

École polytechnique de Louvain

What is wrong with force magnitude? Study of interferences in dual adaptation of human reaching movements with force cues

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Abstract

When people try to learn to adapt in parallel to two force fields of same direction and different magnitudes, interferences are observed. This happens even if they are helped by cues in the form of background loads of different magnitudes and same direction. This work aims to understand why those interferences are observed. Thirty volunteers took part in two experiments to find out if the interferences are due to the fact that the used clues are not efficient, or if it is just harder for human to adapt to force field of different magnitudes than of different directions. After analysis of different learning indicators, we concluded that background loads of different magnitudes are rather inefficient clues to enable the formation of distinct motor memories. The magnitude information does not seem to enable dual adaptation. Moreover, we discovered different learning behaviours in the population, some people seem to have more difficulties than other to adapt to force fields of different magnitudes in parallel.

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Chapter 1

Introduction

One of the most amazing things that human's brain can do is to learn and adapt in a changing environment thanks to the sensory inputs it receives. We can indeed be successful in playing a sport or a musical instrument that we have never heard of, we can adapt our motor control to move in the water or when there is very strong wind and even learn to adapt to injuries and unusual limb conditions. However, sensory acquisition and processing is noisy and not instantaneous. Moreover, during the delay associated to the sensory feedback, the state of the body and the environment may change. To solve those problems, researches have shown that the brain may construct internal models that it can use to predict the output of the motor command and to compensate for persisting changes in the environment [1–5].

The brain may then build multiple of those internal models and switch between them or adapt already existing ones when the body is exposed to changing environments. However, the construction of those models may be subject to interferences when people try to learn a task in two opposing environments (dual learning) [6, 7]. In our day-to-day life, we are very good at acquiring knowledge about different things simultaneously without encountering any interference. A lot of researches have therefore been done on the subject.

In the context of reaching movements, recent studies have tried to understand which conditions allow people to learn and remember motor skills done in two opposing force fields (or visuomotor mappings). This has been studied by exposing participants to different contexts by applying different perturbations or by having different tasks or planning conditions in the two opposed fields. Visual and haptic cues have been shown to be rather inefficient to help participants to build different motor memories [8, 9]. When the task executed in the two different environments is not the same [10, 11], when experimenters use vestibular cues [12] or when the muscle pattern involved is different, dual learning is successful [13, 14]. Participants can also adapt their motor skills, while doing the same task in two conflicting environments, if the training in the two contexts is separated by a few hours [6, 15] although interferences can sometimes still be observed [16, 17]. Finally, dual learning can also be achieved by using different planning conditions, distinct movement goals [18]. Indeed, target remapping [19] and prior or follow through movements even if only planned and not executed [18, 20], enable to avoid the retrograde interferences by constructing distinct motor memories. The important condition that those last cues fulfil and that the static cues (visual, haptic) do not is that they affect the motor plan, they affect the neuronal circuits for sensorimotor control [12].

More recently, Crevecoeur, Mathew and Lefèvre [21] showed that implicit cues in the form of background loads in one or the other direction allow simultaneous learning of opposite velocity dependent force fields. However, they failed to make the same conclusion when the cue and the force field were only related by their magnitude and not by their direction. Indeed, in this last case, they observed interferences in the learning of participants.

This master thesis tries to understand why are these interferences observed. Is it because the background forces only differ by their magnitudes and not by their directions? This then implies that no interference would be observed when using background forces of different directions as cue for force fields in the same direction but of different magnitudes. Are the interferences observed because the velocity dependent force fields always have the same directions and only change magnitude in function of the implicit cues ? We would then observe no interference when using background cues of different amplitudes and same direction as cues to predict force fields of different directions. Or, finally, are the interferences due to a combination of both described phenomena?

To answer those questions, we will first summarize the important aspects of motor adaptation and more precisely dual adaptation in chapter 2. As a next step, in chapter 3, we will describe the settings of the experiments as well as the tools that will be used to analyse the collected data. Finally, the results of the experiments will be described in chapter 4 and discussed in chapter 6. The last chapter will also present the limitations of this work.

Chapter 2

State of the art

The goal of motor learning is to acquire new motor skills and to improve the efficiency of movements, but also to adapt known motor skills to keep the same level of performance in changing environments. Motor skills and so motor control do not only involve the execution of movements, but also the ability to learn to combine different sources of information about the state of the environment and of the body in order to predict the movement that has to be done to reach the best possible outcome. Motor learning is a combination of implicit and explicit learning. Most of the time, when a skill has been practiced a lot, it becomes automatized and implicit. Now, this does not mean that, to acquire this skill, no cognitive and so explicit process were needed [22] or at least influenced the process.

2.1 Adaptation

In the case of this study, the most interesting focus is not the general process of motor learning, but a sub-category of this large process: the adaptation. Motor adaptation is the process in which we adapt already well-practiced actions with the aim of maintaining performance in a modified environment [23]. We often need to adapt in our day-to-day life. When injured, we have to adapt well practiced movements to be able to do them efficiently even with the limitation that the injury brings. When gaining weight or becoming pregnant, we need to adapt the motor commands to be able to move our heavier body. We also need to adapt to weather changes or to the use of different tools having different weights and shapes.

Many studies have therefore looked at motor adaptation thanks to different paradigms. Adaptation can be studied either by modifying the dynamic of the body during movements (force-field adaptation) or by changing the mapping linking the visual feedback to the body movements (visuomotor adaptation). Researchers have then shown that motor adaptation occurs thanks to a temporary adjustment of an already existing internal model. This has two main consequences: the formation of involuntary after-effects after any adaptation tasks and the rapid revert to the baseline when the disturbance is removed.

2.1.1 Internal models

To be able to control a system and reach a defined goal in an unpredictable and perturbed environment, it is necessary to rely on feedback. It indeed allows computing the position error as the difference between the desired one and the actual one and then to adapt the motor command to be able to reach the desired goal. The problem is that the sensory feedback that we have access to, while performing a movement, are noisy and the sensorimotor loop involves a delay of about 80 to 150 ms depending on the sensors [24]. Moreover, our muscles fatigue and the consequences of motor commands can vary over time. Because we know that human beings are able to perform very fast and precise movements and to adapt very quickly, there must be another mechanism than pure feedback control that is involved in motor control.

Researchers have then hypothesised the existence of internal models, i.e. a structural representation of the limb dynamics in the brain. This internal model can then be combined in a state estimator with the delayed feedback and the known motor command to predict the actual state of the system (body and environment). It can also be combined with the goal of the task and the estimate of the system state in the controller to compute the next motor command that is needed to go in the desired trajectory. The central nervous system (CNS) can then combine the state estimator and the controller, as it can be seen on figure 2.1 to form the feedback circuit necessary for learning.

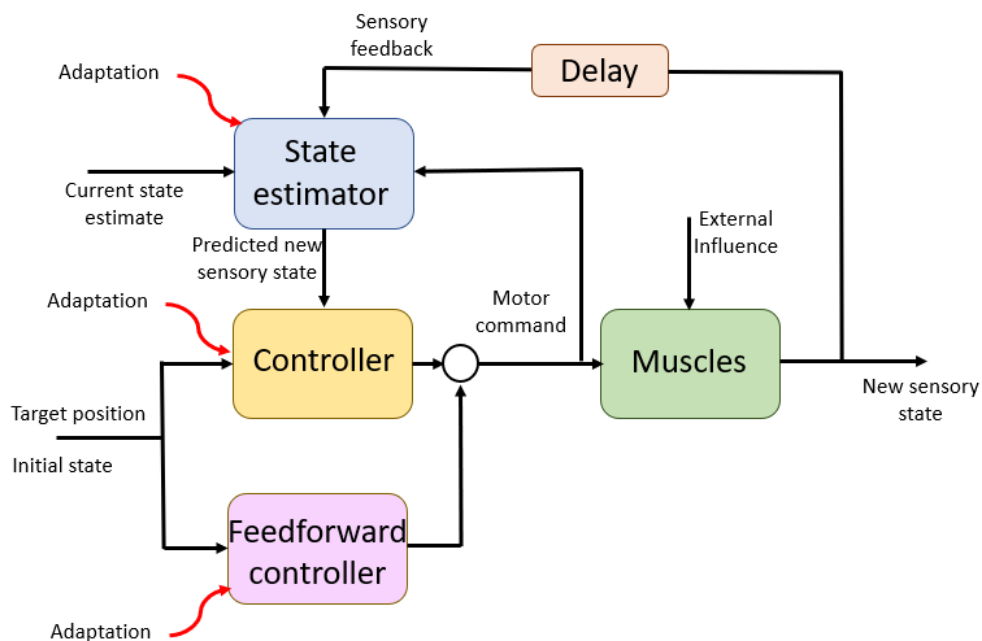


Figure 2.1: Schematic representation of the brain controller where we can see the feedback loop composed of a state estimator and a controller as well as the feedforward path. The red arrows represent the place where an adaptation of the internal model can occur.

There might also be a voluntary component in learning which can be modelled by a feedforward controller which will create a motor command based only on prediction and

not on feedback at all. This controller also uses an internal model to build an adapted motor output to the prior that we have or the explicit strategy that we decide to use.

Both the motor command sent by the controller of the feedback loop and the one sent by the feedforward controller are weighted by a measure of their uncertainty to create the actual command applied by the muscles.

2.1.2 Processes involved in adaptation

To reach good performances when doing a known task in an unknown perturbed environment, it is necessary to adapt the internal model. The error between the predicted consequences of a motor command, calculated by the forward model, and the actual consequences of the movement captured by feedback is the sensory prediction error, and it is the main driver of adaptation. Indeed, to be able to adapt our internal model, we need to actively perform movements or at least evoke reflex responses and so predict the sensory consequences of them [3, 25]. As the internal model is adapting, it will better predict the sensory state and so the sensory error will decrease. We therefore typically observe exponential decay of errors when considering an adaptation task.

It has been thought that motor learning and adaptation happened on a trial by trial basis. Several movements in a modified environment were then required before reaching an accurate model of the limb dynamic in that environment. However, when we experience unexpected perturbations (i.e. a one-time disturbance or during the first movement in a new environment), we also need to rely on a process to reach our goal. There are now more and more evidences showing that the adaptation of the internal model may also happen online and not only between the trials [26]. Because they are fast and combine multiple sensory information, long-latency reflexes have been shown to be of great importance in this process that can happen as fast as 250ms after trial onset [27].

Smith et al. [28] hypothesised the fact that the adaptation process includes both a fast and a slow process that sum to enable learning. There are two possible origins of the fast component. Indeed, it has both been linked to a feedback control adaptation resulting in an increase in long-latency feedback response [29] and to the use of an explicit strategy [30]. The slow component, on the other hand, seems to correspond to an adaptation of the internal model, in the sense that it allows people to better anticipate the sensory consequences of a motor command and so to choose a more adequate command. This adaptation will then result in an improvement of the early phase of movement thanks to a corrected prediction.

Evidence have been provided about the fact that the adaptation of the feedforward controller allows the formation of appropriate motor feedback responses to never encountered disturbances [31]. There is a transfer between the feedback and the feedforward process because they share neural circuits at different levels. This also allows the transfer in the opposite direction, so from the feedback response to the feedforward command [25]. This means that the internal model of the feedforward control can be modified by only exposing the feedback system to a certain environment.

Feedforward and feedback controls are then hard to entirely separate, and Mathews et

al. [32] suggested that it may be more accurate to separate online and offline mechanisms instead of feedback and feedforward processes. The described model is then called an adaptive state-feedback control model, and a schematic representation of it is shown on figure 2.2.

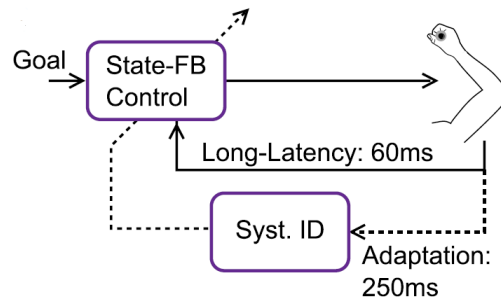


Figure 2.2: Schematic representation of the adaptive state-feedback control model [32]

A state-feedback controller is a parameterised model that describes the reaction of people to a modification of the state variables computed thanks to long-latency feedback (timescale: 60 ms). The model parameters can be modified online thanks to an adaptive loop (timescale: 250 ms). This loop uses the difference between actual and expected sensory input to improve the internal model online. It is important to note that in this model they assumed that the same variables are used for control and adaptation. Those variables include the joint angles, the velocities, the torques as well as the muscles state and potentially their higher order derivatives.

2.1.3 Dual adaptation and interferences

Dual adaptation is a process in which we concurrently adapt to two variants of a same environment [11]. This process needs the building or adaptation of two separate internal models and the switching between those two models.

Dual learning is not trivial and can be subjected to interferences. This means that the learning of a same task in two opposing environments may compete with each other, leading to a retention of none of the two motor memories. There are two types of interferences: the anterograde ones that complicate the adaptation to a second environment after learning to move in the opposing environment, and the retrograde ones that make the retrieval of the first learned environment difficult after the adaptation to the second one.

To be able to learn and switch between the two internal models, it is essential to have a cue that indicates in which of the two variants of the environment the trial will take place. The efficacy of the cues to allow dual adaptation is not trivial to determine. A lot of different cues have been tested, and some of them allowed to anticipate the force fields that were applied during movements, while others did not [9]. However, it has also been shown that when evolving in a totally unpredictable environment (no cue), people anyway adapt their feedback responses during movements to the unanticipated force fields in a very specific manner [27].

2.2 Force cues prior

The force field adaptation paradigm used includes a preparatory phase during which subjects have to wait for a go signal. During this phase, subjects can prepare for the upcoming movement and their neuronal activity is thought to reflect the information that they have about the upcoming movement [33]. The cues that induce differences in the preparatory phase seem to be the ones that have been shown to be successful in helping people to learn a same motor skill in two opposing environments. Indeed, the useful cues affect the motor plan, they affect the neuronal circuits for sensory motor control.

It has also been shown that continuous state feedback control is a good way to model how the long-latency reflexes allow to coordinate multiple effectors [34]. Moreover, one of the necessary state variables of such controller in addition to the positions, velocities, and accelerations of joints, seems to be an estimate of the applied load computed thanks to the feedback response [34]. There are also evidences showing a close link between the adaptation of feedback and anticipatory control, where the two processes might be hard to dissociate [32]. It is then coherent to think that the brain uses an estimate of the externally applied forces for control, but also for adaptation. Because doing prior movements, i.e. having distinct state variable history (in this case position, velocity and or acceleration), has been shown to enable dual learning, it is reasonable to think that it will also be possible by changing the applied force (another supposed state variable) history.

Chapter 3

Methods

3.1 Set-up

Thirty healthy volunteers (ageing between 19 and 25) participate in the experiment. The machine that was used to conduct the experiment is called KINARM (Kinesiological Instrument for Normal and Altered Reaching Movements) and a representation of it can be seen on figure 3.1.



Figure 3.1: Representation of the KINARM robot [35]

This robot allows to create a complex mechanical environment while collecting many kinds of data. In this experiment, it applies different forces on the hand of the subjects while measuring the position of the handle as well as the forces applied on it. The volunteers were not able to see their hand, but a screen displaying a cursor representing their hand's position, as well as the starting and goal target.

3.2 Experiment procedure

The experiment is divided into two parts. Half of the participants started with the first part and the other half started with the second one. The goal is to quantify the effect of the order of the two parts on the results. All participants took part in both experiments.

The steps of a trial and the instructions given to the subjects were the same for both parts. A schematic representation of the course of a trial is illustrated on figure 3.2. The participants were asked to take the handle of the KINARM and to place the hand-aligned cursor in the circle representing the start target (radius of 1.2 cm). They were requested to wait for a random delay, uniformly distributed between 2 and 4 seconds, before the filling in red of the goal target (radius of 0.6 cm) located 15 cm straight away from the start one indicated them to go. And then they had to do a movement towards the goal target and to stabilise for at least one second, the hand-aligned cursor in it. This had to be done within 600 ms to 800 ms after the onset of the GO signal for the trial to be considered as successful.

After each trial, the participants received feedback on their performance. If the goal target turned green, it meant that the trial was successful. On the other hand, if it turned in an open or filled red circle, it respectively meant that the participant was too fast or too slow. This difference in result is important to keep the velocity and so the applied force field magnitude (which is proportional to the velocity) in about the same range for all the trials. For the analysis, the “too slow” and “too fast” trials were also used. Finally, to keep the volunteer’s attention, a counter reflecting the number of successful trials was visible on the screen.

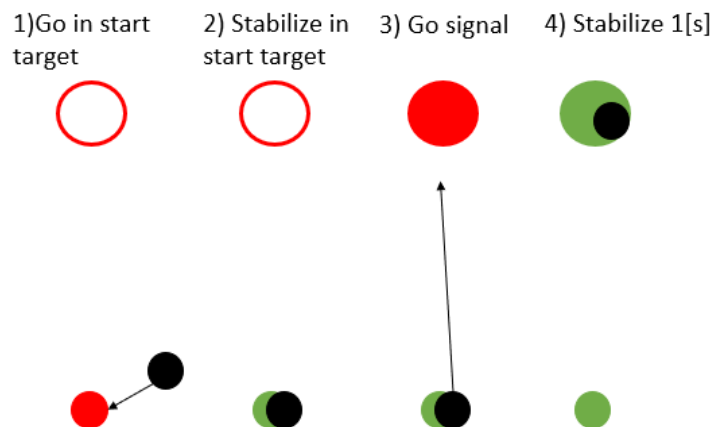


Figure 3.2: Steps of the task realised by all the subjects in both experiments

At the beginning of each trial, a constant lateral background force was applied on the handle. Participants had then to stabilise the hand-aligned cursor on the start target while compensating for this background force. A force field proportional to the velocity was added to the already present background force during the movement toward the goal target. This force field had the form:

$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} 0 & c \\ -c & 0 \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} \quad (3.1)$$

where c can be negative or positive depending on the trial.

Before the first trial with forces, participants performed a series of 20 trials to get used to the setup of the experiment.

3.2.1 Experiment 1

This experiment aims to determine if the interferences observed in experiment 2 of the paper of Crevecoeur et al. [21], come from the fact that they used force field of different magnitudes and same directions.

We then used heavy or light background forces (namely of 2.5 N or 5 N), and clockwise or counter-clockwise force fields with magnitude given by $c=15$ Ns/m or $c=-15$ Ns/m in (3.1). A light background force corresponded to a counter-clockwise force field (red condition) while a heavy background force was uniquely associated to a clockwise force field (blue condition). A schematic representation of the forces can be seen on figure 3.3.

The design of this experiment fulfils its goal. Indeed, if we do not observe interferences, this would mean that the magnitude of the background load can be extracted and used as a cue to enable learning. However, it may potentially be hard for humans to learn force fields that go into the same direction.

Participants were asked to realise 240 reach movements divided in 4 blocks of 60 trials. Those 60 trials per block included 25 trials per conditions (blue or red on the figure) and 10 catch trials that were randomly mixed. The catch trials included 5 trials with a light background force and 5 with a heavy background force, all of them without any force field added during the reaching movement. Between each block, participants could ask for a pause to avoid fatigue.

3.2.2 Experiment 2

In this second experiment, we investigate if the interferences observed in experiment 2 of the paper of Crevecoeur et al. [21] are due to the use of background load cues of different magnitudes. This would mean that it may not be a problem for humans to learn force fields that only differ by their magnitude, but that the magnitude of the background loads is not used by the brain as a cue to enable adaptation.

In this experiment, the background forces were then always of 5 N but either positive or negative, while the force field was either light or heavy (namely $c = 8$ Ns/m or $c = 15$ Ns/m). The background force to the left (negative) was the cue for a light force field magnitude (red condition) and the background force to the right (positive) to a heavy force field magnitude (blue condition). A schematic representation of the forces can again be seen on figure 3.3.

Like for experiment 1, 4 blocks of 60 trials composed of 5 trials per conditions and 10 catch trials randomly mixed were performed by the participants. Between the two experiments, a washout block composed of 40 reaches in an environment without any forces applied was performed.

It is interesting to notice that there is a common condition in both experiments. Indeed, in both experiments, the condition that is represented in blue in figure 3.3 consists of a heavy background force to the right (positive) and a heavy clockwise force field ($c=15$ Ns/m).

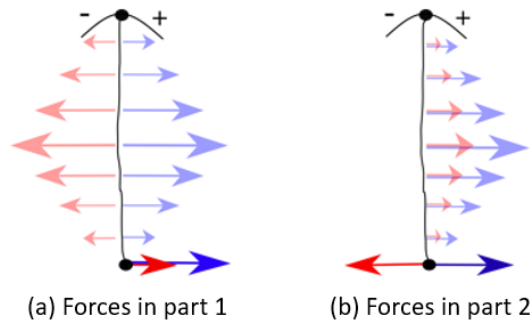


Figure 3.3: Schema of the forces applied in both parts of the experiment

3.3 Data pre-processing

When the 30 subjects completed the two experiments, we extracted from the data collected by the KINARM the X and Y coordinates of the hand-aligned cursor, as well as the components of the endpoint force that subjects apply on the handle. Those data were collected with a sampling frequency of 1kHz, then filtered using a dual low-pass second order digital Butterworth filter with a cut-off frequency of 50 Hz. Finally, the data were aligned on the GO-signal so that we only keep the data that lie between 200 ms before the GO-signal and 1s after this signal.

Thirty participants took part in the experiments, but two of them had to be (partly) removed of the sample. The first one was only removed from the forces and correlation analysis because we have great evidences that show that the force captors were not well calibrated. The second subject was removed from all the group analysis because this participant showed clear sign of being an outlier that would bias the results. Moreover, during some trials, subjects got distracted and did not start the movement at all. Because those trials are then not relevant and would bias all the results, we first had to remove them. To do so, we excluded from the data set all the trials for which the subjects did not succeed in reaching the target before the end of the trial (1s after the go signal). In total 0.86 percent of the trial were removed in experiment 1 and 0.55 in experiment 2.

For the remaining trials, the hand velocity was computed using the coordinates of the cursor and a fourth-order central-differences algorithm. With this computed velocity, we could calculate the force that the KINARM applied on the hand using (3.1).

3.4 Learning indicators

To have a general idea about what happens in both experiments, it is interesting to look at the hand path. However, it is not enough to determine if the subjects succeed in adapting to the changing environment. Fortunately, to do so, we can rely on some commonly used indicators.

3.4.1 Path length

The first indicator that is used is the path length. To compute this parameter, we consider that the movement starts at t_0 when the cursor leaves the start target. The t_{end} corresponds to the moment when the velocity of the cursor becomes smaller than 0.03 m/s and the cursor is in the goal target. The path length is then computed as the integral of the norm of the velocity vector over that interval:

$$Path\ length = \int_{t_0}^{t_{end}} \sqrt{v_x^2 + v_y^2} dt \quad (3.2)$$

This parameter can intuitively be used as an indicator for learning. Indeed, when the participants will learn to evolve in the used force fields they will be able to do straighter path and so shorter ones but also to stabilise the cursor quicker and so reduce the overshoot.

3.4.2 Initial angle

The second indicator that is used is the initial angle. It is computed as the angle between first, the vertical line passing by the point corresponding to the position of the cursor when it leaves the start target, and secondly, the line joining this same point to the one corresponding to the position of the cursor at the crossing of a virtual line located at one third of the distance between the start and goal targets (see Figure 3.4).

This angle is a good indicator because feedback adaptation approximately occurs after 250ms [27] and this is typically later in the movement so that everything that occurs before the crossing of the virtual line can be linked to predictive behaviours. Changes in the initial angle can then be linked to anticipation of the force fields.

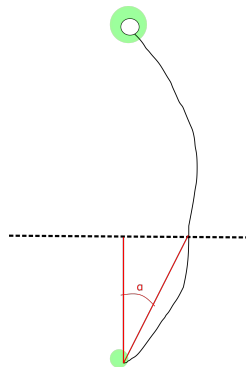


Figure 3.4: Measurement of the initial angle

3.4.3 Correlation

The third criteria that is used is the correlation between the force applied by the handle on the hand of the subject (computed as the sum of the background load and the force

field found using (3.1)) and the one measured by the KINARM. The latter corresponds to the response force of the subject applied on the handle to counteract the robot force. The correlation between two quantities X and Y is defined as:

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

where Cov denotes the covariance, \mathbb{E} the expectation and σ the standard deviation.

In the beginning of the experiment, the subjects are not able to anticipate the force field and a delay will be observed between the application of the force by the handle and the response of the subject. As they begin to learn, they should be able to anticipate the force field and so to decrease the delay so that both forces become more aligned and so more correlated. An increase in correlation is not necessarily linked to anticipation. Indeed, this indicator is calculated over the whole trial path and an increase in correlation due to a better alignment of both forces at the end of the trial can be linked to an improvement in the feedback controller.

3.5 Statistics

To be able to quantify what we can observe on graphics, different statistical tools were used, those are described in this section.

3.5.1 Mean and standard error

Because we are initially interested in the sample behaviour, we have to average the result over the participants. Two quantities are then interesting, the arithmetic mean and the standard error of this mean, which is given by :

$$SE = \frac{\sigma}{\sqrt{n}}$$

where σ and n are respectively the standard deviation and the size of the sample.

3.5.2 t-test

The t-test is used in this work to test if a parameter in a fitted model is significantly different from 0. The goal of the t-test is to decide if we should reject or accept a null hypothesis. In our case, the null hypothesis H_0 is that a model parameter, let's call it β , is not significantly different from 0. The t-test supposes that under the H_0 hypothesis, the t-statistic $t = \frac{\hat{\beta}}{SE(\hat{\beta})}$ is drawn from a student distribution with $n-p$ degrees of freedom. We assumed that n is the number of observations, p the number of coefficients in the model, $\hat{\beta}$ the estimated value of β and that $SE(\hat{\beta})$ is its standard error.

We can then compute the probability of observing a result at least as extreme as t under the null hypothesis. This probability is given by the p-value. In most of the works, including this one, 0.05 is taken as threshold for the validation or not of H_0 . This means that a p-value smaller than 0.05 will imply the rejection of the null hypothesis, and so

in our case the acceptance of the fact that the parameter value is significantly different from 0. However, if we obtain a p-value greater than 0.05, this means that we do not have enough proof to reject the null hypothesis.

3.5.3 Exponential curve

As explained in the state of the art, because the main driver of adaptation is the sensory prediction error, the decay/increase of the learning indicators typically follows an exponential curve. It is therefore interesting to try to fit exponential curves to the evolution of the different indicators. This is done for both experiments to see if the evolution is indeed exponential or if it is closer to a linear curve. The fitted exponential model has the form:

$$y = a + b e^{-cx} \quad (3.3)$$

After fitting this model, it is possible to perform a t-test on the parameter c to see if the data actually follow an exponential curve or if it is closer to a linear curve, i.e. c is not significantly different from 0.

3.5.4 Linear mixed-effect model

At one point it will be important to determine if the evolution of the learning indicators is due to distinct processes (e.g. adaptation of distinct internal models) in different conditions. To do so, it is interesting to fit a linear model, including as predictor an interaction term between the trial number and the trial type, to the time-series of the learning indicators. Indeed, if the coefficient in front of this term is significantly different from zero, this means that the evolution of the learning indicator, in the distinct conditions, does not follow the same time-course. An interesting model would then be of the form:

$$y_{ij} = a + b i + c \text{ type} + d i \text{ type} + \epsilon_{ij}$$

where ' y_{ij} ' is the value of the learning indicator for subject ' j ' at trial ' i ', ' type ' is the trial type (red or blue condition) and ϵ_{ij} are independent normally distributed error terms. The parameters a , b , c and d are estimated from data.

The problem with such basic models is that the error terms are supposed to be independent, while in our case the $\epsilon_{.j}$ are certainly not independent because they relate to the same subject. To account for this intra-subject correlation, it is best to use mixed effect models. Those are indeed powerful tools to analyse grouped data because they allow to take into account both fixed and random effects.

In our case, the fixed effects are parameters that will be common for the whole set of subjects and the random effects are different for each individual subject and are then drawn from a certain distribution. The model takes then the following form:

$$y_{ij} = a + b i + c \text{ type} + d i \text{ type} + s_j + \epsilon_{ij}$$

where the s_j are independent random variables representing the random effect. They actually represent the deviation from the mean intercept ' a ' and are distributed as $s_j \sim \mathcal{N}(0, \sigma_1^2)$. We now have that the ϵ_{ij} may be considered as independent zero mean normally distributed random variables and as independent from the s_j .

3.5.5 ROC analysis

The receiver operating curve (ROC) is a graphical tool that is normally used to evaluate a binary classifier. In our case it will be used to determine if the distribution of two quantities in the sample are the same or if the two quantities can be dissociated easily i.e. classified in the two correct distinct groups easily.

Classically, the ROC is described as the plot of the true positive rate (TPR) against the false negative rate (FNR) while varying the threshold of the classifier. As a reminder, if we define group 1 as the positive group and group 2 as the negative group ¹, the TPR is the number of data that both actually belong to group 1 and have been classified as belonging to group 1 divided by the total number of people that actually belong to group 1. The same definition can be written for the true negative rate (TNR) and group 2 and the FNR is then defined as $1 - \text{TNR}$.

The ROC curve can easily be plotted in our case as the cumulative distribution function of the first quantity against the cumulative distribution function of the second one. Effectively, if we start with a threshold for classifying data as belonging to group 1 (positive group) of $-\infty$ then both the TPR and the FNR will be equal to 0. Indeed, all the data will be classified as belonging to group 2. If we then increase the threshold and reach the domain where the distribution of the first quantity is different from 0, then the TPR will increase in the same way as the cumulative distribution function of the first quantity does while the FNR will remain equal to 0. Indeed, until we reach the start of the domain where the distribution of the second quantity is not null, all the data belonging to group 2 will be classified well. If we still increase the threshold, we will reach the domain in which the distribution of the second quantity is not null. Then the FNR will begin to increase in the same way the cumulative distribution function of the second quantity does.

The area under the curve (AUC) is then a good indicator of the performance that can reach a binary classifier, and in our case of the separation of the two distributions. Indeed, if the AUC is equal to 0.5, this means that the classifier is not better than a random classifier and in our case that the distributions are exactly the same (both cumulative distribution functions always increase simultaneously). However, if the AUC gets closer and closer to 1 (or 0), this means that the distributions are more and more separated, with the value of 1 (or 0) corresponding to totally dissociated distributions.

¹In our context the 'positive' and 'negative' words do not have any interpretation but in other context they can for example correspond to true positively/negatively diagnosed person

Chapter 4

Results

The next step of this work is to analyse the results. This analysis is divided into different parts. Firstly, the learning indicators and the trajectories of the normal trials (as opposed to the catch trials) will be analysed. Afterwards, we concentrate ourselves on the catch trials. Finally, we will perform an inter-subjects analysis and see that all the participants do not learn as well.

4.1 Normal trials: general analysis

First, we only consider the normal trials of each subject. We compute for each subject and for each trial the different learning indicators presented in the previous chapter. For each condition (blue and red) in both experiments, the indicators are then averaged over the subjects to extract the global learning behaviour of this small sample of the population.

4.1.1 Hand path

The first thing to do to get a general insight about the learning behaviour is to look at the hand trajectories of the subjects in both experiments. For each of the two normal conditions (blue and red) of each experiment, the mean hand trajectories over the three first and three last trials of each subject are represented on figure 4.1a and b.

For both experiments, we clearly observe that the final part of the path is much more noisy in the first trials than in the last ones. This shows that subjects learn to better stabilise the hand-aligned cursor along the experiment. This could be due to the fact that subjects just get used to using the robot and understand better the “rules of the game” but it is not the case. Indeed, when they start with their second experiment (for one half of the subject it is experiment 1 and for the other half experiment 2) they face again the challenge to stabilise the cursor.

Secondly, it is easy to see that, in both experiments, the hand paths are still deviated for the last trials in the direction of the force field applied. Nevertheless, for most of the subjects, this deviation from the straight path is more present in the last trials from experiment 1 than it is in experiment 2. For the red conditions this may be due to the fact that the force field applied is lighter in experiment 2, but the difference in deviation is

also observed in the blue conditions, for which the forces applied are exactly the same in both experiments. We may then hypothesised that the learning in experiment 2 is bigger than the one in experiment 1, but this hypothesis has to be further explored.

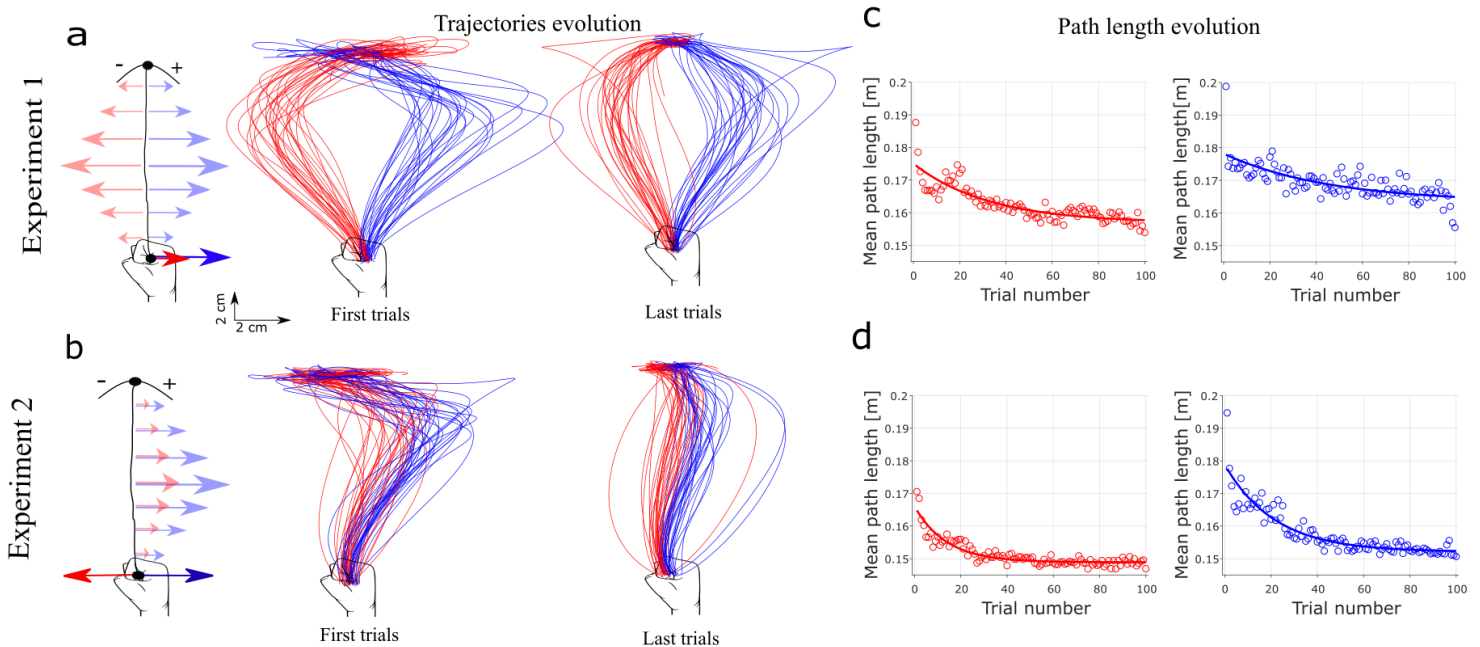


Figure 4.1: **Mean analysis of the normal trials: trajectories and path length:** **a**, schematic representation of the forces in experiment 1 (image on the left), mean trajectories for each subject ($n=29$) over their 3 first (image in the middle) and their 3 last (image on the right) trials in both the red and the blue conditions of experiment 1. **b**, same as **a** for experiment 2. **c**, evolution of the mean path length of the subjects across the normal trials in both the red (on the left) and the blue (on the right) conditions of experiment 1. The dots represent the mean path length over the subjects for a given trial, while the curve represents the result of the exponential fit on the data. **d**, same as **c** for experiment 2.

4.1.2 Path length

Now that we have looked at the hand paths and have made some hypothesis, we can try to find out if the subjects succeed in making the link between the force cues and the force fields by looking at the three learning indicators previously described.

The first one is the path length, and its evolution for experiment 1 and 2 can respectively be seen on figure 4.1 c and d. First, we observe that for the two conditions in both experiments, the path length decreases over the trials. This means that the subjects succeed in both experiments in making straighter and straighter trajectories and/or to stabilise more easily the cursor in the goal target. In experiment 1 the final path length is bigger than the one in experiment 2 which is aligned with what was observed when looking at the hand trajectories.

In order to have a more quantitative insight about the kind of decay that is observed, we try to fit exponential models to the data. Those fits are also shown on figure 4.1 c and d. To be able to define if the decays really follow exponential ones, typical of learning processes [23], we can perform t-tests to see if the exponent in the exponential model 3.3 is significantly different from zero. The t-test are done with 97 degrees of freedom (100 observations -3 parameters).

Parameter	Value	Standard error	t-stat	p-value
a	0.157	$1.01 \cdot 10^{-3}$	155	$< 10^{-117}$
b	0.0182	$1.11 \cdot 10^{-3}$	16.4	$< 10^{-29}$
c	0.0307	$5.72 \cdot 10^{-3}$	5.36	$< 10^{-6}$
a	0.163	$2.24 \cdot 10^{-3}$	72.8	$< 10^{-85}$
b	0.0149	$1.84 \cdot 10^{-3}$	8.13	$< 10^{-11}$
c	0.0220	$8.46 \cdot 10^{-3}$	2.60	0.0108

Table 4.1: **Experiment 1: mean path length exponential fit:** Parameter's values and standard errors, as well as results of the t-tests that evaluate if the model's parameters are significantly different from 0.

Parameter	Value	Standard error	t-stat	p-value
a	0.149	$2.43 \cdot 10^{-4}$	612	$< 10^{-175}$
b	0.0171	$9.48 \cdot 10^{-4}$	18.0	$< 10^{-32}$
c	0.0723	$6.90 \cdot 10^{-3}$	10.5	$< 10^{-16}$
a	0.152	$6.24 \cdot 10^{-4}$	243	$< 10^{-136}$
b	0.0267	$1.33 \cdot 10^{-3}$	20.0	$< 10^{-35}$
c	0.0463	$5.14 \cdot 10^{-3}$	9.00	$< 10^{-13}$

Table 4.2: **Experiment 2: mean path length exponential fit:** Parameter's values and standard errors, as well as results of the t-tests that evaluate if the model's parameters are significantly different from 0.

In table 4.1 and 4.2, we can see that all the parameters, in particular the exponent parameters 'c', are significantly different from zero (all the p-values are smaller than 0.5). This means that in both experiments, the path length exponentially decreases with the number of trials. It can be seen as a first indicator to let us think that the participants succeed in learning to make the link between the background load cues and the force fields, but it is not enough. Indeed, while an anticipation of the force fields would reduce the path length, the opposite is not necessarily true. The decrease in path length can also be due to a better control at the end of the movement thanks to an online modification of the feedback system. This does not require to reach optimal internal models and so to be able to anticipate the presence of the force fields thanks to the background load cues. It is also interesting to note that for both the red and the blue conditions the value of the parameter c is bigger in experiment 2 meaning that the decrease is faster in experiment 2 and maybe that the whole movement and not only the end of it is improved across trials. To confirm the significance of this hypothesis, further statistical tests have to be conducted.

4.1.3 Initial angle

Because the decrease in path length is not a sufficient criterion to conclude that there is learning, we look at the second learning indicator, i.e. the initial angle. As a reminder, the initial angle is computed as the angle α represented on figure 4.2 e. Its evolution for the two conditions in both experiments can be seen on figure 4.2 c and d.

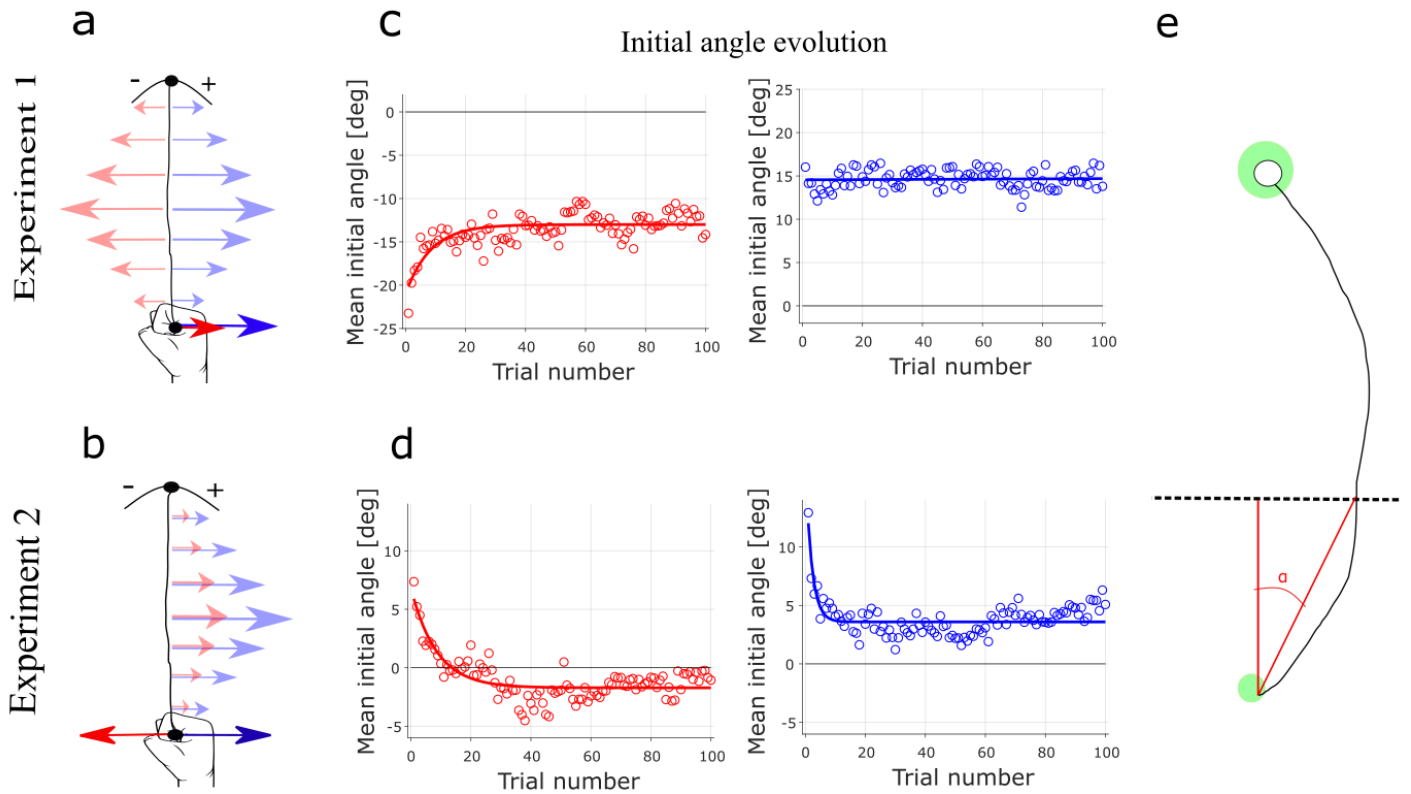


Figure 4.2: **Mean analysis of the normal trials: initial angle:** **a** and **b**, schematic representation of the forces in experiment 1 and 2. **c**, evolution of the mean initial angle over the subjects across the normal trials in both the red (on the left) and the blue (on the right) conditions of experiment 1. The dots represent the mean path length over the subjects for a given trial, while the curve represents the result of the exponential fit on the data. **d**, same as **c** for experiment 2. **e**, schematic representation of the way the initial angle is measured.

As expected, we observe for the first trials that, when the force field is counterclockwise, the initial angle is initially negative, while it is positive when the force field is clockwise.

In experiment 1, we can notice that for the red condition the initial angle increases a bit during the 4 first trials to get closer to zero but seems to stay relatively constant for the rest of the experiment. For the blue condition, it does not seem to evolve at all. These observations do not go in favour of an anticipatory behaviour in this experiment.

In experiment 2 however, in both conditions the evolution is more pronounced. Indeed, for both the blue and the red conditions the initial angle decreases towards zero but for the red condition it exceeds zero and stabilises around -2 degrees while for the blue condition it does not reach zero and stabilises around 4-5 degrees. This could be due to the fact that the participants do not succeed in making the distinction between the two conditions, and tend instead to adapt their internal model to an intermediate force field amplitude and use it for both conditions. Indeed, this would result in an overcompensation of the light force field and thus a negative initial angle in the red condition and in an under compensation of the heavy force field and so in a positive initial angle in the blue condition.

Again, to have a more quantitative insight about the evolution of this learning parameter, we fit an exponential model to the data in each condition of each experiment. Those fits are shown on figure 4.2 c and d. Again, 12 t-tests with each 97 degrees of freedom are performed (one per parameter for each condition and each experiment) to determine if the parameters are significantly different from zero. The results of those tests are given in table 4.3 and 4.4.

Parameter	Value	Standard error	t-stat	p-value
a	-13.0	0.170	-76.6	$< 10^{-87}$
b	-8.01	1.09	-7.34	$< 10^{-10}$
c	0.120	$2.43 \cdot 10^{-2}$	4.94	$< 10^{-5}$
a	-89.8	0.110	-819	$< 10^{-189}$
b	104	0.110	952	$< 10^{-195}$
c	$-1.30 \cdot 10^{-5}$	$3.88 \cdot 10^{-5}$	-0.335	0.738

Table 4.3: **Experiment 1: mean initial angle exponential fit:** Parameters's values and standard errors, as well as results of the t-tests that evaluate if the model's parameter are significantly different from 0.

Parameter	Value	Standard error	t-stat	p-value
a	-1.71	0.133	-12.9	$< 10^{-21}$
b	8.56	0.839	10.2	$< 10^{-16}$
c	0.117	$1.72 \cdot 10^{-2}$	6.83	$< 10^{-9}$
a	3.59	0.110	33.0	$< 10^{-53}$
b	13.7	2.54	5.39	$< 10^{-6}$
c	0.483	$9.97 \cdot 10^{-2}$	4.84	$< 10^{-5}$

Table 4.4: **Experiment 2: mean initial angle exponential fit:** Parameters's values and standard errors, as well as results of the t-tests that evaluate if the model's parameter are significantly different from 0;

We can see that all the parameters except the one corresponding to the exponent in the blue condition of experiment 1 are significantly different from zero. This was expected by looking at the graphs of figure 4.2, indeed there is no clear evolution of the initial angle in the blue condition of experiment 1. Moreover, if we try to fit an exponential model to the data corresponding to the red condition of experiment 1 from which we have removed the

4 first trials then we obtain an exponent coefficient 'c' that is not significantly different from 0 either (t-stat=1.64 and p-value=0.105). This means that the significance of the exponent coefficient is only due to the first 4 trials that may be biased by the fact that some subjects are surprised by the amplitude of the force and so have big difficulties in the first trials to perform the movement correctly. Aside from that, there is no clear evolution in the initial angle in experiment 1.

In experiment 2, we see that the parameter 'c', in the blue condition, is bigger than in the red one. This would mean that the possible adaptation that we observe happens faster in the blue condition of experiment 2 than in the red one (to confirm this, further statistical tests to compare the two parameters have to be performed). This may be explained by the fact that adaptation of the internal model is thought to be driven by the sensory prediction error [3]. Indeed, this error is smaller in the red condition because the force field is of low amplitude and the hand will then be less deviated. However, this explanation would imply that two distinct internal models are used for the blue and red conditions, which contradict our first hypothesis of the use of a single model optimal for an intermediate condition. Moreover, the change in initial angle is not necessarily due to a change in internal model. It may also be due to the adoption of a robust control strategy, resulting in an increase of control gain associated with muscle co-contraction [36]. There is then an increase in reaction to any kind of perturbation, partly due to a bigger importance given to the feedback loop compare to the feed-forward one.

4.1.4 Correlation

To further investigate learning, we can analyse the evolution of the third learning indicator: the correlation between two forces components. The first one is the x-component of the force applied by the subject on the robot, called measured force. The second one is the x-component of the one applied by the robot on the subject, called applied force. To help the visualisation we will look at and make the correlation with the opposite of the applied force. On figure 4.3 c and d the evolution of the mean correlation across trials is shown for both conditions in both experiments.

We can observe that in the four conditions, the correlation increases with the number of trials, meaning that applied and measured forces become more and more aligned with training. This finding can be linked to the fact that the subjects succeed in anticipating the force field that is going to be applied. However, because the correlation is measured on the whole length of the trial, it may also be due to an online adaptation of the feedback control that enables the alignment of the forces at the end of the trial.

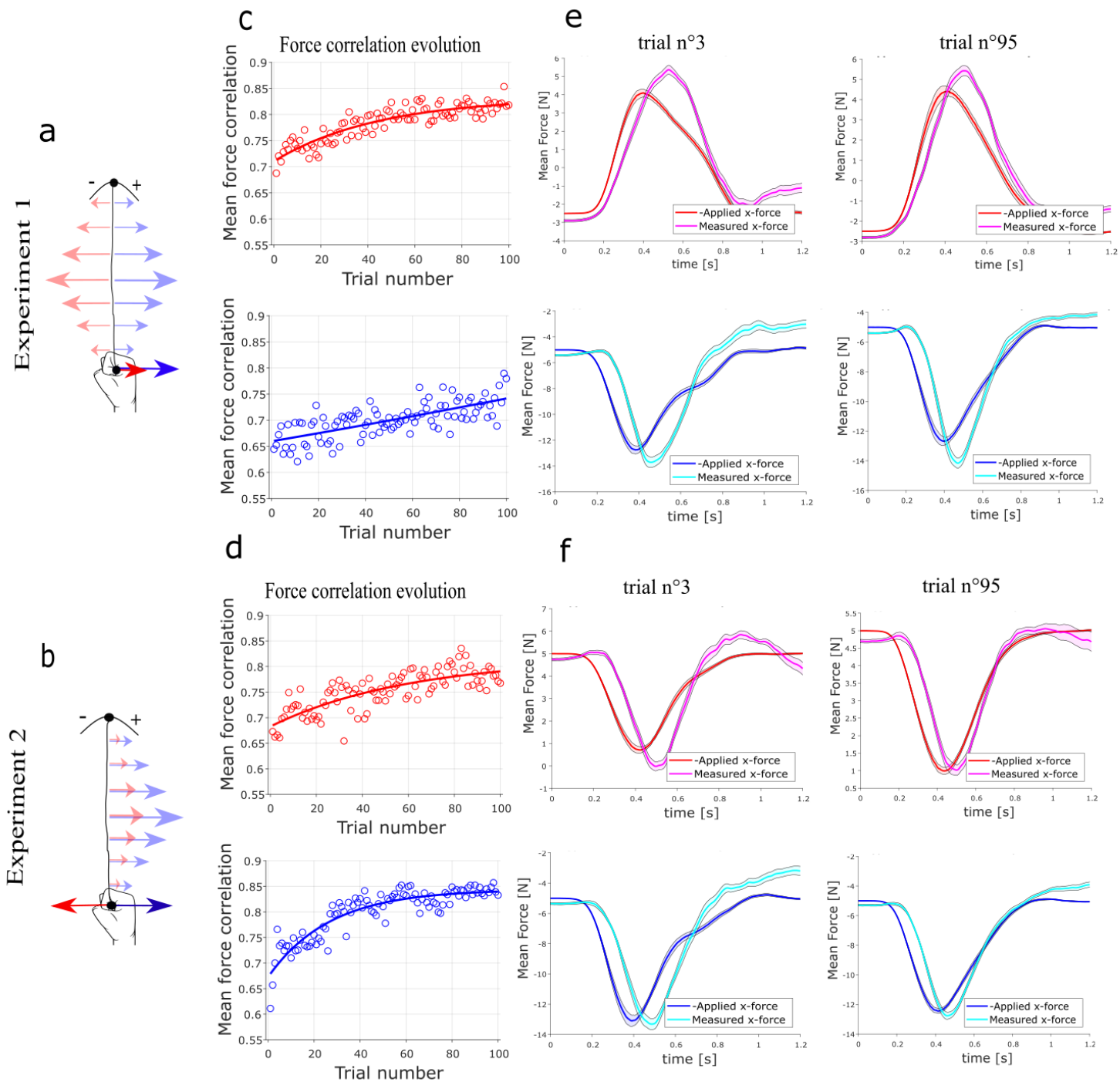


Figure 4.3: **Mean analysis of the normal trials: Correlation** : **a** and **b**, schematic representation of the forces in experiment 1 and 2. **c**, evolution of the mean correlation over the subjects across the normal trials in both the red and the blue conditions of experiment 1. The dots represent the mean path length over the subjects for a given trial, while the curve represents the result of the exponential fit on the data. **d**, same as **c** for experiment 2. **e**, Representation of the opposite of the mean applied force on the hand of the subjects and the mean measured compensatory force exerted by the subject on the handle for the third (on the left) and the 95th trial (on the right) and for both the red (on the top) and the blue (on the bottom) conditions of experiment 1. **f**, same as **e** for experiment 2

To better understand the evolution of the correlation, we can look at the change in alignment of the x-component of the measured and the opposite of the applied forces between the beginning and the end of the experiment. On figure 4.3 e and f, we can see the means as well as the standard errors of both measured force and the opposite of the applied force in each of the 4 conditions. These representations are made for one of the first and one of the last trials.

We clearly see an evolution in the alignment of the forces in the four conditions. This improvement in alignment is even more pronounced in experiment 2, where during the second half of the last trials, the two forces are nearly perfectly aligned. In the first half, however, even if there may be a small decrease in the delay between the two forces, this delay does not disappear. This observation goes in favour of an improvement in the online feedback control that can or not be accompanied of a kind of improvement of the internal model. It is also interesting to notice that while the amplitude of the peaks of both forces perfectly matches in the last trials of both conditions in experiment 2, it is not the case in experiment 1 where the peak of the applied force is systematically bigger.

Like for the two other learning parameters, we fit an exponential model to the data in each condition of each experiment and show those fits on figure 4.3 c and d. Again, 12 t-tests with 97 degrees of freedom are performed to determine if the increases in correlation are really exponential. The result of those tests are displayed in table 4.5 and 4.6.

We can see that the only evolution of correlation that does not follow an exponential curve is the one corresponding to the blue condition in experiment 1. When looking at the data, it indeed seems that the correlation increases linearly with the number of trials instead of exponentially. Similarly to the initial angle, the increase in correlation seems faster in the blue condition of experiment 2 than it is for the red conditions. This can be seen by observing that the parameter 'c' is bigger for the blue condition of experiment 2. Again, the reason might be that the sensory prediction error is smaller in the red conditions, decreasing the learning speed in those conditions. This will be further analysed in the next section.

Parameter	Value	Standard error	t-stat	p-value
a	0.832	$9.41 \cdot 10^{-3}$	88.4	$< 10^{-93}$
b	-0.122	$7.76 \cdot 10^{-3}$	-15.7	$< 10^{-27}$
c	$2.25 \cdot 10^{-2}$	$4.52 \cdot 10^{-3}$	4.98	$< 10^{-5}$
a	$3.17 \cdot 10^{-2}$	4.03	$7.86 \cdot 10^{-3}$	0.994
b	0.628	4.03	$1.56 \cdot 10^{-1}$	0.876
c	$-1.23 \cdot 10^{-3}$	$7.91 \cdot 10^{-3}$	-0.155	0.877

Table 4.5: **Experiment 1: mean correlation exponential fit:** Parameter's values and standard errors, as well as results of the t-tests that evaluate if the model's parameters are significantly different from 0.

Parameter	Value	Standard error	t-stat	p-value
a	0.816	$2.50 \cdot 10^{-2}$	32.6	$< 10^{-53}$
b	-0.133	$2.07 \cdot 10^{-2}$	-6.42	$< 10^{-8}$
c	$1.66 \cdot 10^{-2}$	$6.58 \cdot 10^{-3}$	2.53	$1.31 \cdot 10^{-2}$
a	0.844	$5.64 \cdot 10^{-3}$	150	$< 10^{-115}$
b	-0.171	$8.45 \cdot 10^{-3}$	-20.3	$< 10^{-35}$
c	$3.74 \cdot 10^{-2}$	$4.88 \cdot 10^{-3}$	7.66	$< 10^{-10}$

Table 4.6: **Experiment 2: mean correlation exponential fit:** Parameter’s values and standard errors, as well as results of the t-tests that evaluate if the model’s parameters are significantly different from 0.

Now that we have analysed all the learning indicators for the normal trials, we can already make some assumptions. In experiment 1, it seems like the anticipation is difficult and the only improvement that occurs is at the end of the path, mainly in the stabilisation of the cursor in the target. Indeed, there is no clear evolution of the initial angle (except maybe for the 4 first trials in the red condition). Moreover, the decrease in path length as well as the increase in correlation may result from the better ability to control the end of the trajectory and to stabilise the cursor in the target, which is not linked to any kind of anticipation. The learning seems to only take place in the online improvement of the feedback control at the end of the trial, and not in an adaptation of two different internal models for each condition.

In experiment 2, it however seems that the participants may, in addition to improving the feedback control, adapt their internal model. This adaptation seems to be made in order to take into account an intermediate condition with a force field of medium size. This hypothesis of the unique model has to be further deepened, as we also noticed that the rate of learning in both conditions seemed to be different. Now, no test, to quantify this difference, were done yet.

4.1.5 Mixed model

To confirm or reject the hypothesis about the unique internal model that might be used in experiment 2, we can fit a linear mixed-effect model to the evolution of the indicators. As a reminder, the chosen model has the form:

$$y_{ij} = a + b \cdot i + c \cdot \text{type} + d \cdot i \cdot \text{type} + s_j + \epsilon_{ij}$$

where ' y_{ij} ' is the learning indicator for subject 'j' at trial 'i', 'type' is the trial type (red or blue condition), s_j are independent random variables representing the random effect and ϵ_{ij} are independent normally distributed error terms.

The value of the found parameters as well as the results of the t-tests (with 5537 degrees of freedom) are displayed in table 4.7 for the three indicators. We can clearly see that all the parameters in the mixed linear model are significantly different from zero. The parameter that mostly interest us is 'd'. Indeed, the fact that it is significantly different from zero means that the fitted curves do not have the same slope for the red and the blue conditions for the three indicators. This means that according to this linear approximation, the mean

learning does not follow the same time course in the blue and the red conditions. This can not directly be interpreted as the use of different internal models for the two conditions by all the subjects. Indeed, there may also be distinct groups in the population that adapt differently.

Indicator	Parameter	Value	Standard error	t-test	p-value
Path length	a	0.162	$8.95 \cdot 10^{-4}$	181	$< 10^{-3}$
	b	$-1.49 \cdot 10^{-4}$	$4.79 \cdot 10^{-6}$	-31.1	$< 10^{-3}$
	c	$7.57 \cdot 10^{-3}$	$3.92 \cdot 10^{-4}$	19.3	$< 10^{-3}$
	d	$-6.19 \cdot 10^{-5}$	$6.77 \cdot 10^{-6}$	-9.14	$< 10^{-3}$
Initial angle	a	2.24	0.696	3.21	$1.30 \cdot 10^{-3}$
	b	$-1.30 \cdot 10^{-2}$	$2.73 \cdot 10^{-3}$	-4.76	$< 10^{-3}$
	c	2.13	0.223	9.56	$< 10^{-3}$
	d	$2.27 \cdot 10^{-2}$	$3.86 \cdot 10^{-3}$	5.89	$< 10^{-3}$
Correlation	a	0.715	$1.22 \cdot 10^{-2}$	58.8	$< 10^{-3}$
	b	$1.20 \cdot 10^{-3}$	$5.43 \cdot 10^{-5}$	22.1	$< 10^{-3}$
	c	$2.30 \cdot 10^{-2}$	$4.44 \cdot 10^{-3}$	5.18	$< 10^{-3}$
	d	$2.18 \cdot 10^{-4}$	$7.69 \cdot 10^{-5}$	2.84	$4.60 \cdot 10^{-3}$

Table 4.7: **Experiment 2: mixed model fit:** Parameter’s values and standard errors as well as result of the t-tests that evaluate if the model’s parameters are significantly different from 0

By deepdiving into the individual data of each subject, we can observe that there are in fact two different behaviours for the evolution of the initial angle in the blue condition, as shown on figure 4.4.

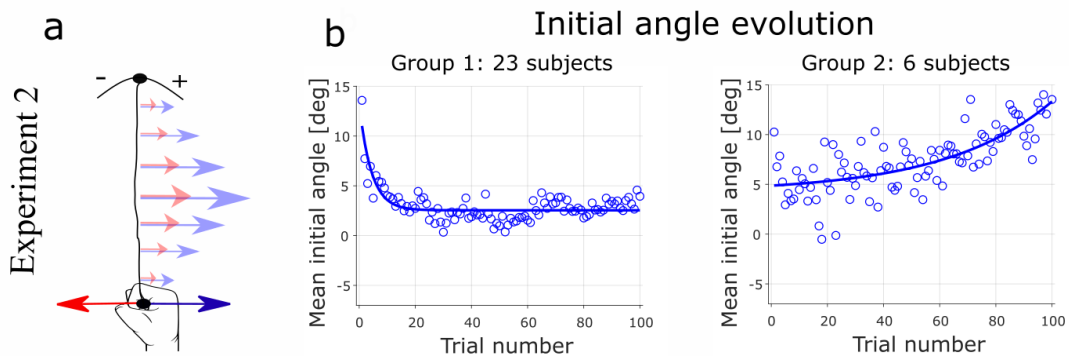


Figure 4.4: **Experiment 2: Inter-individual difference in the evolution, across the normal trials, of the mean initial angle in the blue condition :** a, schematic representation of the forces in experiment 2. b, evolution of the mean initial angle across the normal trials in the blue condition for a subgroup of subjects (n=23) on the left and the rest of the subjects (n=6) on the right. The dots represent the mean path length over the subjects for a given trial, while the curve represents the result of the exponential fit on the data.

We clearly see that, while the initial angle of group 1 (23 subjects) decreases to get closer to 0, the evolution goes in the other direction for group 2 (6 subjects) with an increase of the initial angle with the trial number. The evolution of this same indicator in the red condition, as well as the ones of the other parameters in both conditions, are qualitatively the same in both groups.

If we now perform a new mixed model fitting on the data of group 1, we obtain that the trial-type interaction coefficient 'd' is not significantly different from 0 for both initial angle and correlation (p-value of 0.309 and 0.136 respectively) while the other coefficients are still significantly different from 0. This means that for this group of subjects, the rate of evolution of both initial angle and correlation in both red and blue conditions are not significantly different. So, this may go in the direction of our hypothesis to say that most people seem to use a unique internal model that is optimal for a medium force field.

The fact that the trial-type interaction coefficient 'd' for the path length is significantly different from zero and thus that its speed of evolution is not the same in both conditions might be due to two things. The reason might be that the data are too noisy or too complex and the linear model do not capture well their behaviour. But it may also be due to the fact that the path length is mostly impacted by what happens at the end of the trial (for example, the decrease in overshoot). At that moment people may be able to recognise the amplitude of the force field and adapt the feedback controller online as already observed in [27].

In group 2, the situation is however very different. As the initial angle increases in the blue condition and still decreases in the red one, they can clearly not have a parallel evolution. The increase in the initial angle, in the blue condition, may be due to the use of an explicit strategy adopted by those participants. Indeed, 4 of the 6 subjects in this group explicitly reported (even if it was not asked) that they used the following strategy : When the force field was large, they let themselves be dragged by the forces and only applied a big compensating force at the end of the trial to be able to reach the target. It would then be interesting for further studies to explicitly take into account this factor by asking all the participants if they use explicit strategies or not (which was not done in this study). For now, it is hard to make a conclusion for this group based on the mixed model but if they indeed use an explicit strategy, it does not exclude the fact that they also have a same internal model for both conditions.

4.2 Catch trials: general analysis

Until now, none of the analysis done could conclude with certainty that there was or that there was no anticipation of the force field. Indeed, the evolution of the learning parameters could each be linked to another learning mechanism than the building and the continuous adaptation of two internal models that allow anticipation. Looking at the catch trials will remove the doubt we can still have. Indeed, if there is an adaptation of the internal models, then there should be noticeable after-effects, after the perturbation is removed i.e. in catch trials. If we succeed, for example, in anticipating a force field to the right and to compensate for it from the start of the trial, then in catch trials we would also apply a stronger force to compensate. This would result in a deviation to the left of the hand path from the straight path.

4.2.1 Hand path

Similarly to the normal trials, we will first look at the hand path to get a first insight into what happened. On figure 4.5 a and b we can observe, for both conditions of the two experiments, the mean hand path of all the subjects over the three first and three last trials.

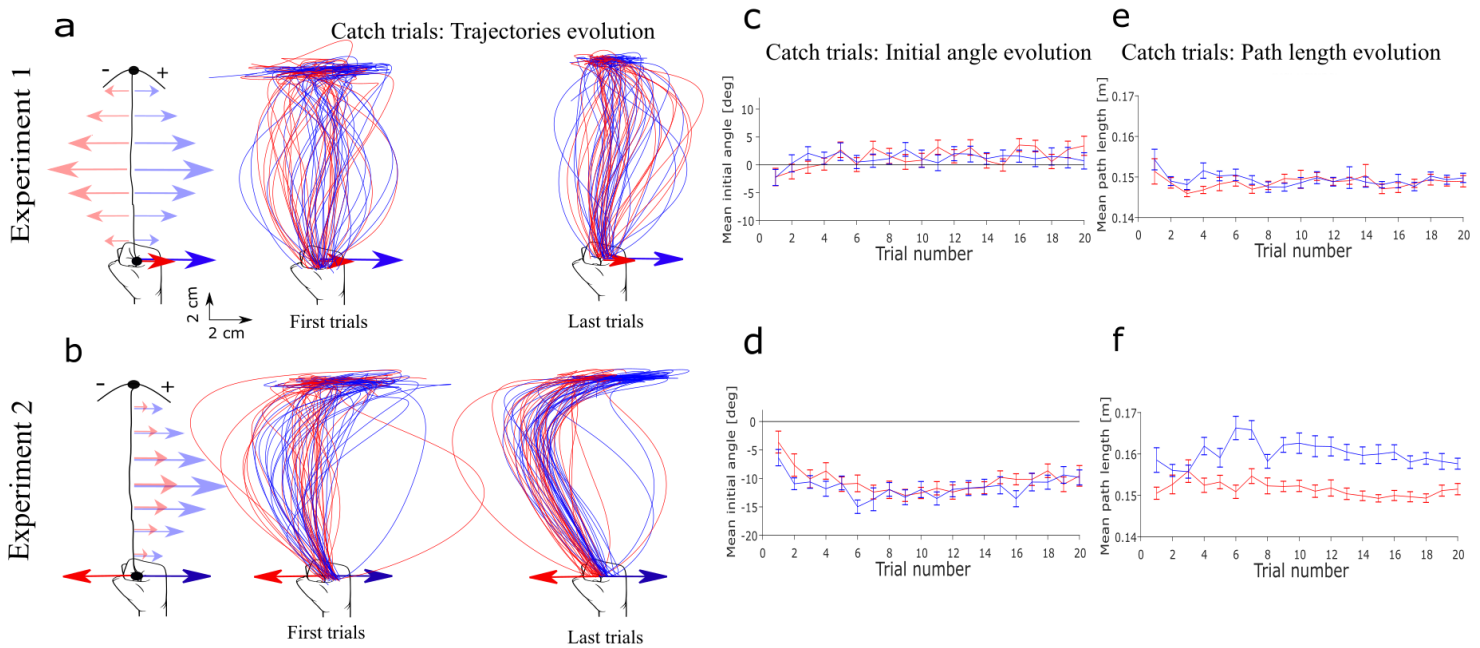


Figure 4.5: **Mean analysis of the catch trials: trajectories, initial angle and path length:** **a**, schematic representation of the forces in experiment 1 (image on the left), mean trajectories for each subject ($n=29$) over their 3 first (image in the middle) and their 3 last (image on the right) catch trials in both the red and the blue conditions of experiment 1. **b**, same as **a** for experiment 2. **c**, evolution of the mean initial angle over the subjects across the catch trials in both the red and the blue conditions of experiment 1. The mean over the subjects as well as the standard error is represented. **d**, same as **c** for experiment 2. **e**, same as **c** for the path length. **f**, same as **d** for the path length.

For experiment 1, the paths in the red and blue conditions seem totally intertwined, whether we look at the first or last trials. There is no clear trend to observe, the path is sometimes deviated to the left, sometimes to the right. There is no obvious difference between the catch trial paths from the beginning and from the end of the experiment, with the exception that it becomes easier for the subjects to stabilise their cursor in the goal target liked it was already observed for the normal trials. There is also no clear visible difference between the paths made in the blue or in the red conditions. This is an indicator that there is no persistence of after-effect, and so no continuous modification of two distinct internal models that would then allow the subjects to anticipate the force field. Indeed, if at the end of the experiment, subjects used two optimal internal models, we would observe different effects for the two different conditions. For the catch trials of the blue condition, we would observe that the path is deviated to the left because the

force field is supposed to be to the right. In the same way, for the catch trials of the red condition, the path would be deviated to the right because the force field is supposed to be to the left. This is not the case here, allowing to reinforce the hypothesis that the subjects do not make the link between the background load cues and the force fields and so do not succeed in anticipating in experiment 1. However, it does not exclude that they succeed in adapting their feedback control to the force field online. Indeed, this would create small after-effects in each trial, but that counterbalance themselves as they will be sometimes to the left and sometimes to the right. This is due to the fact that the mean force field applied is of magnitude 0 N.

For experiment 2, we see that in the first trials and the red condition, the paths are for most subjects straight and in the blue condition they do a kind of 'S' upside down shape. In both conditions, in the last trials, the path is deviated to the left with a bigger maximal deviation than the one observed in the first trials. This is, at least, the case for almost all the subjects. This is an after-effect. Indeed, in the first few trials when they have not yet succeeded in adapting entirely their internal model, the subjects make straighter paths. However, at the end of the experiment, they will use their adapted internal model(s) to compensate for the normally present force field. This compensation will translate in a deviation of the hand path to the opposite direction of the normally present force field, i.e. here to the left. And this is what we indeed observe here, reinforcing the belief we had about the possible adaptation that occurs in experiment 2.

We hypothesised by looking at the normal trials that there was adaptation of the internal model, but to an intermediate condition with a medium-sized force field to the right. This hypothesis is also reinforced by looking at the catch trials because the blue and red hand paths are inter-winded in the last trials. Subjects compensate as much when there is supposed to be the light force field than when it is supposed to be the heavy one. This makes us think that the subjects do not succeed in extracting the force field magnitude from the cue.

4.2.2 Learning indicators

Like for the normal trials, we can also compute some learning indicators for the catch trials. We will again use the initial angle and the path length, the correlation is however not calculated since there is no applied force field. The evolution of the mean and the standard error of the two computed indicators for both conditions in both experiments are shown on figure 4.5 c and d for the initial angle and e and f for the path length.

For experiment 1 the mean initial angle in the blue and the red conditions always stays roughly the same and around zero degree, i.e. there is no after-effect.

In addition, the mean path length always stays roughly the same and smaller than 15 cm in both conditions. This means that the hand path stays relatively straight, as a perfectly straight path measures 13.2 cm ¹.

¹It is calculated as the distance between the centre of the start and goal target (15 cm) minus the radius of both targets (0.6 cm + 1.2 cm)

In experiment 2 the mean initial angle also stays roughly the same in both conditions, but this time it reaches -10 degrees after the 5 first catch trials. This confirms again that there is an after effect, but it is the same for both conditions, i.e. we think that it is the result of a common internal model for both conditions.

The mean path length in experiment 2 is not the same for both conditions. When looking back at the hand path on figure 4.5 a and b, it seems that it is mainly due to the fact that in the blue condition, the cursor exceeds the target before reaching it. It is so due to a problem of stabilising the cursor at the end of the trials, and not linked to any kind of anticipation.

The analysis of the catch trials allowed us to confirm our hypothesis that there is no continuous adaptation of the internal model in experiment 1, while in experiment 2 subjects adapt a same internal model to reach one that is optimal for a medium-size force field.

4.3 Individual analysis

Most of the studies done on adaptation or learning consider the mean learning behaviour of a group of subjects, and it is also what we have done in this work so far. However, every teacher would agree that there is not a single way to learn and that the learning processes vary a lot between individuals. Moreover, until now we concluded that for both experiments, the subjects could not build different motor memories thanks to the given cues. But this does not mean that no subject can do so. To investigate if there exist differences between individuals in the experiment of this work, and to see if some of them succeed in building different motor memories, we decided to perform an individual analysis, and tried to separate subjects in different groups in function of how well they learn.

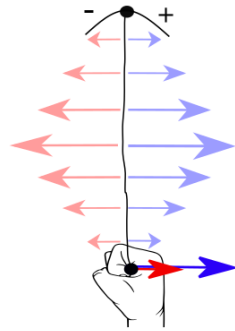
4.3.1 Separation of the subjects in learning groups

To investigate the inter-individual differences in learning, we look at the best indicator of internal model adaptation that we have, i.e. the presence or not of an after-effect in the catch trials by looking at the initial angle. For both experiments, we then plot the final initial angle of each subject in the blue condition against the one in the red condition. The graph obtained for experiment 1 and 2 are respectively shown on figure 4.6 b and d.

In experiment 1 we can see that for most of the subjects, the final initial angle in the blue and the red conditions is approximately the same. Most of the points ($n=25$) on the graph, each representing a subject, fall around the line $x=y$ and are then circled in red. Moreover, most of them are located close to the point $(0,0)$, namely 16 on 30 points are located in the square of edge's half-length corresponding to 5 degrees centred in zero and 20 on 30 in the square of edge's half-length corresponding to 7 degrees and centred in 0.

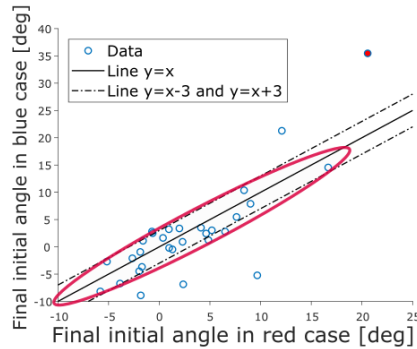
Experiment 1

a



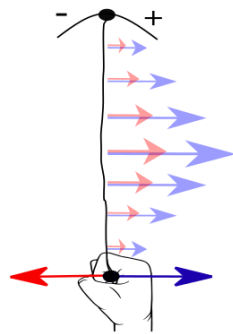
b

Catch trials: Classification of subjects



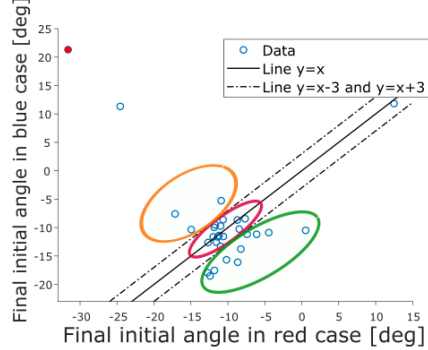
Experiment 2

c



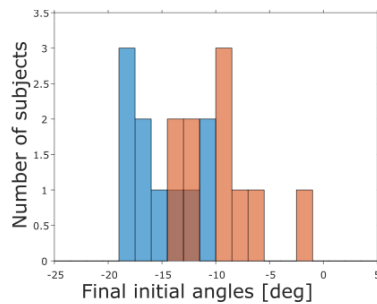
d

Catch trials: Classification of subjects



e

Catch trials : distribution
green group



f

Catch trials: Evolution of the indicators

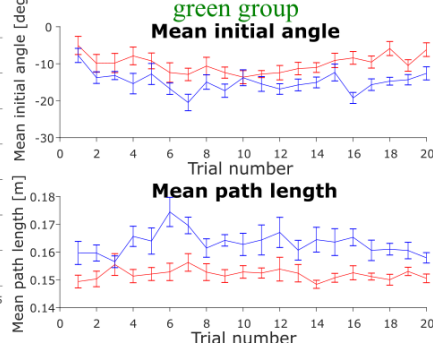


Figure 4.6: Separation of the subjects in different learning groups according to their catch trials: a, schematic representation of the forces in experiment 1. b, graphic of the mean initial angle across the three last catch trial in the blue condition against the one in the red condition. Each dot represents a subject. Most of the subjects have the same initial angle in both conditions and are circled in red. c, schematic representation of the forces in experiment 2. d, same as b for experiment 2. This time the subjects are divided in three different groups that are circled in orange (n=3), green (n=10) and red (n=14) as they have different learning behaviours. e, histogram representing the distribution of the mean initial angle of the three last catch trials in both the red and the blue condition of experiment 2 for the subjects that were in the green group of figure d. f evolution of the mean initial angle (top) and of the mean path length (bottom) of the subjects that were in the green group of figure d across the catch trials in both the red and the blue conditions of experiment 2.

On figure 4.6 d we can see that for experiment 2 the situation is a bit different. We observe mainly three groups of subjects.

First, the subjects with the data points circled in red (14 subjects) seem to have around the same final initial angle in the red and blue conditions. This angle is around -10 degrees, i.e. their hand path is deviated to the left in both conditions. This corresponds to an after effect of an internal model that is optimal for a medium-size force field to the right, like already explained in the general analysis. The conclusion for those subjects seems to be the same as the one that was made for the 'mean subject' in the previous section. Indeed, if we try to again fit the same linear mixed-effect model as in section 4.1.5 to the data, we obtain an interaction coefficient between the trial number and the type which is not significantly different from zero for both the initial angle and the correlation (p-value of 0.0606 and 0.401 respectively). In fact, there are two subjects in this red group that also belong to the group that we think uses an explicit strategy. If we remove them before fitting the model, the coefficient for the initial angle is even less significantly different from zero. Moreover, the subjects of this red group show a decrease in path length, an increase in correlation and a decrease in initial angle towards 0 (the graphs are not shown here). However, similarly to the analysis of the 'mean-subject', the initial angle decrease stops before reaching zero in the case of the heavy force field and exceeds 0 degree in the case of the light one. It is then relatively reasonable to think that this group indeed uses a common internal model for both conditions, but may adapt their feedback control online at the end of the movement.

The subjects corresponding to the points circled in orange (3 subjects) have an initial angle that is smaller in absolute value in the last trials of the blue condition than in the ones of the red condition. This means that they associate the cue to the right (blue condition) to a lighter force field than the cue to the left (red condition) while it is in reality the opposite. This kind of phenomenon was already observed by Crevecoeur et al. [21] when they tried to use light and heavy background loads to respectively help to predict light and heavy force fields. But the reason why some people do that is not yet understood, and because this group represents a minority of subjects, we will concentrate ourselves on the other groups.

The last group of subjects is the one corresponding to the data points circled in green (10 subjects). The subjects of this group have a negative initial angle that is smaller in absolute value in the last trial of the red condition than in the one of the blue condition. This means that the hand path of those subjects is always deviated to the left, but the deviation is bigger when the force field was supposed to be bigger. Those subjects compensate from the start of the trials more when the cue is the one of the heavy force field than when it is the one of a light force field. We can then hypothesise that one third of the subjects succeed in making the link between the background load cues and the force fields thanks to the construction of different internal models.

There are three subjects that are not in any groups. The point in red (in both figures 4.6 b and d) corresponds to the subject that was removed from the general analysis because this person is an outlier, and these images show that is indeed the case. The two other points correspond to subjects who seem to be outliers in this precise analysis. We however

do not have enough proof to remove them entirely, as they present normal behaviours in other kinds of analysis.

4.3.2 ROC analysis

To confirm the hypothesis that one third of the subjects learn the link between cues and force fields in experiment 2 we can go a bit deeper in the analysis. First, the separation of the subjects in groups as well as the hypothesis are made using a visual criterion. To have a stronger argument to confirm the learning of the individuals in the green group, we perform a ROC analysis. If the distributions of the initial angle in the catch trials of the blue and red conditions in this group of subjects are really different, then it should be easy to separate those angles in their respective conditions thanks to a binary classifier. The histogram of those distributions is shown on figure 4.6 e.

The area under the ROC for experiment 2 is 0.88. As a control we have also calculated the area under the curve for experiment 1 which is given by 0.525. This shows that whereas in experiment 1 the initial angle in the catch trials are hard to dissociate in their respective condition groups, for experiment 2 the classification is a lot easier. This results from the fact that in experiment 1 the initial angles in both conditions have strongly overlapped distributions, while in experiment 2 they are relatively distinctly distributed.

4.3.3 Analysis of the learning indicators for the subjects who adapt

We have identified a subgroup in our sample which seems to build an internal prior about the force fields thanks to the presented cues in experiment 2. We can now make the same analysis as the one done on the whole set of subjects in the previous section, but this time taking only the subgroup of subjects corresponding to the data circled in green on figure 4.6 d.

Catch trials

On figure 4.6 f we can observe the evolution of the mean initial angle and the mean path length in the catch trials. We can see that both indicators are different in the blue and the red conditions. In the red condition, the initial angle is smaller in absolute value, the path is then straighter and the path length smaller. In the blue condition the initial angle is bigger in absolute value, the path is more deviated and the path length is then bigger. This is what is expected for people with a prior about the force fields, and so of people who have adapted two different internal models.

Normal trials

On figure 4.7 we can observe the evolution of the three learning indicators for both conditions in the normal trials. Like it is expected for subjects who learn, there is a decrease

in path length and an increase in correlation across trials in both conditions. The initial angle decreases to reach a value close to zero, and so to make straighter hand paths.

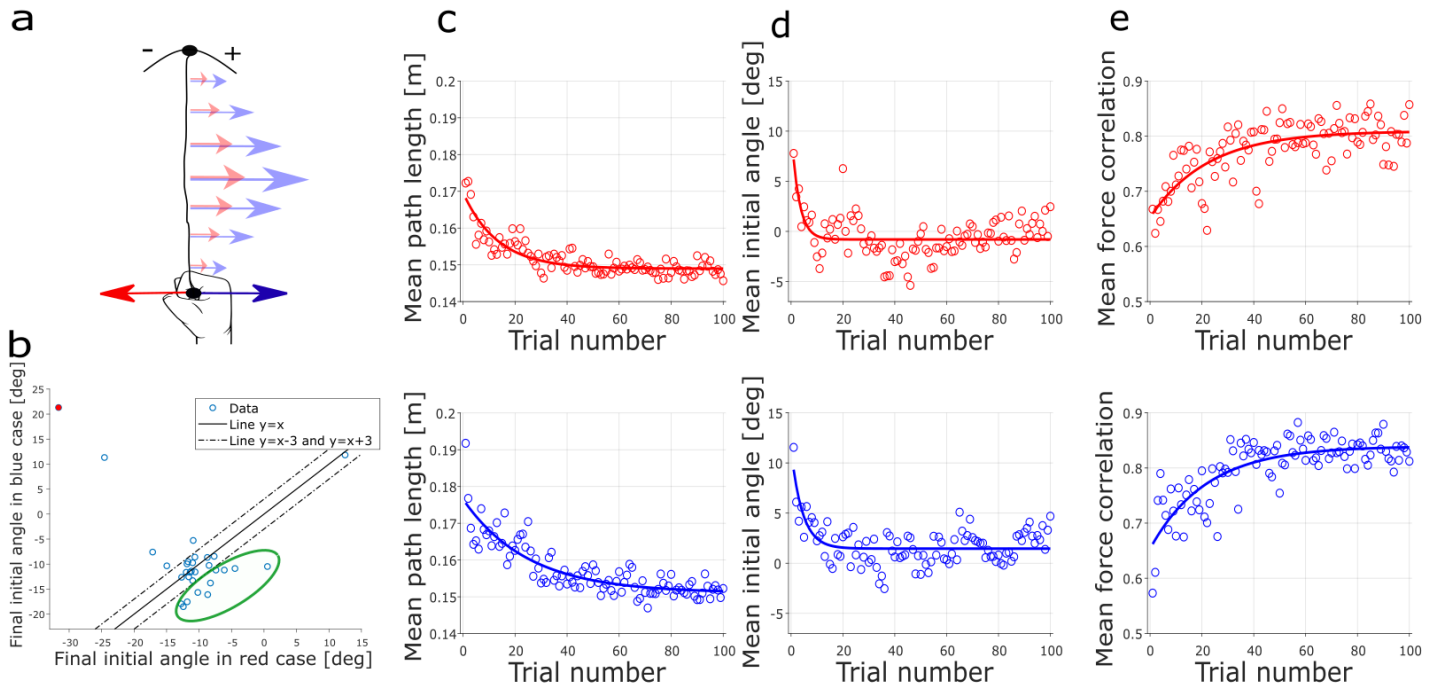


Figure 4.7: **Experiment 2: Analysis of the normal trials for the subgroup of the sample with subjects who adapt:** **a** Schematic representation of the forces in experiment 2. **b** graphic of the mean initial angle across the three last catch trials in the blue condition against the one in the red condition. Each dot represents a subject, and the dot circled in green are the subjects for which the behaviour is analysed in this figure. **c**, **d** and **e** show respectively the evolution of the mean path length, the mean initial angle and the mean correlation over the subjects circled in green ($n=10$) in image **b** across the normal trials in both the red (on the top) and the blue (on the bottom) conditions of experiment 2. The dots represent the mean of the indicators over the subjects for a given trial, while the curve represents the result of the exponential fit on the data.

To quantify the evolution of the indicators, we fitted an exponential model to the data. The resulting curves can be seen on figure 4.7 c, d and e. T-tests were performed to verify if the fitted curves are indeed exponential curves like we would expect for learning behaviours. The results of those tests (not shown here) show that all the parameters are significantly different from 0 meaning that the curves are indeed exponential ones.

Chapter 5

Discussion

In this section, we will look back at the results and put them into context of the current literature to see what they imply. Moreover, we will, of course, try to give an answer to the question for which this work was made: Where does the interferences observed by Crevecoeur et al. [21] in their article “*Separability of Human Motor Memories during Reaching Adaptation with Force Cues*” come from?

5.1 Experiment 1

The first experiment was designed to determine if the magnitude of background forces could be used as a cue to enable the formation of distinct motor memories when they are uniquely associated to force fields of different directions. It has been shown that the adaptation to two force fields of opposite directions is possible if subjects are given adequate cues. The design of experiment 1, where the force fields are of different directions and the background load cues of same direction but different magnitudes, enables to determine the efficacy of background loads that only differ by their magnitudes as cue to enable dual learning.

Three learning indicators (the path length, the initial angle and a measure of force’s correlation¹) were used to determine the extent of the adaptation that was possible in the context of experiment 1. The path length was shown to decrease across trials, the initial angle to stay rather constant, and the correlation to increase. Knowing that the initial angle does not change much (except during the first 4 trials) and by looking at the hand trajectories of the subjects, it seems that the decrease in path length is mainly due to an improvement of control at the end of the trials. Indeed, the main improvement seems to be the better ability to stabilise the cursor in the target without overshoot.

The results obtained in this experiment are very similar to the ones observed by Crevecoeur et al. [27] when they exposed subjects to totally unpredictable force fields. They asked subjects to perform blocks of 60 trials where 10 or 20 of them were perturbed with force fields of different directions. They concluded that there was no anticipation of the force fields because as force fields in the two opposite directions were randomly mixed, the

¹the correlation is computed between the x-component of the opposite of the force applied by the robot on the hand of the subjects, and the x-component of the force applied by the subjects and measured by the KINARM.

estimate of the force field in the experiment is in average zero. However, participants succeed in adapting their feedback controller online. Because this adaptation is possible thanks to the knowledge of the perturbation measured through feedback during the trial, it takes some time to have a non-negligible impact. It is the motor execution that enables the formation and recall of distinct internal models.

In our experiment, a similar conclusion can be made. Indeed, as there is no clear change in the initial angle, there does not seem to be any anticipation of the force fields. However, the decrease in path length and the increase in correlation indicate that there is still an improvement that occurs. This improvement may be due, like in [27], to the adaptation of the feedback controller online.

The observations of the catch trials also go into the direction of that conclusion. The trajectories made in both force fields were intermingled, the initial angle of those trials stays in the whole experiment around 0 degree and the path length around 0.15 m, i.e. quite small. This means that for every trial there is no anticipated force field. This is aligned with what was concluded. Indeed, even if there may be an adaptation of the internal model online and so a small after-effect in the following trial, because the force fields go in both directions, the total consequence is an estimate of the force field approximately null and so no deviation from the straight path is observed in the catch trials.

Because subjects do not succeed in anticipating the force fields thanks to the given cue and seem to only rely on an online adaptation of the feedback controller, using background forces of different magnitudes as cue to enable dual learning, seems rather inefficient. This means that even though it has been shown that the magnitude of externally applied forces is encoded in the brain [37] and used for control, it does not seem to be an information that plays a role in this kind of adaptation. What enables dual learning when using background loads of different directions may be the fact that they require activation of different muscles, which is not the case for background loads that only differ by their magnitudes.

5.2 Experiment 2

The second experiment aims to determine if the simultaneous adaptation to two force fields in the same direction, but different magnitudes, is possible if each force field is uniquely associated to adequate cues. Background loads of different directions were then used as cue because they have been shown to enable the formation of distinct motor memories [21].

In this experiment, the results are more nuanced. Indeed, it seems to have different learning behaviours in the population. The first group of individuals includes the majority of the subjects, who seem to be unable to learn to anticipate the magnitude of the force fields in that timescale. Those subjects seem to adapt a unique internal model to a medium size force field and use this model for both the heavy and the light force field, as was already observed in [38]. Indeed, subjects in this group show a decrease in path length, an increase in correlation and a decrease in initial angle towards 0. However, the initial angle decrease stops before reaching zero in the case of the heavy force field and exceeds 0 degree in the case of the light one. Moreover, the catch trials show clear signs of the presence of

after-effects. Indeed, in those trials, the hand path is deviated to the left while the force field is always supposed to be to the right. However, there is no clear differences between the catch trials with the two different cues. The fact that those subjects only use a single internal model for both force fields does not mean that they do not adapt their feedback controller online like it is done in experiment 1. This hypothesis is supported by the fact that the evolution of the path length in the two different conditions (light or heavy force fields) is not parallel. Indeed, a mixed-effect linear model was fitted to the time-course of the learning indicators. This model included an interaction term between the context and the trial number, which was significantly different from 0 for the path length.

The second group, the smallest one, includes subjects that have a behaviour similar to the one that was observed by Crevecoeur et al. [21] when they used background loads of different magnitudes as cues for force fields of different magnitudes. Those subjects show bigger after-effect for catch trials with the cue associated to the light force field. This means that the internal prior about the force field associated with the cue corresponding to the heavy force field was lighter than the one for the cue associated to the light one. The reason why some people adopt this behaviour and the link with interferences is still not totally understood, and further researches have to be done.

The third group includes one third of the participants that seem to succeed in forming distinct motor memories for the two different force fields. Those subjects show a decrease in path length, an increase in correlation and a decrease in initial angle towards 0. Moreover, they have catch trial's initial angle that become bigger in absolute value when the clue is the one of the heavy force field than when it is the one of the light one. This means that the subjects succeed in making the link between the clue and the force fields, and that it is possible to simultaneously adapt to two environments with force fields that differ by their magnitudes.

Aside from this separation of subjects in those three groups, another one can be done. Indeed, some subjects increase their initial angle across trials in the context of the heavy force field. They let themselves be dragged by the force field and only compensate at the end of the trials to reach the target. Other subjects try to compensate for the force field from the start of the trial and reduce then their initial angle across trials. This difference could be associated to the use or not of an explicit strategy to avoid having to compensate for the force field during the whole trial. Further researches have to be done to say if this hypothesis is correct.

Bringing those results together, it is clear that learning to simultaneously adapt to force fields of different magnitudes is harder than to force fields of different directions. Not everyone seems to be able to create distinct motor memories to force fields of different magnitudes in the timescale of the experiment. This inter-individual variability in the way people adapt is not a new phenomena [39] but the subject differences that cause it are not totally understood. Further studies have to be conducted to determine if the subjects that had difficulties to create distinct motor memories in this experiment can succeed in doing it if they perform more trial blocks.

5.3 Limitation and perspective

We have found some interesting results helping us to answer to the main questions of this master thesis. Indeed, we know that both the use of force fields and of background loads of different magnitudes make the adaptation harder. However, the reason why it is the case is still not totally understood.

This work shows that background load of different magnitudes are not efficient clues to enable the formation of distinct motor memories. This finding was unexpected. Indeed, it is known that human beings adapt their grip force when displacing objects of different mass. This means that they use the mass of the object as a clue to determine the forces and so the control strategy that they must adopt. However, this clue does not seem to be used in the case of our dual adaptation experiment. Further experiments have to be conducted to find the reason why it is the case.

There is also a lack in knowledge to determine why do some people adapt while others do not. What makes people able to learn or not? More and more inter-subjects analysis are realised nowadays. However, more have to be conducted if we want to understand all the aspects of motor adaptation because there are more and more evidences emphasizing the differences between subjects in the way they adapt and learn.

This work does not include any objective way of determining if the subjects use an explicit strategy or not. Even if there have been studies showing signs of the use of explicit strategies in force field adaptation [30], the importance of the explicit learning component in this paradigm is under debate. Indeed, it is harder for subjects to develop an explicit strategy in experiences using this paradigm than in those using visuomotor perturbations. Still, because the use of an explicit strategy is hypothesised in our set-up for some subjects, further studies that explore that learning component have to be conducted.

5.4 Conclusion

This work allowed to make a step towards the understanding of the reason why interferences are observed when background loads of different magnitudes are used as clue for force field of different magnitudes. First, those cues seem to be unused by the brain for adaptation, while it has been proven that the magnitude of forces can be extracted and is encoded in the brain. Moreover, the parallel adaptation to force field of different magnitudes and same direction is not trivial. Everyone does not have the same facility in this adaptation task.

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