position of the handles and the forces applied on them at a frequency of 1kHz. It also computes the forces that the robots need to apply. In my experiments, the forces are dependent of the speed of the handles. These are calculated by the real-time computer using finite differences. The participants held the handles during the experiments, but they didn't see them directly. Instead, they saw 2 cursors on a screen, corresponding to the positions of the two handles.

(a) 3D - reprensentation of the KINARM (Source: [21])



(b) View of the subject during the experiments, the head and arms were added for illustration purposes only (Source: Adapted from Dexterit-E Explorer)

Figure 3.1: Set-up of the KINARM

Besides the positions and forces of each hand, it is also interesting to measure the muscular activity during the trials. This was done using EMG. In this case, the biggest perturbations were perpendicular to the reaching movement. Thus, the muscles that interest us are the Pectoralis Major (PM) and the Posterior Deltoid (PD). The position of the muscles is the following:

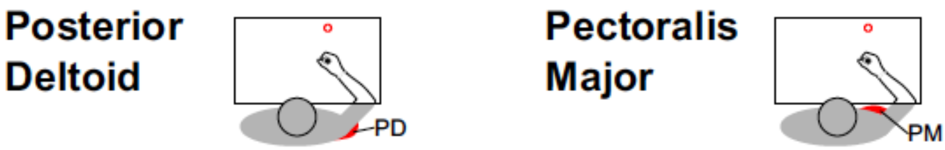


Figure 3.2: Position of the muscles (Source: [5])

The perturbations are mainly towards the outside. Thus, they require the use of the Pectoralis Major to compensate them. This muscle is also used for the reaching movement. On the other hand, the Posterior Deltoid is mainly used for stabilization. Both arms were working, so it required 4 EMG sensors. An additional sensor was placed on the malleolus of the subject. This part of the body should remain neutral during the trials and serves as a reference signal. The signals captured by the sensors are very low, just a few mV. Therefore, an amplifier of 10^4 was used.

3.2 Task

At the beginning of each trial, the participants see a red spot appear on the screen, this is their start target. They need to stabilize their cursor inside this target while a lateral force is applied. A few centimeters further, they can see an empty, red circle. This is their final target. When the empty circle becomes full, that's the go signal. At this moment, they have to reach towards the final target. They must arrive there between 600 and 800 ms after the go-signal, and then stabilize. By doing so, the speeds of the participants are comparable. The start target can be on the left side or on the right side. The participants should use the corresponding arm. They did 6 series of 70 trials each, half of these trials were with the right arm. This is quite a long experiment, but it is important to keep the participants focused. Otherwise, it will bias the data. For this purpose, there is a score target on the side of the screen. Every time a trial is succeeded, the score is incremented. The participants were motivated to do their best and try to beat the score of the previous series. They may think otherwise, but it is pure motivation, the score was not used for the analyses. Figure 3.2 shows a recap of the task:

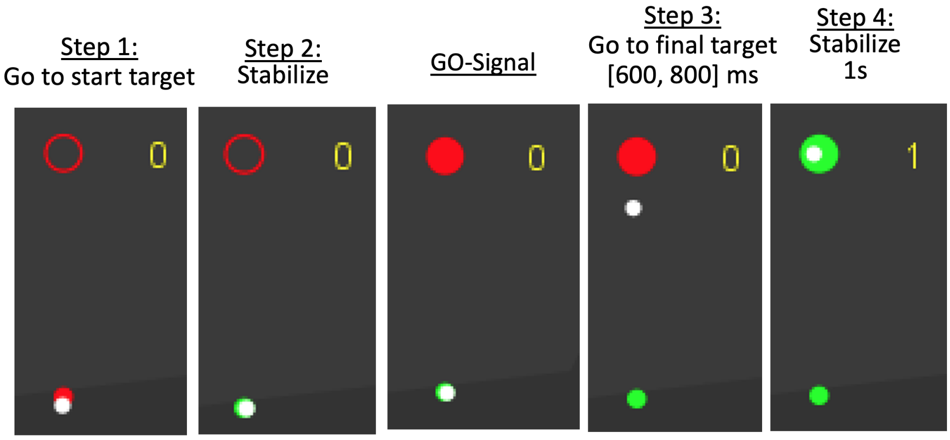


Figure 3.3: Task (Source: Adapted from Dexterit-E Explorer)

3.3 Trials

As it was mentioned in the state of the art, previous studies have investigated differences between left and right in a block design. One potential issue is in the case of asymmetric transfer: one limb would inherit more from adaptation in the other limb due to lateralization in the brain. To reduce this potential bias, we designed a randomized learning experiment. By doing so, both arms learn at the same time and the interlimb learning is neglected. The normal trials have a curl force field, proportional to the speed of the handle. They are symmetrical, such that both arms use the same muscles to counter the perturbation. The force field is clockwise for the right arm, and counter-clockwise for the left arm. Thus, the biggest component of the force is towards the outside. We have that:

$$\text{For the right arm: } \begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} 0 & A \\ -A & 0 \end{bmatrix} * \begin{bmatrix} v_x \\ v_y \end{bmatrix}$$

$$\text{For the left arm: } \begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} 0 & -A \\ A & 0 \end{bmatrix} * \begin{bmatrix} v_x \\ v_y \end{bmatrix}$$

With $A = 13Ns/m$.
There are 30 normal trials per arm per series. The other 10 are called "catch trials". These are trials with no perturbation (null field), designed to surprise the participants and see their anticipation to compensate the force fields. There are 5 of them per arm and per series. This makes of total of 70 trials per series. All of them were randomly distributed.

3.4 Data analysis

After conducting the experiments, the data was edited to make it usable. The response latency of a participant has an impact on the time the participant takes to reach the target. It also has an influence on the time at which muscles are activated and peak times of forces and velocities. For this purpose, all the analog data were scaled based on the instant when the cursor leaves the start target. The corresponding vectors start 500ms before this moment, and end 1000ms after. It also has the advantage that all trials will be analyzed for a period of the same duration.

The biggest part of the editing concerns the four EMG signals. Below a certain frequency, there can be noise related to the cable of the sensor. Physiologically, the useful EMG signal only goes up to a certain frequency. To remove these unwanted signals, a 6th-order Butterworth bandpass filter of 15 Hz-350 Hz was applied on the EMG signals. This was done following standard procedures of the literature like in [22],[23]. The obtained signals were still noisy, so they were smoothed them with a moving average of 50 ms, centered around each millisecond. This result is still sensitive to the set-up and to the anatomy of the participant. The electrodes will not be positioned at the exact same place on the muscle for all the participants. Neither will all the participants' anatomy be exactly the same. To correct this, a calibration was performed for each EMG signal. The participants were instructed to keep their cursor stable in the start target, while a constant lateral force was applied on the handle. The maximal amplitude of the EMG signal was measured for each participant and for each muscle during this calibration and was used to scale all the signals of the corresponding participant and muscles.

3.5 Statistics

Like often in research, statistics were used to analyze the results quantitatively. The tests and measures used in the next chapter are defined here.

3.5.1 Average and standard error

Throughout the description of the analyses, the terms "average" and "standard error" are used. It's important to note that the average corresponds to the arithmetic mean of the sample. The standard error (of the mean) measures how far the sample mean of the data is likely to be from the population mean [24]. It is computed as:

$$\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$$

Where:

- σ is the standard deviation of the sample
- n is the size of the sample, in most cases it will be on all the participants, thus $n = 12$

Most plots of data show the results of the left and right arm. They include the average curve $\pm$ the standard error. This gives an idea to the reader of how big the difference is between both arms.

3.5.2 Correlation

The correlation measures the linear relationship between 2 random variables. It is computed as:

$$Cor(X,Y) = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E(XY) - E(X)E(Y)}{\sigma_X \sigma_Y}$$

where:

- Cov is the covariance
- E is the expectation
- σ_X, σ_Y are the standard deviations of X and Y respectively

The correlation is always between -1 and 1. A positive correlation means that one variable tends to increase if the other increases. If it equal to 1, there is a perfect positive linear relationship between them. In this thesis, the correlation is used as a measure for learning and to measure the relationship between the ability to learn and control gains. On MATLAB, the correlations were computed using the function *corr*. The correlations were used as a measure for learning, and to describe the relationship between learning and control gains.

3.5.3 Student's t-test

The Student's t-test, is a hypothesis test in which the test statistics follow a Student's t-distribution [24]. In this type of test, we assume a hypothesis, called the null hypothesis (H_0), and check whether or not we can significantly reject it. The alternative hypothesis is H_1. In this thesis, the t-tests are used to compare samples from the left and right hand. We make the hypothesis that they have the same average, and check whether we can reject this hypothesis. All the t-tests performed are two-sided, which means we don't suggest which of the samples has the higher mean. Thus:

- H_0 : We assume that: $\mu_{left} = \mu_{right}$
- H_1 : The alternative hypothesis is that: $\mu_{left} \neq \mu_{right}$

To determine whether or not we can reject H_0, we compute the test statistics t. Using this, we can find the p-value. This value is then compared with a significance level α. The smaller α, the more significant we want our test to be. The most common value for the significance level is $\alpha = 0.05$. It is also what is used in the analyses of this thesis. If the p-value is smaller than α, the test is said to be significant, we can thus reject the null hypothesis. This makes the p-value interesting, because it gives us a good idea of how significant the test is. An other interesting value is the number of degrees of freedom, df. It depends on the type of t-test that is performed. In this case, all the t-tests were paired. This means that each pair of data comes from the same unit. It is the case here, because we compare the differences in left and right arms for the same participants, or the same trials, among others. The degrees of freedom are computed as $n - 1$, with n being the number of pairs in the data. These relevant values are provided for each t-test. The paired t-tests were computed on MATLAB with the function *ttest*.

3.5.4 Exponential learning curve

Learning curves in reaching movements with perturbations often have an exponential shape. The participants learn a lot in the beginning, making the curve very steep. As they perform more and more trials, they learn less, which makes the curve more and more flat. Therefore, it can be useful to fit an exponential function in the learning curves, in order to analyze its parameters. This will be done for both arms in order to compare them. The exponential function has the following parameters:

$$y = Ae^{(-x/\tau)} + B$$

Where:

- B is the value at the end of the curve, when it is flat
- $A + B$ is the value at the beginning of the curve, when it intersects with the y-ax
- τ is the time-constant. Conventionally, it represents how steep the curvature is when $A = 1$. If A increases, or τ decreases, the curve becomes steeper.

Knowing the parameters of the curves of the left and right arm doesn't allow us to make significant conclusions. For this purpose, we use a bootstrap method.

3.5.5 Bootstrap

The bootstrap method is a resampling method [25]. It is used to obtain information about the inference of the population from the sample. The idea is to randomly resample the data from the original samples. In this case we have 12 samples of the left and right arm. By using the bootstrap method, we randomly resample 12 subject numbers (with replacement) from the original 12 samples. Thus some are left out or appear multiple times randomly. Afterwards, an exponential function is fitted in the learning curves obtained with this new sample. This procedure was repeated 1000 times. It allows us to analyze the statistics of the parameters of the curves. It was used to determine which parameters where significantly different between both arms with t-tests.

Chapter 4

Results

Now that the models have been defined, we can analyze the results. They are compared with the assumptions of Yadav and Sainburg and show why the robust controller is promising. This chapted is divided in 4 sections. We first analyze the dynamics and general results from the normal trials. Secondly, we analyze the dynamics of the catch trials. Afterwards, the EMG signals of the normal trials are analyzed. Finally, the results of the inter-subjects analysis are presented.

4.1 Normal trials

4.1.1 Learning curves: Length of the path and Work

When the participants started the trials, it was very difficult for them. They had no idea how the perturbations would be, and how fast they needed to go. As they did 180 "normal" trials per hand, they had plenty of time to learn and to improve. The analyses start by looking at these improvements. It is what we call the "learning curves" of the experiments. This was done for both hands, such that we can analyze the differences between them. The participants should make the most improvement during the first few trials. Thus, we can expect the learning curves to be very steep during the first trials, then become more and more flat. At the end, when the participants have reached their maximal level, the curve is flat. An interesting approach to do the analysis is to fit an exponential function in the learning curve, as it was explained in 3.5.4.

Now the questions is: how can learning be measured ? Many criteria are used for that. Fortunately, most of them are very correlated and should give similar results. One common used criteria was chosen : the length of the path made by the hand during the trial. Intuitively, as the participants learned the perturbations, they anticipated them and their path was straighter, thus also shorter.
It is calculated as:

$$\text{Length of path} = \int_0^{t_f} \sqrt{v_x^2 + v_y^2} dt$$

Where:

- t_f is the length of the trial, it is 1.5s
- v_x, v_y is the velocity of the handle in X and Y respectively

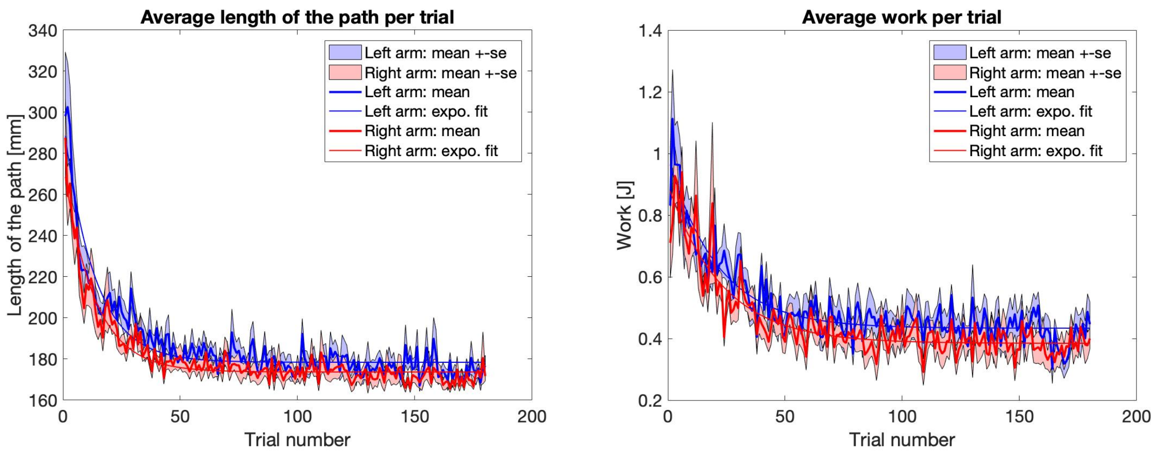
The second criteria is more creative and less used: it is a measure for the work applied on the hand of the subject. It is interesting to analyze how these criteria compare and what they can tell us about motor learning. Intuitively, we can expect them to be very correlated: if the handle is perturbed a lot by the robot, it will necessarily do a longer path. At each moment, the perturbations are perpendicular to the speed of the subject. Therefore, the net work is always zero. The modified work that interests us here is the sum of the absolute values of the components in X and Y:

$$\text{Work} = \int_0^{t_f} |F_x * v_x| + |F_y * v_y| dt$$

Where:

- F_x, F_y is the force commanded by the robot in X and Y respectively

My data were discrete measurements, so these integrals were approximated with sums. The learning curves were computed using only the normal trials, for each subject. Then, the curves were averaged on all the participants. Once in a while, a subject is distracted by something and misses a trial. These trials are outliers and shouldn't be taken into account in the statistics. Thus, every time the length of the path of a trial is below a certain threshold, it is not taken into account. The distance between the two targets is 15cm, the threshold used was 10cm. The following results were obtained:



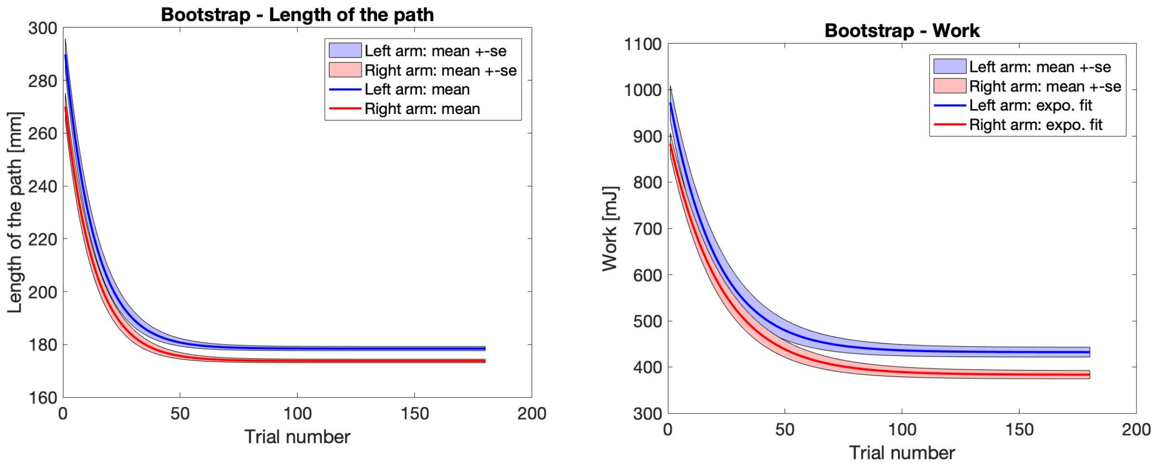
(a) Length of the path (Source: MATLAB)

(b) Work (Source: MATLAB)

Figure 4.1: Learning curves

It is interesting to see that for both criteria, the right arm starts and finishes better than the left arm. Nevertheless, the curvatures of both arms seem very similar for each criteria. The models and previous results all suggest that the right arm is more efficient. This implies having shorter and smoother paths, thus having a smaller length of path and work. Figures 4.1a and 4.1b agree with this. They suggest that the right arm is more specialized for efficiency. As mentioned earlier, we can expect the length of the path and the work to be very correlated. One will directly have a big influence on the other. The fact that we have similar results for both learning curves agrees with this.

Let us now have a look at the exponential functions that were fitted. It is interesting to analyze which parameters are significantly different for both arms. For this purpose, a bootstrap method was implemented. This allows us to analyze the statistics of the curves and to have significant results. The average curves and standard errors were plotted on Figure 4.2.



(a) Bootstrap: Length of the path (Source: MATLAB)

(b) Bootstrap: Work (Source: MATLAB)

Figure 4.2: Bootstrap of the learning curves

As we expected, the curves look very similar to the previous ones. It is interesting to see that the standard errors are quite small, especially for the length of the paths. So far, there seems to be significant differences between both arms. As mentioned earlier, the goal is to analyze the differences in parameters. Six paired t-tests were performed, one per parameter and per criteria. The null hypotheses were that the parameters of the blue and red curve are equal. The tests were two-sided with a significance leve $\alpha = 0.05$. The results are in the following table, with the corresponding values:

Length of path	t-value	df	p-value	H
A	28.10	999	$< 10^{-6}$	1
B	118.24	999	$< 10^{-6}$	1
τ	-1.37	999	0.171	0

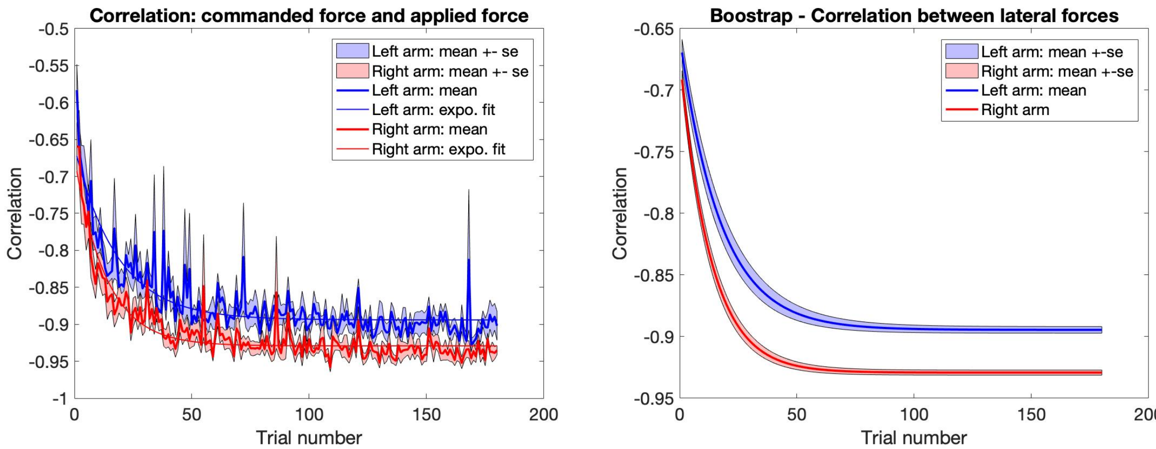
Work	t-value	df	p-value	H
A	20.93	999	$< 10^{-6}$	1
B	70.28	999	$< 10^{-6}$	1
τ	11.40	999	$< 10^{-6}$	1

We can not say anything about the parameters τ for the length of the path. In fact, for each criteria, the curvatures of both arms look quite similar. On the other hand, the parameters A and B are significantly different. Thus, the right arm starts and ends better than the left arm. It makes sense, because it is more efficient. It agrees with the previous observations and models. Further analyses will tell us more about this result.

4.1.2 Learning curves: Correlation

Since these criteria were very close and gave similar results, a third criteria was analyzed. It is the correlation between the lateral force commanded by the handle, and the lateral force applied by the subject. As the participants learn to anticipate the perturbations, they will know exactly which lateral force to apply, in order to keep their paths as straight as possible.

The two forces have different signs, so it will be a negative linear relationship. When one variable increases, the other one tends to decrease. For the first trials, the correlation should be small in absolute value, but negative. As the subjects learn, it will decrease and get closer to -1. It can obviously never reach -1. It would mean that the two forces are always the same is absolute values and that the path is completely straight. In theory, the correlation would also be -1 if one force was always proportional to the other, not necessarily by a factor -1. This doesn't make sense in this case, the subject would have no benefit in doing so. Furthermore, 1 in 6 trials is a catch trial that has no perturbation. These trials can have an influence on the learning of the participants, as they want to perform well for both types of trials. This is another reason why the correlation never gets to -1. Nevertheless, the influence of the catch trials is only on the anticipation and it is quite small. Thus, we can make the assumption that participants who have a correlation close to -1 are good learners. Here also, the bootstrap method was used to show the standard errors of the exponential fits and to analyze their parameters. The following results were obtained:



(a) Correlation of the commanded lateral force and the lateral force applied by the subject (Source: MATLAB)

(b) Bootstrap: Correlation of the commanded lateral force and the lateral force applied by the subject (Source: MATLAB)

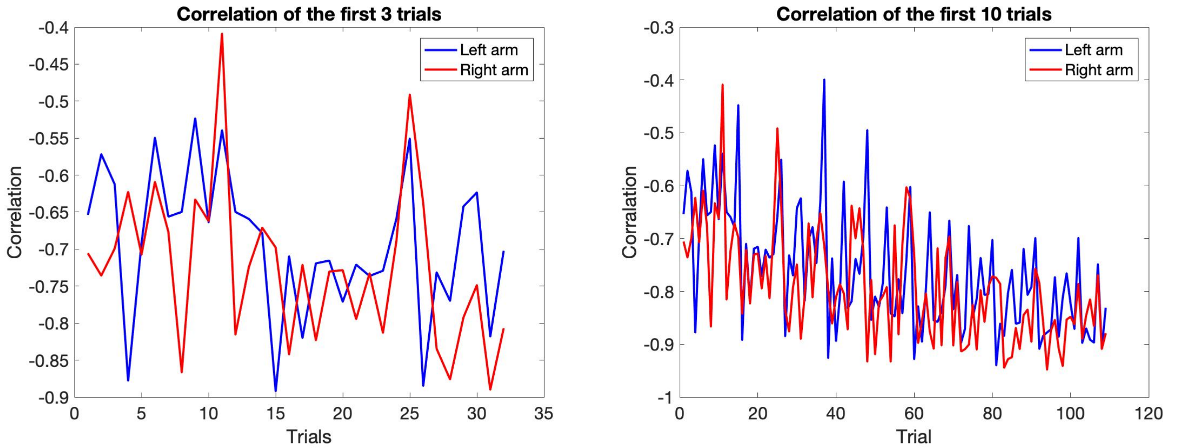
Figure 4.3: Correlation of the lateral forces for the first trials

This result is indeed different from the previous learning curves. This time the curvatures are quite different and the curves are much closer in the beginning than they were before. The same hypothesis t-tests were performed. They all showed that the parameters were significantly different with very small p-values.

Correlation	t-value	df	p	H
A	-11.18	999	$< 10^{-6}$	1
B	152.37	999	$< 10^{-6}$	1
τ	-16.10	999	$< 10^{-6}$	1

If we look at the curves of the bootstrap, after the first 50 trials, the difference between both arms is very clear. The standard errors are very small, and both curves have a relatively big distance between them. The reason why the right arm is better than the left arm in the long run matches with the ideas that it is more skillful and better to develop a new dynamic model [9]. The correlations reach around -0.9, which is very low and compares to other studies [26].

Nevertheless, it is not enough to say that the correlations are different at the beginning. To push this analysis even further, the correlations for the first few trials were computed. There didn't seem to be a difference. The problem here is that the variability of the first few trials is very high, which makes it almost impossible to get significant results. A solution for that is to take more than just the first 3 trials, and to take, for example, the first 10 trials. This is done for each participant, except for one, because it failed a few of its first trials. Thus we either look at 3 trials times 11 participants or 10 trials times 11 participants. While this is better to get significant results, learning starts to have an influence. Thus, there is a trade-off to be made between the variability and the influence of learning. The results are on Figure 4.4. The first 11 trials on the figure correspond to the first trial for the 11 subjects, and so on.



(a) Correlation of the commanded lateral force and the lateral force applied by the subject for the first 3 trials (Source: MATLAB)

(b) Correlation of the commanded lateral force and the lateral force applied by the subject for the first 10 trials (Source: MATLAB)

Figure 4.4: Correlation of the lateral forces

The results of the hypothesis testing are the following:

Correlation	t-value	df	p-value	H
First trial	1.38	10	0.20	0
3 first trials	1.57	31	0.13	0
10 first trials	3.29	109	0.0014	1

The t-test is significant if we take the first 10 trials into account. If we look at the figure, we can clearly see the effect of learning, as the curve begins to decrease. Thus, we can not reject the hypothesis that the correlations are the same at the beginning. This suggests that left-right differences at the beginning are more subtle than they seem on the learning curves.

4.1.3 Stability

The learning curves confirmed the previous observations that the right arm is more efficient and skillful, better to develop a new dynamic model. Now, it would be interesting to check if we can also observe specializations of the left arm. Analyzing the precision wouldn't make a lot of sense, because the participants were only instructed to stabilize in the final target, which was quite big. Nevertheless, we can analyze their ability to stabilize at the end of the movement. To do so, the length of the path was computed during the last moments of the trials (after 750ms). This was called the "stability error" of the trial. We obtained the following results:

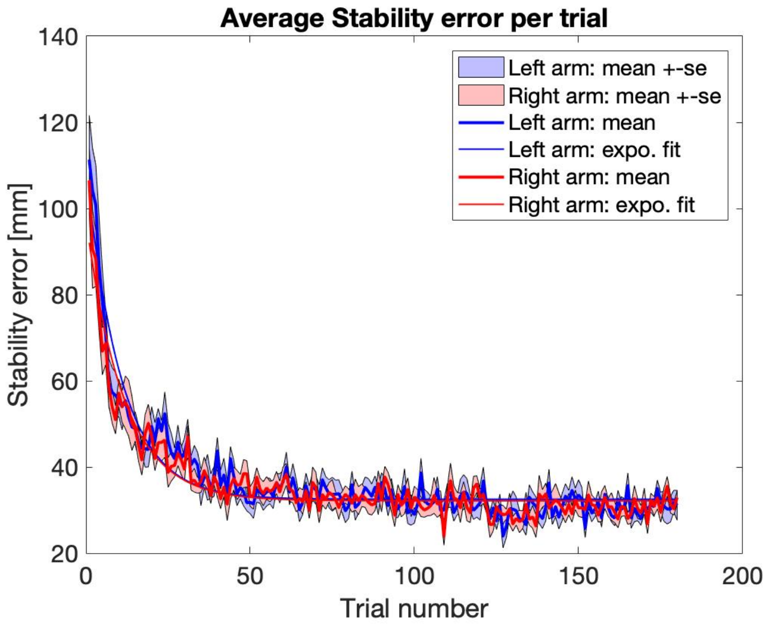


Figure 4.5: Stability error= length of the path during the last miliseconds of the trials (Source: MATLAB)

We can still see the characteristic shape of the exponential curve. Apart from that, the results are very different than what we had before! This time, both curves are almost exactly the same. They start and end at the same place, and their curvature is very similar. Thus, the left arm has more work applied on him, does a longer path to reach the target, but it has the same ability to stabilize around an equilibrium position. This suggests that the left arm is better in stabilization. It confirms the specialization of the left arm that had been observed in previous research [10]. It agrees with the hybrid control scheme of Yadav and Sainburg. This is still quite general. It doesn't tell us if it is due to an increase in stiffness of the arm or something else. At this stage, we don't really know where this difference between left and right precisely lies. Checking the kinematics to see if or what is the difference would give us more information about this.

4.1.4 First trajectories

To go deeper into the kinematics of the trials, let us have a look at the first trajectories. We know from previous research that the right arm is better to develop a new dynamic model and is more skillful. Thus, it makes sense that the right arm will be better in the long run. Furthermore, we explained earlier that the right arm was more efficient. From what we have observed so far, it seems that it can also have a (small) influence for the first trials. Let us now analyze in details where this difference lies in the first trials, before any learning. To do so, the trajectories of the first 3 trials per hand are plotted for all the participants. The following results were obtained:

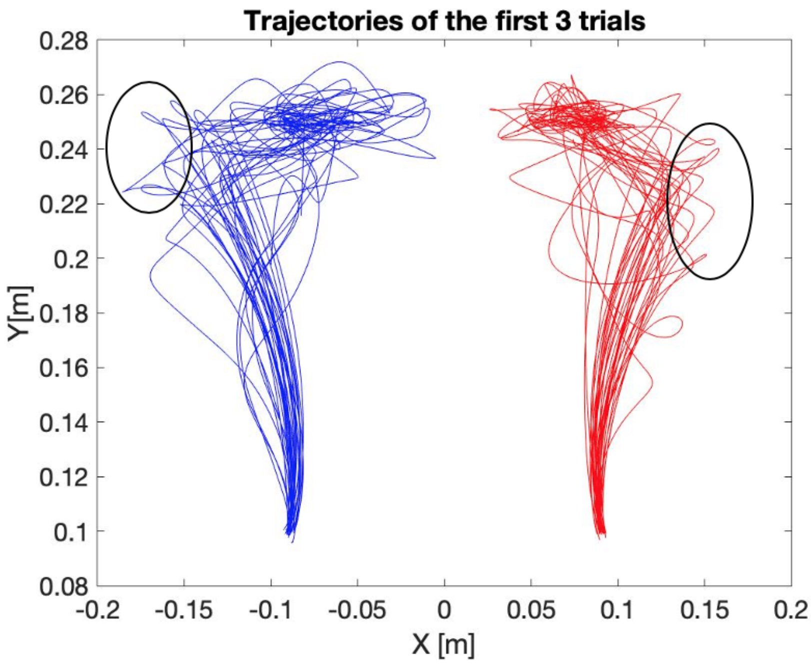


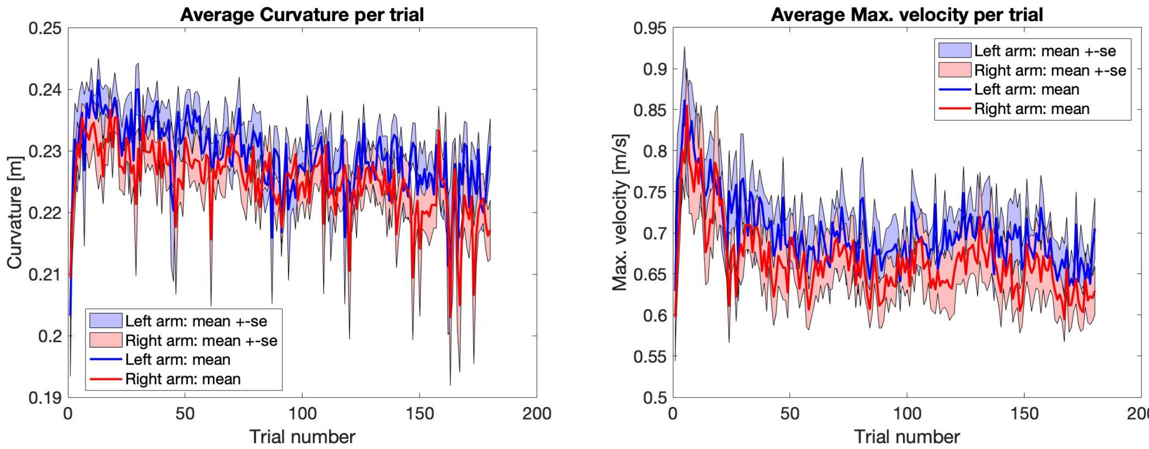
Figure 4.6: First 3 trajectories of all the participants (Source: MATLAB)

The first thing that we see is that there is a lot of variations. This makes sense, because the participants are very unfamiliar with the trials and with the experiments. It was also observed for the correlation between lateral forces. The problem with this, is that it makes it almost impossible to get any significant result from a statistic point of view.

Secondly, we can see that the left arm seems to turn later in the trajectory. If we look at the Y coordinate of the turning point, for the left arm it's mostly between 22 and 26 cm, while for the right arm it is 20 and 25 cm. Does this mean that the left arm has a slightly longer response latency than the left arm ? This was checked, it doesn't. Thus, the left arm turns later in the trajectory, but at the same moment in time. There can be only one explanation for this: the left arm goes faster ! It is important to remember here that the force applied on the hand is proportional to its speed. Thus, a higher speed will imply a bigger deviation. If the left arm is more deviated and turns later in the trajectory, it is natural that it will make a longer path and have more work applied on him. This indicates that the speed has a big influence on the results. At this point, two questions are raised: "Is it just an observation valid for the first trials ?", and "Why does the left arm go faster ?".

4.1.5 Curvature

Let me start with the first one. This can easily be checked. I plotted for each trial, the average "curvature". This can be measured in different ways, which should give similar results. It was decided to analyze the Y-coordinate of the turning point, same as what we observed earlier. The results are on Figure 4.7a. The maximal speed for each trial are plotted on Figure 4.7b. This way, we can verify that the maximal speed is indeed higher for the left arm.



(a) Average curvature per trial, computed as the Y position of the turning point (Source: MATLAB)

(b) Average maximal velocity per trial (Source: MATLAB)

Figure 4.7: Curvature and velocity

The results are what we expected. The curvature is indeed always bigger for the left arm, same for the maximal speed. Another observation is that the curvature and the maximum velocity tend to decrease. This makes quite a lot of sense, a smaller velocity implies a smaller curvature. Since the subject needs to arrive in a certain timing in the final target, if its curvature decreases, it will also decrease its speed. This decrease is also coherent with the learning curves of work and length of the path. As the speed decreases, the perturbations decrease, thus the length of the path and the work will also decrease.

Surprisingly, we can see that the very first trial has a very low speed and curvature. By looking back at Figure 4.6, with the trajectories of the 3 first trials, we can understand why. Since the participants have no idea of how fast they need to go, sometimes they go very slowly. Then, they realise that they reached the target too late, and increase their speed for the next trials. Since we are computing averages, a few trials with a very low speed will have a big impact on the average. One way to solve this would be to consider them as outliers. Since there are a few of them, and they were only observed during the first trial, it seemed more logical to keep them.

To verify whether the difference in maximal velocities and curvatures are significantly different for both arms, let us use the statistics. Unfortunately, the curves don't have an exponential shape here, so we can not do the same procedure as with the learning curves. It is always possible to run a t-test on all trials for all the participants. This is not the best idea here, because of the decrease in both curves. Therefore, it was chosen to run 2 hypothesis t-tests per criteria, one on all the trials of the first series and a second one on all the trials of the last series. The maximal speeds are significantly different with $t(358) = 4.25, p = 2.73 * 10^{-5}$ for the first series and $t(358) = 6.15, p < 10^{-6}$ for the last series. The same tests were conducted for the curvature. We obtained $t(358) = 5.06, p < 10^{-6}$ for the first series and $t(358) = 5.09, p < 10^{-6}$ for the last series. All the tests were significantly different. It was verified that this result is also valid for the other series. Thus, this seems to confirm that the difference in maximal speeds are responsible for most of the differences between left and right arm that we have observed so far. It would be the case if the velocity profiles of both arms are very similar, and if the maximal speeds occur at the same time. We will show later that this hypothesis is confirmed.

Until now, everything makes sense, and agrees with the previous observations about the dominant and non-dominant arm. We can also conclude that the learning curves of the work and length of the path can be explained by the fact that the speed of the left arm is higher. On the other

hand, nothing about the models can be concluded so far. As we will see later, finding the reason behind the higher speed of the left arm explained a lot of things.
The final trajectories look like this:

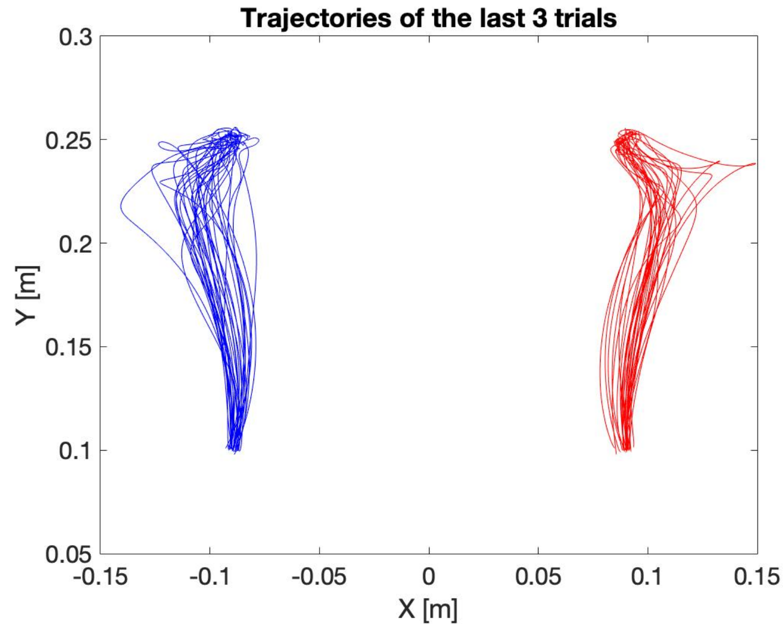
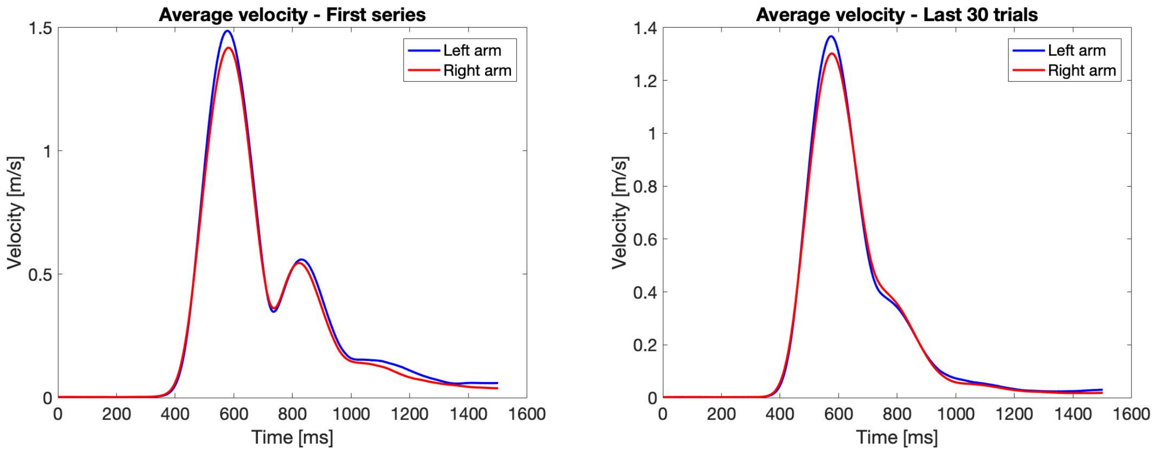


Figure 4.8: Last 3 trajectories of all the participants (Source: MATLAB)

As we can see, the trajectories are much straighter. The turning point takes place earlier in the trajectory. We can also see that the variability between the different curves is much smaller. The differences between both arms look much more subtle than they did when looking at the learning curves.

4.1.6 Velocity profiles

Let us have a look at the velocity profiles of both arms during the first and last series. As a reminder, a series corresponds to 30 trials per arm. We already established that the maximal speed had a direct influence on the curvature. This conclusion assumes that the velocity profiles of both arms are very similar, with the main difference being the maximal speed. The moment at which the maximal speed is reached can also have an influence. This analysis shows another perspective of the influence of the maximal speed. It allows as to confirm the assumptions made before. These are the results that were obtained:



(a) Average velocity profiles of the first 30 trials (Source: MATLAB)
(b) Average velocity profiles of the last 30 trials (Source: MATLAB)

Figure 4.9: Velocity profiles

It was chosen not to plot the standard error on the mean here. Since we have 12 subjects, and we take 30 trials into account, the standard error of the mean is very small and does not show any useful information. These figures show how close the velocity profiles of both arms are. We can see that the maximal velocities take place at the exact same time for both arms. The difference in maximal velocities is quite subtle, but it is the main difference between both arms. Their difference was shown to be significantly different for both series in 4.1.6. This validates the hypothesis that the maximal speed is the main parameter responsible for the difference in curvatures. If we look at the difference between the first and last series, we can see that the maximal velocity decreased for both arms.

After around 800ms, we can see a "bump" in the velocity profiles of the first series, which is not present in the velocity profiles of the last series. This corresponds to the turning point in the trajectory. For the first trials, we can really see a clean angle in the trajectory: the participants decelerate, than accelerate again in the correct direction. This bump shows quite well the learning of the participants. As they learn it becomes more and more flat. The participants learn how to react to the perturbation and have a much smoother deceleration. The bump becomes almost invisible. This is the natural tendency of healthy adults to recover a straight path with bell-shape velocity profile, as shown by Shadmehr and Mussa-Ivaldi in [12].

On this figures, we can also see that the stabilization is almost equal for both arms, even though the left arm had a bigger maximal speed.

4.1.7 The origin of the speed difference

We have established that the speed had a big influence on the results. Nevertheless, we haven't yet explained where the differences in maximal velocity come from. To do so, let us first have a look at the current model that describes motor lateralization: the hybrid control scheme of Yadav and Sainburg. Their experiments, which lead to the hybrid control scheme, were different than ours, and didn't involve force fields. They also didn't observe any difference in maximal velocity between both hands. On the other hand, they described a difference in curvature. The path of the left hand is less straight and has a bigger curvature. This could imply that we were maybe looking at the problem the wrong way: We know that both hands need to arrive in the final target at the same time, but the left hand has a bigger curvature, thus a longer path. To do so, the left hand would have to go faster to reach the final target at the same time as the right hand. Thus, maybe it is the longer path of the left arm that implied its higher speed ? And not the other way around ?

This would make sense in the trials of Yadav and Sainburg which lead to the development of the hybrid control scheme, because they didn't involve force fields [2], [3]. It wouldn't make sense here, because the difference in curvature was also observed for the first trials, before any learning. Both arms start by going straight, and are then deviated by the perturbations. Since the left arm goes faster, it is more deviated. The nature of the perturbations here shows that it is the higher velocity that implies the bigger curvature and not the other way around. There is another reason why the other explanation doesn't make sense. The hybrid control scheme assumes that both arms start with the same controller (predictive) and end with the same controller (impedance). If this is the case, both arms would start with the same acceleration and have the same maximal velocity. It is not the case here, so we can say that both arms use different controllers, even at the beginning. As we discussed in the state of the art, there are some potential flaws in the hybrid control scheme. This is a new one, the first one that comes from our experiments.

At this point, we can see that many results can be explained by the difference in maximal speed between both arms. The hybrid control scheme can not give a reasonable explanation to this higher speed. Thus, it was needed to go through the literature to find a similar result with an explanation. There are previous research with curl fields, which also observed the decrease in maximal speed and the effect it had on the learning curves. This was presented in an article of 2019 by Crevecoeur, Scott and Cluff [5]. It shows the differences in behaviour between an LQG and a robust controller and how they match with strategies of the brain for expected and unexpected perturbations. As explained in the state of the art, one of the main characteristic of the robust controller here is that the control gains are higher. One consequence of this was observed in [5]: the speed of the hand towards the target was higher for the robust controller. This explains why the forces and velocity profiles of the right arm are smoother. The differences in learning curves are coherent with this discovery.

It was suggested in the state of the art that the increase in stiffness and viscosity of the arm was probably smaller than expected by the hybrid control scheme. It wouldn't explain the better ability to stabilize. The robust controller explains this by an increase in control gains, which would increase the neural feedback or reflexes.

So far, the robust controller gives the best explanation for motor lateralization. We observed larger speed that are not explained in the hybrid control scheme. In contrast, higher speed is expected if the left arm is more "robust". This means larger perturbation magnitude, but behaviourally, the stabilisation was comparable. This implies more "involved control", which is consistent with the larger control gains of the robust controller.

4.1.8 Learning

What does this tell us about learning ? As explained in the state of the art, the LQG and robust controller are complementary, but not exclusive. Most situations require a trade-off between sensitivity to model errors and efficiency. This can be obtained by weighting the contribution of each controller.

In this case, the dynamic model is most uncertain and unexpected at the very beginning. Thus, this is the moment when the contribution of the robust controller is very high. The control gains are at the highest, the speed towards the final target as well. The robust controller is the specialization of the left arm, thus the left arm have the highest initial speed. One may wonder, since the robust controller is built to counter unexpected perturbations or model errors, and it is the specialization of the left arm: why are the results of the left arm worse during the first trials? As we explained, for most general cases, the left arm should indeed give better results. This is not the case here, because the maximal speed has a huge influence on the performance. For this reason, the results of higher control gains are worse than expected in this case.

As the subjects learn, their knowledge of the dynamic model gets better. They are tempted to decrease their speed. This makes the movements more energy efficient, and has an extra advantage in our case because it decreases the amplitude of the perturbations. In the final trials, the participants have had time to fully learn the perturbations. At this point, the control gains are at the lowest, the contribution of the LQG controller is at its highest. This was observed in the learning curves of the work and the length of the path, they are minimal. The LQG controller is the specialization of the right arm, thus it performs better in the long run.

4.2 Catch trials

So far, we have concluded that the robust controller was probably a good candidate to represent the specializations of the left arm. It is complementary to the LQG controller, and can explain most of the results of the normal trials. In this section, we will analyze the catch trials. As a reminder, they were "surprise" trials, without perturbations, which occured randomly once every 6 trials. The subjects didn't know when the catch trials would take place, so it surprised them. It shows us the anticipation of the subjects.

4.2.1 Deviation

The part of the catch trials that interests us here is the beginning of the trial. The participants anticipate the lateral perturbation and push towards the inside. Their trajectories are the opposite of the trajectories during the normal trials. The deviation is towards the inside. Analyzing the work applied on the subjects makes no sense here, because the handles don't apply forces. Thus, the work will always be zero. On the other hand, the length of the path could be an interesting measure. It would give us a very good idea of how far the subjects deviated because of the anticipation. Nevertheless, the response latency of the subject after realizing it is a catch trial would have a big influence on the length of the path as well. This part of the trial is not really interesting for us here. For this reason, we will look at the lateral deviation instead. It can be computed in the following way:

$$\text{Deviation of the right arm} = x_{start,right} - min(x(t))$$

$$\text{Deviation of the left arm} = max(x(t)) - x_{start,left}$$

Where:

- $x_{start,right}$ is the X coordinate of the starting and final target on the right side
- $x_{start,left}$ is the X coordinate of the starting and final target on the left side
- $x(t)$ is the lateral position of the arm

Once again, this was computed for each trial and averaged on all the subjects. These are the results I obtained:

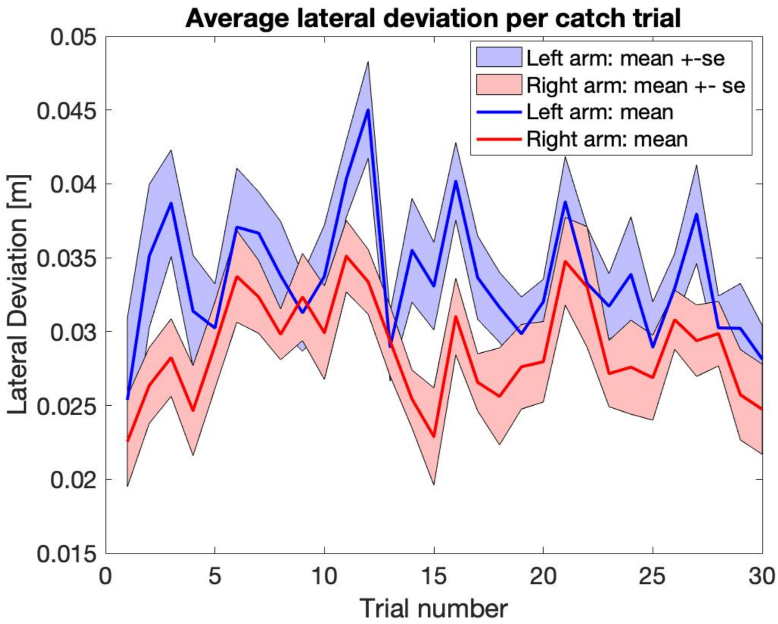


Figure 4.10: Average lateral deviation during the catch trials (Source: MATLAB)

We can see that the left arm is more deviated than the right arm. This may seem to contradict the concept of the robust controller. It is supposed to give the best result in case of unexpected perturbations. This is clearly the case with the catch trials. The fact that there are no perturbations is equivalent here to unexpected perturbations. The reason why the left arm is more deviated, is because it is used to having bigger perturbations than the right arm. Thus, it anticipates with a bigger lateral force, and is more deviated during the catch trials. This will be verified later by analyzing the forces.

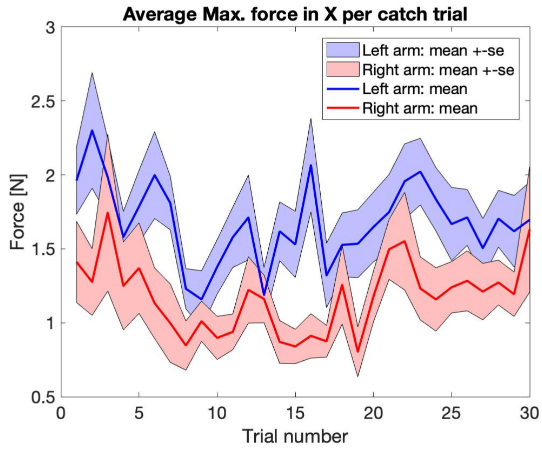
Another observation concerns the general trend of both curves. It wasn't very obvious what type of trend to expect. On the one hand, the speed tends to decrease, which means that the lateral perturbation also decreases. Thus, this would lead to a decrease in the deviation for the catch trials. On the other hand, the more the subjects learn the perturbations, the more they will anticipate them. Thus, they would tend to be more and more deviated during the catch trials. As we can see, the trend remains at the same level.

Finally, we can see that the variability of the data here is huge. The curve remains flat, but it is very noisy. The explanation for that is that the variability tends to decrease as the subject learns. This was observed in the trajectories of the normal trials. In this case, each subject only did 30 trials. This is 5 times less than for the normal trials. Thus, they will be less adapted to the catch trials. The goal is for the subjects to be surprised. The variations are probably bigger because of this.

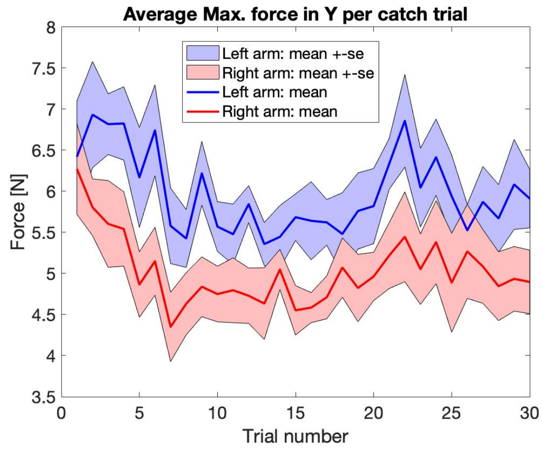
At this stage, we can not really say anything about the evolution of the variances, nor about the differences between the left and right arm. A more thorough analysis of this is presented later.

4.2.2 Forces

During the analysis of the deviations, it was explained that the bigger deviations of the left arm could be explained by the fact that it was used to counter bigger perturbations. We know that the perturbations are indeed bigger for the left arm during the normal trials. Let's now see if we can also verify that the forces in X and Y are also bigger for the left arm during the catch trials. To do so, the maximal forces in X and Y during the catch trials were plotted for both arms. These results were obtained:



(a) Average maximum lateral force (in absolute value) during the catch trials. (Source: MATLAB)



(b) Average maximum forward force during the catch trials. (Source: MATLAB)

Figure 4.11: Forces during the catch trials

It's important to note that the maximal forces in X that were measured here are not the maximal forces of the whole trials. They are the ones of the anticipation: at the beginning of the movement, when the subjects try to compensate the perturbations. When the subjects realise that it is a catch trial and are deviated, they push towards the final target with a much bigger lateral force than the one from the anticipation. This force wouldn't give any useful information to validate the controllers, so it is not analyzed here. On the other hand, the force in Y that is plotted here is the maximal forward force of the whole trial. Since the turning point is quite late in the trajectory, the force in Y after the turning point is smaller.

The differences between the left and the right arm are quite clear on these figures. The blue curve is always above the red curve. We can not say much about a general trend in the curves. The curves seem to decrease during the first 15 trials. This is coherent with the decrease of the maximal velocity, same as what we had observed earlier.

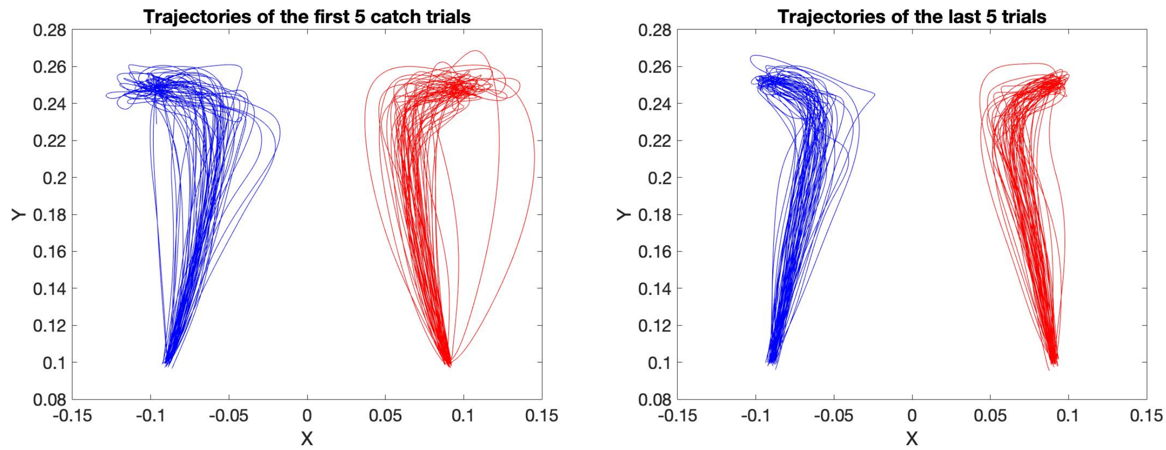
The differences between the left and right arm for the deviation, maximal force in X and maximal force in Y were all verified with hypothesis t-tests. The hypothesis t-tests are two-sided with a significance level of 0.05. The null hypothesis is that the parameters are equal for left and right. The following results were obtained:

Catch trials	t-value	tf	p	H
Lateral deviation	6.84	354	$< 10^{-6}$	1
Force in X	43.78	354	$< 10^{-6}$	1
Force in Y	11.37	354	$< 10^{-6}$	1

The fact that the forces are bigger for the left arm validates its specialization for the robust controller. Its control gains are higher. As we can see, all the tests were significant with very low p-values. So far, the analysis of the catch trials confirms the strong influence of the maximal speed difference on the results.

4.2.3 Trajectories

To further understand the differences between the left and the right arm, let's have a look at their trajectories. The curves of the maximal forces and lateral deviation didn't give a lot of information about the evolution throughout the trials. There weren't many trends in the curves. To analyze this, the trajectories of the first and last series were plotted. As we will see, this shows the evolution more clearly. The results are the following:



(a) Trajectories of the first 5 catch trials (Source: MATLAB)

(b) Trajectories of the last 5 catch trials (Source: MATLAB)

Figure 4.12: Forces during the catch trials

The difference between the first and last trials is quite clear here. The variance becomes smaller and smaller. This was also observed for the normal trials. For the first trials, we can see that a few of them haven't learned the normal perturbations at all and are almost fully straight. Others have perhaps only encountered normal trials so far so they have a much bigger deviation. As we explained before, subjects need to find a trade-off between performing correctly for the normal trials and for the catch trials. We can assume that the catch trials have a very small effect on learning, but this is not the case for the first few trials. This trade-off will be completely influenced by the number of catch trials and normal trials it has experienced before. Think for example of a subject who would start with a catch trial. It would have no reason to deviate its trajectory. On the other hand, a subject who would start with 2 or 3 normal trials on the same side, followed by a catch trial on that side, can be expected to have a very big deviation. Thus, the distribution of the first few trials is going to have a big influence here. Thus, in the beginning, there can be a lot of variations in this trade-off. The variance of the trajectories will be very high. As the subjects do more and more trials, the trade-off becomes more clear and the variance decreases.

As we have seen before, the average deviation is quite similar. We can see on the figure that the lateral deviation is a good way to characterize a trial. On the other hand, averaging them gives the idea that there is no evolution throughout the trials. This figure shows that this is wrong. Looking at the averages only is not enough: the difference here lies in the variance.

While it is very clear that there is a difference in variance between the first and the last trials, it's harder to see if there is a difference between the left and the right arm. If we look at the first 5 trials, there seem to be more "straight paths" and more paths that are very deviated. This could imply a bigger deviation for the left arm. On the other hand, this can not be seen on the trajectories of the last 5 trials.

4.2.4 Variance

The previous result is quite interesting, but we can not be sure of it by only looking at the trajectories of the catch trials. To verify this assumption, the variance of the lateral deviation was plotted for each trial. This analysis will be purely qualitative. The results are on Figure 18:

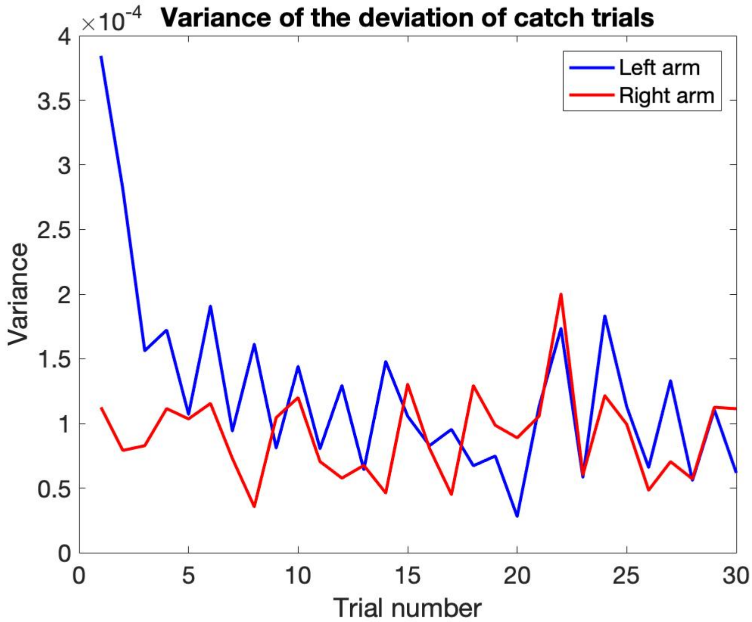


Figure 4.13: Variance of the lateral deviation during the catch trials (Source: MATLAB)

We can clearly see that the variance is higher for the left arm during the first half of the trials. An explanation for this could come from the specialization of the right arm. It is more predictive, and better to develop a new dynamic model. This can give him an advantage for the first trials. This is only a hypothesis and should be taken carefully. Still, it is interesting to see that it matches with the results of previous research.

As we explained earlier, the types of trials which a subject first encounters can have a big influence on how he will react to the first catch trials. Since the distribution of the trials is random, there can be differences between the left and right arm. The distributions of the trials of both arms were checked, to see whether we could observe a difference. There didn't seem to be any significant difference.

With this approach, we looked at the variance between all the subjects, for each trial. To look at the variance from another perspective, the variance is analyzed within each subject. This was done for the first 10 trials, for each subject and each hand. Afterwards, the same analysis was done for the last 10 trials. 9 of out of 12 subjects had a higher variance with the left arm for the first 10 trials. For the last 10 trials, 10 out of 12 had a higher variance for the left arm, though the average difference in variance between both arms was smaller. This is only a qualitative analysis, but it confirms that the left arm has a higher variance than the right arm. The analysis also confirmed that there was a bigger variance for the first 10 trials for both arms (which is not clear on Figure 4.13).

In general, we can conclude that the catch trials validated the strong influence of the difference of maximal speed on the results.

4.3 EMG

Finally, let us have a look at the EMG signals that were measured during the trials. They give us useful information about the activity of the muscles. The muscles that were analyze here are the Pectoralis Major and the Posterior Deltoid. The Pectoralis Major was used for the reaching movement and for countering the perturbation (pushing towards the inside). On the other hand, the Posterior Deltoid was used to push towards the outside, mostly to stabilize at the end of the movement. Both muscles are antagonist, which means they are used to perform opposite movements. Thus, they usually work one at a time. In some cases, both muscles can also co-contract. This doesn't perform any useful movement, but costs metabolic energy. We believe the purpose of this is to increase the stiffness of the shoulder. This helps for the stabilization. The impedance controller used by Yadav and Sainburg is based on co-contraction. The robust controller also suggests the use of co-contraction, as it was observed with unexpected perturbations in [5]. The main difference here is that Yadav and Sainburg only consider the co-contraction to increase the stiffness of the shoulder and stabilize. On the other hand, the robust controller also considers an increase in neural feedback gains to improve the stabilization. Therefore, checking for systematic co-contraction can give us useful information about the type of control strategy. As a reminder, Yadav and Sainburg didn't look at the EMG when suggesting impedance control.

EMG figures are originally noisy and have large variances. They should be analyzed carefully. My goal was to plot the EMG signals in a way to have general and interpretable figures. For this purpose, the EMG signals were smoothed with a moving average of 50ms. This shows rather clean curves and peaks that are easier to interpret. Also, to minimize the variations and make the plots as general as possible, they were averaged on all the participants, for a large number of trials. This way, the results are both general and convenient to interpret. The EMG signals plotted here have no unit, because they were scaled with calibration trials.

EMG signals can be of poor quality, which is hard to see if we average them on all the participants. Therefore, each EMG signal was checked individually before doing the analysis. The EMG signals were removed for 2 of the 12 subjects. One of them had made the EMG sensor fall off during a trial. The other one had a lot of hair on his body, creating a space between the sensors and his skin. We start the analysis by looking at the Pectoralis Major, and than the Posterior Deltoid. The EMG signals will only be analyzed for the normal trials. This makes sense, since the muscles that interest us are for countering the perturbations.

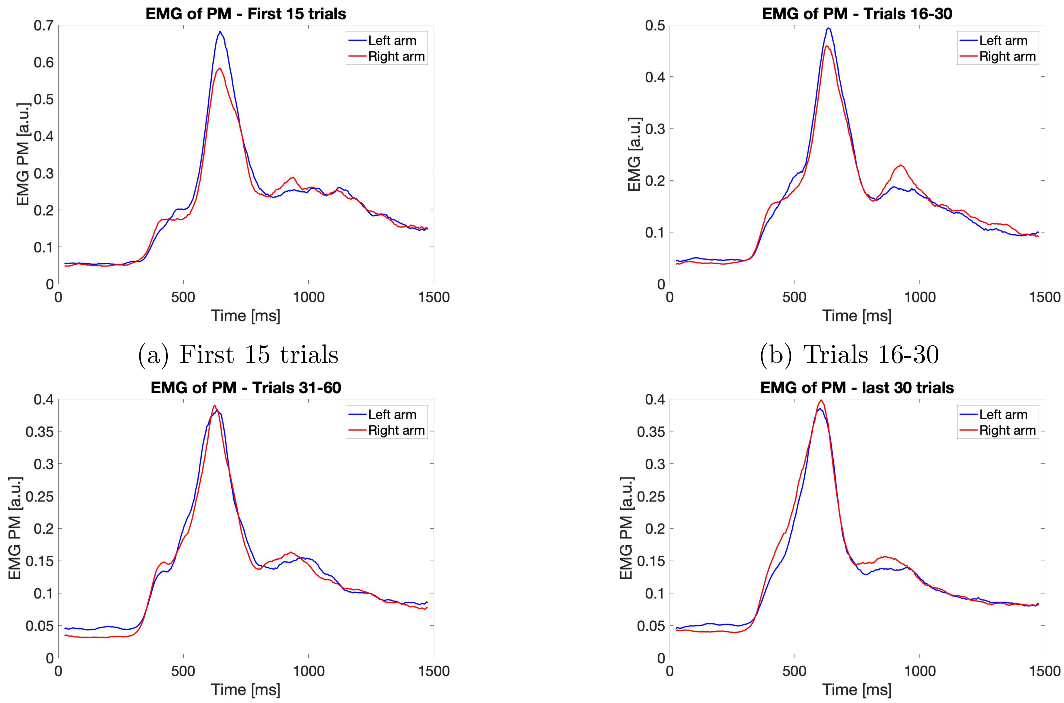
It is quite tricky to analyze EMG signals of different arms. Electrode placement is inherently uncertain and it is not clear that a given signal would result in the same measured voltage given that electrode and anatomical configuration is not exactly the same. Moreover, should there be differences between left and right, it is also possible that the calibration with respect to a reference level corresponds to different amounts of activation, hence a direct comparison across muscles cannot be interpreted. A paper from Sainburg and Kalakanis in 2000 [7] showed that during reaching movements, the contribution of the right shoulder was bigger than the contribution of the left shoulder. On the other hand, the left elbow was more used than the right elbow. This indicates an asymmetry between both arms. Furthermore, we will only have a look at the Pectoralis Major and Posterior Deltoid here. These aren't the only muscles who play a role in this experiment. Therefore, the following analysis should be taken very carefully, especially when comparing different arms.

The general differences between left and right arm were very small. For this reason, the analysis is purely qualitative. It is focused on the evolution of the EMG throughout the trial, and compared with different trials. We start by looking at the results of each muscle individually.

Afterwards, we check whether we can observe co-contraction. Finally, we combine the results to discuss what it tells us about the controllers.

4.3.1 Pectoralis Major

As we explained earlier, the EMG were averaged signals over the subjects and over a few trials. Figure 4.14a shows the signals of the PM for the first 15 trials, 4.14b shows the signals of the PM for the trials 16-30. These are the two halves of the first series. It was decided to split the first series in two figures, because this is the series where the most learning takes place. Figure 4.14c shows the PM signals of the trials 31-60, which correspond to the second series. After the second series, the learning is much smaller. Thus, we only showed the results of the 6th and last series, which are on Figure 4.14d.



(a) First 15 trials

(b) Trials 16-30

(c) Trials 31-60

(d) Last 30 trials

Figure 4.14: EMG signals of the Pectoralis Major (Source: MATLAB)

All the EMG signals of the PM have a peak at about 600-650ms. In fact, all the subjects had their peak activity at around the same time. The reason for that is that all the analog vectors were scaled based on the moment when the subject leaves the target. Otherwise, the response latency would have an influence. It is important to remember here that the subjects leave the target at 500ms. Thus, the biggest peak does not correspond to that. It is the time when the subjects makes the most effort to counter the lateral deviation. As we can see, the amplitude of this peak decreases over time. Between the two halves of the first series, the amplitude goes from 0.7 to 0.5. This is quite a big decrease. After that, the amplitude is 0.4 for the second series, and remains constant until the end. This shows that the subjects learn the perturbation, they can counter it with smaller muscular activity. This is coherent with the decrease in maximal speed. If the speed is lower, the perturbation is lower, thus the muscular activity to counter it is also lower. As we will see, anticipation also plays a role.

Another thing we can analyze on this peak is the difference between the left and right arm. The left arm seems to have a higher peak activity of the PM during the first trial. This difference decreases over time, and by the second series, it looks very close. Since the left arm has to counter bigger perturbations, it would makes sense that it has a higher muscular activity. To push this analysis further, the average peak of the PM for all the trials is plotted on Figure 4.15. From this perspective, we can see that the differences between the left and right arm are very subtle, especially after the first series.

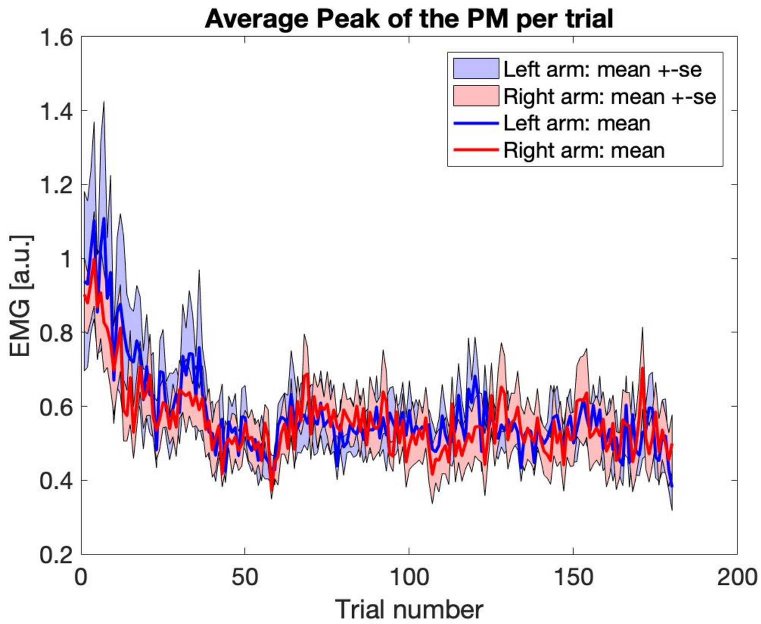


Figure 4.15: Evolution of the average peak of the PM for all the trials (Source: MATLAB)

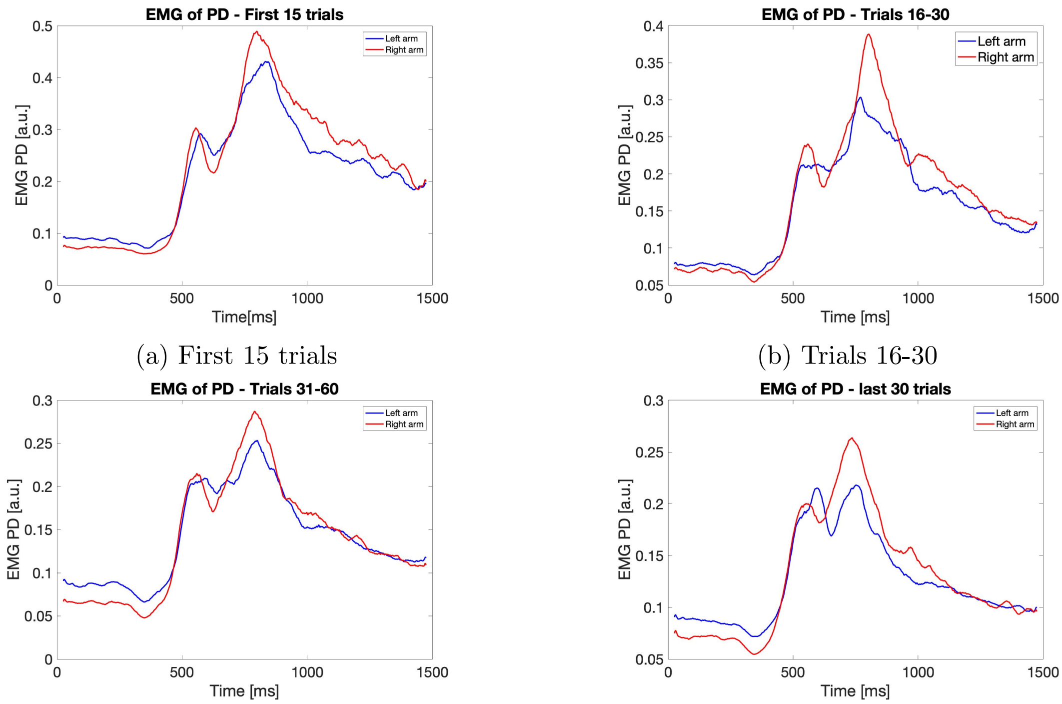
It is interesting to see that we still have an exponential learning curve, though it is less clear here. The standard error is much bigger than for the previous learning curves. Also, we can see that there is barely no difference between the average blue and red curve after 50 trials. For these reasons and because of the uncertainty of EMG signals, it was decided to keep this analysis purely qualitative.

Before the big peak, we can see a smaller peak, at about 400-450 ms. This muscular activity represents the very beginning of the reaching movement. It is not yet used to counter the perturbation. Just like the big peak, its amplitude decreases during the first two series. This is coherent with the decrease in velocity. We can see a "step" between the first and the second peak. It is quite large at the beginning, but it becomes smaller and smaller. For the last 30 trials, there is barely a step any more. The first peak joined the bigger peak. This shows the anticipation of the subject. The step can be visualized as the time between the command of the arm to move forward and the command to counter the perturbation. It is big in the beginning when the subject doesn't know what to expect, but becomes smaller and smaller as the subject anticipates. During the last series, the reaching movement and anticipation take place in one fluent movement. We can barely see the first peak. Furthermore, if the force is anticipated and the compensation occurs earlier, it also counters a smaller force/deviation. This also explains why the biggest peak decreases. The differences between the left and right arm are very thin here. It wouldn't be reasonable to draw any conclusions from the difference between left and right arm.

Concerning the end of the movement, we can see another "step" after the biggest peak. This step decreases between the first and second halves of the first series. After that, it remains almost constant. This concerns the stabilization at the end of the movement. It shows signs of co-contraction. The fact that it decreases in the beginning can be seen as the gains of the robust controller becoming smaller. Once again, we can not see a clear difference between the left and right arm. This will be analyzed more in details later.

4.3.2 Posterior Deltoid

Now, let us have a look at the Posterior Deltoid. The subfigures will be organized in the same way as the Pectoralis Major. This way, we can compare both figures. The results are the following:



(a) First 15 trials

(b) Trials 16-30

(c) Trials 31-60

(d) Last 30 trials

Figure 4.16: EMG signals of the Posterior Deltoid (Source: MATLAB)

The first thing we can see is that there is also a big peak, which comes after a smaller peak. Both peaks take place much later than the ones of the PM. The second peak occurs at about 800-900ms. At that moment, the arm is trying to stabilize. This makes sense, since the PD is primarily used to stabilize the arm. Once again, we can see that this peak decreases strongly during the first series. After this, it remains pretty much stable. The explanation for this is that most of the learning takes place in the first series. If we look at the differences between the left and right arm, there seems to be big differences in the second peak. The right arm has a higher PD activity to stabilize at the end of the movement. This result is very surprising. To analyze this further, the maximal peak of the PD were plotted for all the trials. The result is on Figure 4.17.

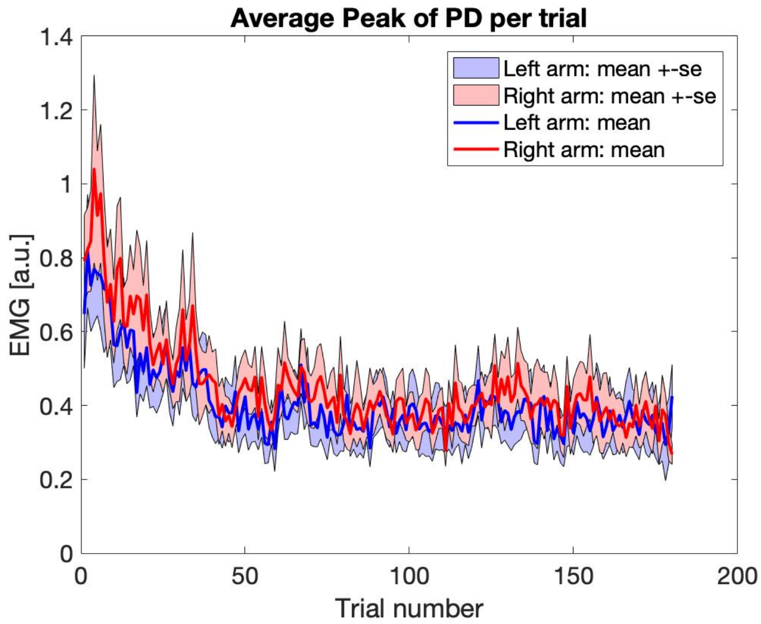


Figure 4.17: Evolution of the average peak of the PD for all the trials (Source: MATLAB)

Once again, the curves seem close to exponential curves. With this new perspective, we can see that the difference in average peak between the left and right arm is quite small. We can see a difference, but it is very subtle. No conclusion about left and right differences can be made here.

The first, smaller peak takes place at around 550 ms. It is interesting to see that there is no EMG activity before that. This seems to validate that the hypothesis that the PD is not used for the reaching movement. We can see that its amplitude decreases as well throughout the trials. There is no clear difference between both arms for the first peak. The moment of the first peak corresponds to right after that the arm starts getting deviated by the perturbation. This suggests the presence of co-contraction.

4.3.3 Potential co-contraction

Even though the PD does not counter the perturbation by pushing in the opposite direction, it can co-contract to stabilize the arm. We have observed earlier that the PD was probably not used for the reaching movement. This would confirm the suggestion that the PD could co-contract here to stabilize. It takes place at around $550ms$. At that moment, the reaching movement has already started, the perturbation has started as well. It occurs at the same time as the decrease in lateral acceleration when the perturbation is countered. The level of activation of the PM is high, because it starts countering the perturbation. We can suggest that the PD is co-contracting here to improve the stabilization. It would stop the arm from getting deviated by the perturbation. It is the first sign of co-contraction observed during the movement.

After this, the activity of the PD is at a down. This takes place at around $650ms$. At that moment, the activity of the PM is maximal: the subjects are pushing towards the inside, with their hands going towards the final target. After that, the hand needs to stabilize in the final target. To do so, the PD of the subjects are at a maximal intensity. This is the second and biggest peak of the PD, which takes place at around $800-900ms$. At the same time, the activity of the PM remains at a medium level. The purpose of this activity is probably also to stabilize, as it comes at the end of the reaching movement. This is a second suggestion of co-contraction.

4.3.4 Comparison of the controllers

Let us now discuss what this tells us about the controllers. First of all, the impedance controller is based on the use of co-contraction to stabilize. We have potential signs of co-contraction here. The first one takes place the beginning of the perturbation, to stop the arm from being deviated by the perturbation. The second one takes place at the end, to stabilize the hand in the final target. We only suggest the potential presence of co-contraction here, which would be very weak. This seems to contradict the impedance controller of Yadav and Sainburg, which is based on the use of co-contraction to stabilize.

On the other hand, it seems to agree with the robust controller. We can see that the supposed co-contraction is higher at the beginning, during the two halves of the first series. This makes sense, because it is the moment when the control gains of both arms are at the highest. Later in the experiment, their control gains decrease. The control strategies used become closer to LQG controllers, thus it makes sense that the co-contraction would decrease. On the other hand we could have expected more signs of co-contraction for the left arm than for the right arm. Since we didn't observe many differences between left and right arm for any of the EMG signals, it is not surprising that we don't observe any difference here either. The main conclusion from the EMG signals is that the differences between both arms are very small. They seem to be more subtle than previously acknowledged. It could also be that they have a limited impact on this kind of reaching adaptation task. The next section shows us these differences from a new perspective.

Throughout the results of the EMG, we have always observed a decrease in the amplitude of the signals. One may wonder if this decrease is impacted by the way the elecrodes are pasted on the skin. Over time, it could be that the electrodes don't fit as good as before, which would have an impact on the measurements. To check this, an analysis of the EMG signals was made right before the movements starts (first 200ms) for all the trials. If these signals tended to decrease, we could have suggested an impact from the adherence of the electrodes. It showed noisy, but overall, constant signals with no particular trend. Therefore, we can validate the hypothesis that the decrease in the signals comes from a decrease in muscular activity.

4.4 Inter-subjects analysis

So far, most of the results were analyzed per trial, by averaging on all the participants. This is very useful to analyze the learning and differences between the average left and right arm. On the other hand, it doesn't tell us if this difference was significant for most of the subjects. Are all the right arms better learners than the left arms ? Is there a lot of difference in how good subjects are among each other ? Does each subject have a right arm that is better than its left arm ?

These are interesting questions that are answered here. This time, the difference between the subjects is analyzed. Also, as we explained in the state of the art, different subjects can use different types of controller. It is interesting to analyze the effect that this has on the ability to learn. This analysis only concerns the normal trials.

Previously, we used 3 criteria to characterize learning in normal trials: the length of the path, the work applied on the subject and the correlation between the lateral forces applied by the robot and by the subject. We have discussed earlier that the length of the path and the work were very correlated. They showed very similar results. For this reason, the work is not be analyzed here.

4.4.1 Length of the path

Let us start with the length of the path. We will start the analysis by looking at the average length of the path, for each subject and for each arm. One may wonder here if it would make more sense to average on all the trials, or only on the trials for which the subjects has fully learned. By looking at both, the results seemed to be very similar. Thus, only the average for all the trials will be analyzed here. On Figure 4.18, we can see for each subject (numbered from 1 to 12), the average length of the path for their left arm (in blue) and for their right arm (in red).

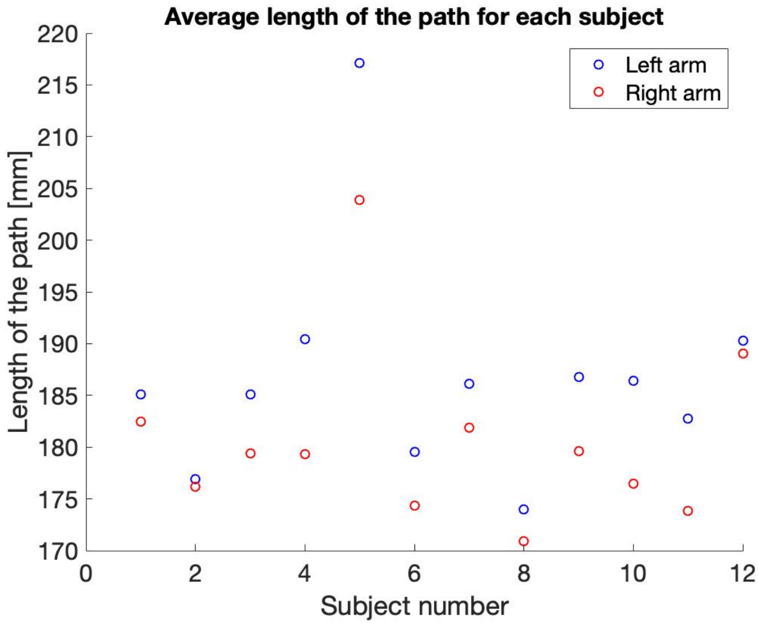


Figure 4.18: Average length of the path for all the subjects, (Source: MATLAB)

We can indeed see that the left arms tend to have longer paths than the right arms. There is quite a lot of variations between the subjects, some have a better left arm than the right arm of other subjects. This is not surprising. On the other hand, we can see that for each subject, the average length of the path was higher for its left arm than for its right arm. All the subjects that were selected were right handed, thus this makes sense. People are usually not 100% right-handed or left-handed. They can also be in between and have different arm preferences for different tasks. The fact that some subjects show bigger differences than others here is probably influenced by that. Though this is probably not the only reason, differences in interlimb learning, for example, can also play a role.

On this figure, we can see that subject 8 seems to be better than the others. Its left arm is better or as good as the other right arms. We can say the opposite about subject number 5. We will see if we observe this same pattern in the other analyses.

An interesting approach would be to analyze if we can establish a link between the length of the path and the type of controller used. In this case, we suggested the main difference to be in the control gains. The left arm was believed to behave more like a robust controller, with higher control gains. The control gains can be observed in many different ways, the maximal speed, maximal forces and so on. Here the maximal speed was chosen to characterize the gains of the controller. This criteria has the advantage that it is more independent than the others. The results are on Figure 4.19.

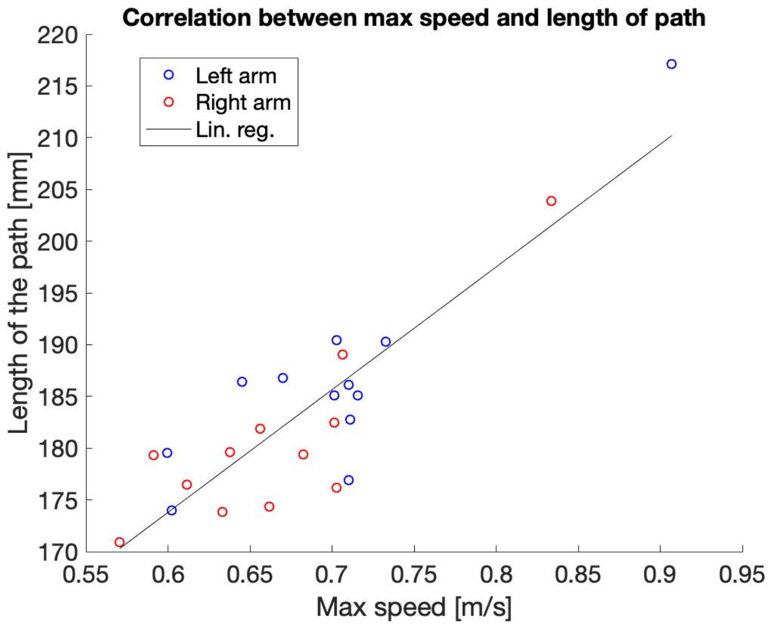


Figure 4.19: Correlation between maximal speed and length of the path (Source: MATLAB)

We can see a quite strong linear relationship between the maximal speed and the length of the path. For this reason, a linear regression was added on the figure. The maximal speed is here the average of the maximal speeds of each trial. We can once again see both arms of subject number 5, who is much worse than the others. It is interesting to see that it still fits the linear regression quite well. The correlation of all this data is 0.87.

We can conclude from this that there is a quite strong relationship between the gains of the controller and the learning. This corresponds to what was observed by Cluff, Crevecoeur and Scott in 2019.

The correlation is quite impressive, but not that surprising. As we had observed, it is quite logical that the maximal speed and the length of the path are strongly correlated. Intuitively, a subject that goes towards the final target with a high speed will encounter stronger perturbations. It will also react later in the trajectory. Thus, it makes sense that it will tend to have longer paths. Therefore, it would be very interesting to compare this with the other criteria, the correlation, and see if we can observe the same results.

4.4.2 Correlation between lateral forces

Let us start by doing the same analysis for the correlation as we did for the length of the path: the correlations are plotted for each subject and for each arm on Figure 4.20.

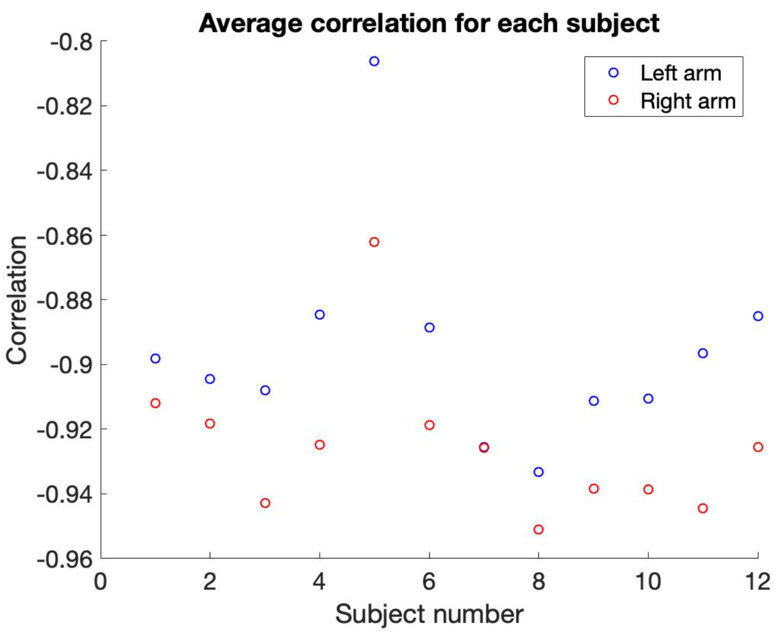


Figure 4.20: Correlation of the lateral forces for each subject and for each arm Source: MATLAB)

This figure is very similar to what was observed before. The differences between left and right arm are on average bigger than they were for the length of the path. An exception can be made for subject 7, where we can see that the correlations of both of its arms are almost equal. This person does a lot of work-out at the gym. This mostly implies learning the exact same movements for both arms. This can explain why its correlations are so similar. Furthermore, we can still observe that subject number 5 is much worse than the rest, with an average correlation for the left arm of only -0.8. Subject number 8, on the other hand, is once again the best subject.

So far, this matches the observations from the length of the path. Let us now have a look at the correlation between lateral forces as a function of the maximal speed. The results are the following:

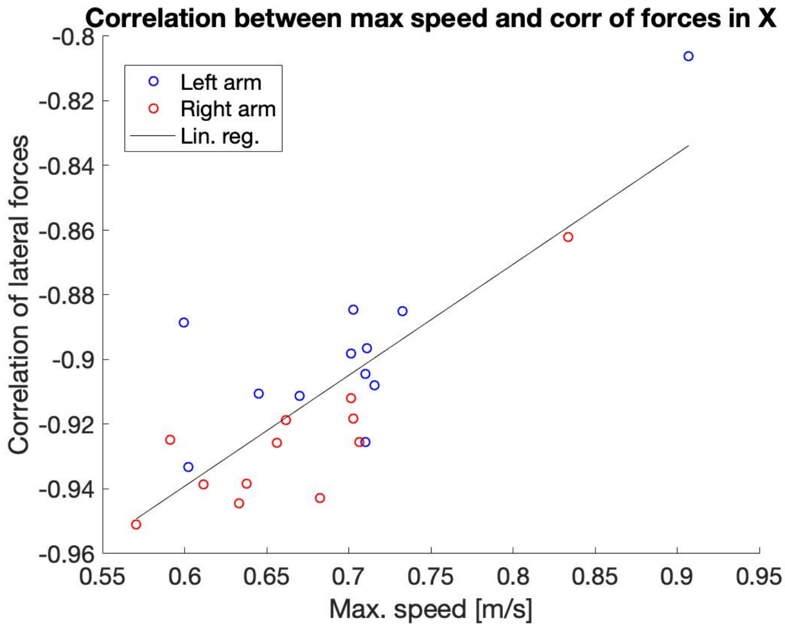


Figure 4.21: Correlation between the correlation of the lateral forces and the maximal speed (Source: MATLAB)

Once again, a linear regression was fitted in the data. Here also, we can see that it fits quite well. The results of subject 5 are as we expected. It is interesting to see that they still fit the linear regression quite well.

The correlation is still quite high, 0.81. Intuitively, the correlation between lateral forces shouldn't be as much correlated to the maximal speed as the length of the path. In fact, correlation of lateral forces and length of the path are criteria that are quite different. Their learning curves were also different. Therefore, it is very interesting that we can observe the same type of results in terms of learning as a function of the maximal speed.

We can conclude from this that subjects who have controllers with higher control gains (more robust controllers) tend to adapt worse than subjects with lower control gains. This corresponds to the results of Cluff, Crevecoeur and Scott in 2019 [6].

Chapter 5

Discussion

Let us take a step back and see what we have learned from the analyses.

5.1 Comparison of the controllers

The first part of the analyses concerned an inter-trials analysis. We started the analyses by looking at the learning curves of the subjects. They matched with the predictions from the hybrid control scheme and previous research: the right arm seemed to be more efficient, skillful and better to develop a new internal model. Also, the analysis of the stabilization suggested that the left arm was better to stabilize. So far, everything matched with the results of previous research.

The trajectories showed differences in the curvature between left and right arm. This was also observed by Yadav and Sainburg [2], [3]. It came with a higher speed for the left arm. One explanation for this would be that the higher speed is implied by the bigger curvature. We know that both arms need to arrive at the final target at the same time. Thus, if we assume that the left arm tends to make bigger curvatures than the right arm, the left arm would need to go faster in order to reach the final target at the same time. This doesn't make a lot of sense in this case, because the difference in curvature was also observed for the first trials, before any learning. Thus, a higher speed of the left arm is not likely to be a compensation for its bigger curvature. On the other hand, we can look at this the other way around: the higher control gains imply bigger curvatures. This is due to the fact that the perturbations are proportional to the speed. Therefore, higher speeds towards the target imply bigger lateral forces to deviate the arm. We also know that the response latency of the participants are the same. Thus, if the arm goes faster, it will react later in the trajectory. This gives a new perspective and a new explanation for the learning curves of work and length of the path. If the subject turns later in the trajectory and needs to counter a bigger force, its path will necessarily be longer and more work will be applied on him. This observation contradicts the hybrid control scheme. It assumes that both arms start the movements with the same controller. It is not the case here, because the left arm has a higher initial speed towards the target. Thus the higher speed of the left arm has a strong impact on the differences between left and right arm in the results. Yet, the hybrid control scheme can not give a reasonable explanation to this

The best explanation came from Crevecoeur, Scott and Cluff who observed the same in 2019 with curl force fields [5]. In their research, participants used a more robust controller, with higher control gains, when being confronted with unexpected perturbations. One of their observation was that the robust controller implied higher initial speed towards the target. This is the main reason why the robust controller would be a perfect candidate to explain motor lateralization.

Furthermore, as it was explained in the state of the art, Yadav and Sainburg conducted other experiments in 2014 [17]. They involved consistent and inconsistent curl force fields. Nothing specific was mentioned in the article about a difference in maximal speed. On the other hand, the left arm showed better results than the right arm for inconsistent force field. They suggested that this would confirm impedance control. If we look at this from the perspective of the robust controller, this result can be explained by the increase in control gains. The robust controller was shown in [5] to be better than the LQG controller for unexpected perturbations.

As the participants learn, their speeds tend to decrease. The perturbations become more and more expected. Thus, the controllers of both arms tend to behave more like a LQG controller. It's interesting to see that even when both arms have fully learned, the right arm is still better. It also has a lower maximal speed. Furthermore, the robust controller gives another explanation to the better stabilization of the left arm. It would be due to its higher neural feedback, including reflexes.

The results of the catch trials seem to confirm the big influence of the maximal speed on the results. The left arm showed bigger lateral deviations than the right arm. Since it has higher control gains, it goes faster and is used to countering bigger perturbations. Therefore, it makes sense that it is more deviated. We also observed bigger peak forces in X and Y. The differences between left and right arm were very significant here. It shows the big influence that the difference of speed has on the results. On the other hand, the average forces and deviations remained more or less constant throughout the trials. For this reason, we also had a look at the trajectories and the variance. It seems like the left arm has a bigger variance than the right arm. This can be explained by the fact that the right arm is more predictive and better obtain an internal model. Also, the variance for both arms tended to decrease over time. This was purely qualitative, this analysis is just a suggestion.

Finally, the analysis of the EMG didn't show a lot of differences between the left and right arm. This suggests that differences between left and right may be more subtle than previously acknowledged or that they have a limited impact on this kind of reaching adaptation task. It was interesting to observe that the amplitudes of the signals tended to decrease over time. There could be co-contraction at the beginning of the perturbation and at the end of the trial. It was very weak and decreasing over time. This makes sense from the perspective of the robust controller. As both arms learn to anticipate the perturbations, their control gains decrease. Thus, the co-contraction also decreases. On the other hand, the hybrid control scheme predicted bigger co-contractions. The impedance controller is based on an increase in stiffness and viscosity of the arm at the end of the movement. Therefore, the fact that we didn't observe clear co-contraction here is contradictory with the concept of the impedance controller. As a reminder, Yadav and Sainburg didn't perform any verification of the EMG signals to validate the hypothesis of the impedance controller.

5.2 Inter-subjects analysis

The last part of the results concerned an inter-subjects analysis. The criteria for learning were the length of the path and the correlation between lateral forces. It was interesting to see that participants who had a good right arm, also tended to have a good left arm. We could see that some people had bigger differences between both arms than others. This makes sense, because some people are more ambidextrous than others. No subject showed a better left arm than right arm.

It was suggested by Cluff, Crevecoeur and Scott in 2019 [6] that there was a link between the control gains and learning. Arms/participants with lower control gains would tend to be better learners. To verify this, we first needed to choose a criteria for the control gains. The maximal speed of the subject was selected. This was compared with learning criteria that were used before: the correlation in lateral speeds and the length of the path. We computed the correlation between maximal speed and the learning criteria. It was strong for both criteria.

These correlations seemed to confirm the observations from Cluff, Crevecoeur and Scott [6] that controls gains had an effect on learning. We suggest that people/arms with lower control gains tend to be better to adapt to reaching movements.

5.3 Limitations and perspectives

The robust controller is promising, but this thesis contains a few limitations. First of all, the influence of catch trials on learning is not considered. As subjects are instructed to perform well on all trials, they need to find a trade-off between performing well on the catch trials and on the normal trials. This can have an effect on the results. The main effect is probably on the first trials. A subject who encountered a catch trial in the first few trials would learn differently than one who didn't. This increases the variability during the first few trials, making it harder to get significant results. Though the catch trials gave us useful analyses, it would be interesting to see what the results would be without catch trials.

Secondly, this thesis only considers right-handed people. Therefore all the analyses that are made consider right-left differences for right-handed people. There can be differences in the brain between left and right, which are independent from the handedness. Therefore, we would need to conduct experiments with left-handed people to generalize the conclusions to dominant and non-dominant arm.

Finally, the differences between left and right arm were quite subtle here, especially in the analysis of the EMG signals. We could look at other muscles involved in the reaching movement to see if there are more significant differences there. Another way to solve this would be to select the subjects based on whether they are very right-handed or ambidextrous. The participants can test this with the Edinburg handedness inventory [27]. It is a set of questions which determines how left-handed or right-handed the person is.

Chapter 6

Conclusion

We have seen that the difference in maximal speeds can explain most of the results and have suggested that differences in terms of control robustness could be at the origin of differences in speed. The learning curves of the length of the path and work showed that the right arm was better. By looking at the trajectories and velocites, we discovered that this can be explained by the higher maximal speed of the left arm. A higher speed implies bigger perturbations, thus more deviations. Furthermore, the participants react later in the trajectory if they have a higher speed. Therefore, their path is longer and less smooth, and more work is applied on them. Thus, these results can be explained by the difference in maximal speed. The deviations and forces of the catch trials validated this suggestion. The left arm was more deviated, and used bigger peak forces than the right arm.

The first results matched with the hybrid control scheme of Yadav and Sainburg: better learning curves for the right arm as it is more predictive and better stabilization for the left arm as it uses impedance control. However, we were concerned that these differences had to find an alternative explanation given that we observed potential flaws in their model. The main one is that values of impedance are likely much lower than what they predicted. Furthermore, the difference in maximal speed doesn't find an reasonable explanation in the hybrid control scheme of Yadav and Sainburg. They assume that both arms start with the same controller. This contradicts the observation that the left arm has a higher initial speed towards the target. The best explanation came from the robust controller. It assumes that the left arm has higher control gains than the right arm. Over time, the control gains of both arms decrease. Their control strategies tend to a LQG controller. The EMG signals didn't show strong co-contraction, which contradicts the hybrid control scheme. Instead of co-contraction, the robust controller suggests that the higher neural feedback, including reflexes, are mainly responsible for the better ability to stabilize of the left arm.

The results showed that the differences between left and right arm are quite subtle. Their EMG signals barely showed any difference between them. The inter-subjects analysis allowed us to see this from a new perspective. We can indeed see that for each subject the right arm is better than the left arm. On the other hand, some subjects were much better than others for both arms. The correlation between the control gains and learning were analyzed. The criteria that were used are the maximal speed for the control gains, and the correlation in lateral forces and length of the path for learning. The correlation was strong for both criteria. Therefore, we can suggest that people/arms with lower control gains tend to be good learners.

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