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Motor Adaptation with Passive Machines: a First Study on the Effect of Real and Virtual Stiffness

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Abstract

Motor adaptation to novel force fields is considered a key mechanism not only for the understanding of skills learning in healthy subjects but also for rehabilitation of neurological subjects. Several studies conducted over the last two decades used active robotic manipulanda to generate force fields capable of perturbing the baseline trajectories of both healthy and impaired subjects.

Recent studies showed how motor adaptation to novel force fields can be induced also via virtual environments, whereas the effects of the force are projected onto a virtual hand, while the real hand remains constrained within a channel. This has great potentials of being translated into passive devices, rather than robotic ones, with clear benefits in terms of costs and availability of the devices. However, passive devices and virtual environments have received much less attention at least with regard to motor adaptation.

This paper investigates the effects of both the real and virtual stiffness on motor adaptation. In particular we tested 20 healthy subjects under two different real stiffness conditions (Stiff Channel vs Compliant Channel) and two different virtual conditions (Viscous vs Springy). Our main finding is that compliance of the channel favours a better adaptation featured with less lateral errors and longer retention of the after-effect. We posit that the physical compliance of the channel induces a proprioceptive feedback which is otherwise absent in a stiff condition.

Keywords: Virtual force field learning, internal models, motor adaptation

1. Introduction

In the last three decades an increasingly large number of rehabilitation robots have been designed, often re-adapting industrial machines, to alleviate the burden on therapists and healthcare systems. Robot-aided therapy complements conventional therapy with features such as exact repetitive movements using a forced-use strategy for the affected limb and programmable resistance/assistance levels[9]. In addition, robotic devices can accurately measure kinematic (e.g. position, speed) and dynamic (interaction forces) parameters, providing fine and objective assessment which complements the available clinical scales.

Many robotic devices have been developed which target post-stroke rehabilitation of the upper-limb [1, 16], however very few are commercially available and, in any case, their use in hospitals and clinics is still very limited due to high costs and complexity.

An effective neurorehabilitation process, with permanent improvements of motor functions, relies on intensive training of the impaired part. In this perspective the motor adaptation paradigm has been considered an important step for studying, quantifying and improving the motor recovery course [5].

Motor adaptation manifests whenever

changes in the body or external disturbances produce unexpected errors in movements. In order to create a discrepancy between the expected hand trajectory and the executed trajectory or between visual and proprioceptive feedback, force fields and visuomotor rotations have been commonly used [2, 7, 15].

Although several studies have shown that healthy subjects are capable of well adapting to different kinematic [6, 12] and dynamic perturbations [15, 13], experiments conducted with impaired subjects have revealed contrasting results [4]. Such findings are generally not comparable due to differences in tasks and subjects' characteristic therefore a unifying picture is still lacking [4]. An important direction to increase the amount of available data would be the use of simpler and cost-effective platforms which could be deployed in community centres as well as at home.

Under this perspective, recent findings [10, 11] concerning adaptation to *virtual tasks* might suggest a paradigm shift to design simpler and low-cost devices.

A virtual task is characterized by a mismatch between the visual and the proprioceptive feedback. An example of virtual task is the *isometric reaching* [11] where subjects move a cursor on a screen by applying forces on a static load cells. However, the visually perceived movement of the cursor does not generate the proprioceptive feedback of the hand (which does not move in isometric tasks).

Virtual tasks have been implemented with robotic manipulanda that *channel* subject movements along specific directions (by stiff-

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ening the robot end-effector in the directions orthogonal to the desired movement direction). In fully isometric conditions adaptation has been investigated for both kinematic (e.g. visuomotor rotations)[11] and dynamic conditions [8] (where subjects learned to balance a virtual inverted pendulum pushing on a static force sensor). Very recently, in [10], the possibility to move the hand along specific channels has extended virtual tasks to study adaptation to *virtual curl force fields* (which perturb the controlled cursor proportionally to the hand velocity).

For virtual tasks, motor adaptation might be affected both by the virtual dynamic of controlled system as well as by the channel stiffness used to constrain hand movements. Indeed, this latter parameter is chosen by the experimenter that arbitrarily decides the controller gains that stiff the channels.

In [14], it has been shown that the introduction of a channel, during the washout phase, affects and in particular slows down the re-adaptation to the unperturbed hand condition. In [11], where the handle was completely rigid (isometric conditions), no learning differences have been reported between subjects experiencing two different cursor dynamic.

In this paper we present a passive two degrees-of-freedom (DOF) planar manipulator designed for the study of virtual tasks adaptation. The lack of actuators and the possibility to include mechanical constraints of the handle (in order to reduce its DOF) makes it a suitable and cost-effective alternative to investigate virtual tasks learning without using robotic manipulanda. We have pre-

sented a first version of a one DOF prototype of such platform in [17]. However, successive tests have shown difficulty for subjects to adapt to virtual tasks. In this paper we question whether this issue is due to the implemented virtual dynamics of the cursor or to the rigidity of the channel, or both. To this end, the additional degree of freedom is used in this paper to evaluate the effect of the channel lateral stiffness. In particular, by locking the horizontal DOF we can implement a *Stiff Channel* (SC) constraining subjects to move only along forward-backward directions. In contrast, we can implement a *Compliant Channel* by simply constraining the lateral motion via elastic bands (for a total lateral stiffness of about $3200 \frac{N}{m}$). Hence in this latter condition, when applying lateral forces to the handle, subject's hand can be physically displaced along the lateral direction, generating proprioceptive feedback.

In addition, for both the stiff (SC) and compliant (CC) channel condition, to disambiguate if the motor adaptation is due to the type of channel or to the implemented virtual task, we test two different virtual dynamics: a virtual viscous (VV) dynamic and a virtual spring (VS) dynamic (see sec. 2.2).

2. Materials and Methods

2.1. The mechatronic platform

Unlike conventional machines or robots which are based on complex designs (often readapting industrial mechanisms) to match all possible conditions and severities of impairments, this platform has been primarily conceived to be intrinsically lightweight,

portable and simple. Originally developed as an active platform¹, it is used in this work without motors.

The passive platform consists of a Cartesian linear guide with 2 DOF, a H-shaped cabling systems, a handle sensorized with 3D force/torque sensor, two encoders and a PC with data acquisition system (possibly scalable down to microcontroller). The handle motion is transmitted to the encoders via an H-shaped cable mechanism. A schematic is shown in Fig.1-a while Fig.1-b shows how planar motion is simply achieved with the two orthogonal linear guides.

[Figure 1 about here.]

The mechanism is in fact an H-cabled differential whereby a frontal (y-direction) motion of the handle results in the encoders to move in-phase while a lateral (x-direction) motion of the handle results in out-of-phase motion of the encoders. Handle positions are therefore linearly mapped into encoders motions.

The advantage of the Cartesian configuration is that a stiff channel can be easily implemented via mechanical stoppers on the later guide (see Figure 2-a) while for the compliant channel it is sufficient to constrain the same lateral DOF with elastic bands (see Figure 2-b), selected to induce a lateral stiffness of 3200 N/m.

[Figure 2 about here.]

¹For which a provisional US patent was filed, application number 61/735,295

The handle position along the platform is estimated with two Faulhaber optical encoders (HEDL5540), each connected to a single driving pulley. It has a resolution of 500 lines per revolution, thus for a 27.5 mm pulley diameter, its resolution is <0.2 mm in the xy plane. The encoder count is acquired through an input port on the dSPACE system and the rotations of both encoders are suitably converted into the xy position of the handle. The handle is connected to an ATI-Mini40 load cells capable of measuring torques and forces components (up to 2 Nm and 40N respectively) along the three orthogonal axis x-y-z. The load cells is connected with a differential configuration to dSPACE and measure the forces that subjects apply during movements.

The dSPACE allows real-time data acquisition (and control) and interfaces, via a serial port, the platform's sensors with the PC hosting the virtual environment controlled by subjects.

2.2. Experiment Protocol

In this experiment we investigate virtual tasks motor adaptation during point-to-point reaching movements. Figure 3 shows a sketch of the experiment: subjects had to perform outbound reaching movements from a starting position to a target position (15cm center-to-center). Subjects' hand and forearm were not visible to the subject during the entire duration of the experiment.

[Figure 3 about here.]

The controlled cursor and the target (both with 1 cm radius) were drawn on a computer

screen positioned in front of the subject. In particular, while the y coordinate of the cursor was mapped 1:1 with the y coordinate of the subject's hand on the platform, the x coordinate was the result of the actual lateral force (F_s) of the subject (sensed via the force sensor) and a virtual curl force (F_{vf}):

$$F_{vf} = B_{vf} \cdot \dot{y} \quad (1)$$

with $\dot{y}$ the hand speed along the y direction.

The first dynamics

$$b_1 \cdot \dot{x} = F_{vf} + F_s \quad (2)$$

corresponds to a *Virtual Viscous* (VV) condition whereby the cursor velocity results proportional, via the viscosity coefficient b_1 , to the total lateral force.

The second dynamics

$$K \cdot x + b_2 \cdot \dot{x} = F_{vf} + F_s \quad (3)$$

implements a *Virtual Spring* (VS) with stiffness K whereby the cursor position (rather than the velocity, as in the previous condition) is proportional to the total lateral force (again due to both the virtual force and the force applied by the subject).

As explained in sec.2.3 a small viscous term (b_2) was added to avoid a visual trembling of the cursor due to the noise from the load cell readings.

Besides the effect of the virtual dynamic, this work wants to assess the effect of the lateral channel stiffness on motor learning. To this end, we tested two lateral channel conditions: a *Stiff - Channel* was realized using mechanical stops (see Figure 2-a) which avoid

any lateral displacement, hence providing an isometric condition for the application of lateral forces. By removing the stops, the handle has two DOF, however, we constrained the lateral displacement (or the x coordinate) using several elastic bands for a total lateral stiffness of about $3200 \frac{N}{m}$ (see Figure 2-b).

Twenty healthy subjects (16 males 4 females) aged between 23 and 36 took part to the experiment. In order to address differences in motor adaptation due to the channel stiffness and due to cursor dynamics, the subjects were randomly split in four groups of five subject each: Stiff Channel - Virtual Spring (SC-VS); Compliant Channel - Virtual Spring (CC - VS); Stiff Channel - Virtual Viscosity (SC- VV) and Compliant Channel - Virtual Viscosity (CC - VV).

Subjects were instructed to perform movements as accurately as possible and to reach the target in a given amount of time (the time window was not explicitly given to subjects): in particular, at the end of each trial they received a visual feedback stating: "TOO SLOW" if the target had been *reached* after 0.7 seconds since the *beginning* of the trial; vice versa "TOO FAST" appeared on the screen if the target had been reached in less than 0.5 seconds. The beginning of the trial was triggered when subjects left the starting position ($y > 0.5cm$) while a target was considered hit if the distance between the center of the cursor and the center of the target was less than 1 cm (target radius) and v_y was less than 0.2 m/s. This latter condition constrained subjects to perform movements avoiding overshooting of the target. At the end of each trial, subjects move the

handle back to the initial position. However, to avoid any influence of this movements on the movements under investigation, no visual feedback was provided during this phase. Every subject performed 175 reaching trials: 50 Baseline trials (virtual force deactivated), 100 Adaptation trials (virtual force active) and 25 Washout trials (virtual force deactivated).

2.3. Parameters tuning

According to eq. 2 - 3 we need to set B_{vf} , b_1, b_2 and K . The departing point for our tuning has been considering that the minimum time allowed to perform a movement is $T=0.5$ seconds. We therefore used this information to compute a minimum-jerk trajectory[3] (eq. 4 - 5) to predict the highest hand speed between the starting position and the target (center-to-center distance equal to $l_m = 0.15$ m).

$$y_{mj}(t) = l_m \left[10 \left(\frac{t}{T} \right)^3 - 15 \left(\frac{t}{T} \right)^4 + 6 \left(\frac{t}{T} \right)^5 \right] \quad (4)$$

$$\dot{y}_{mj}(t) = \frac{dy_{mj}}{dt} \quad (5)$$

With this model we can hence compute the speed profile of the movement along the y direction and in particular its peak (about 0.58 m/s).

We conducted preliminary tests where different subjects (both male and female) where asked to apply a maximal lateral force for $T = 0.5$ seconds (the maximum time allowed to perform a movement as stated above). The minimum of these forces (equal to 8 N) was selected as the maximal lateral force F_s^{MAX}

to tune the coefficient of the virtual curl force field (B_{vf}):

$$B_{vf} = F_s^{MAX} / \dot{y}_{mj}^{MAX} = 14.1 \left[\frac{Ns}{m} \right] \quad (6)$$

The predicted virtual curl force is shown in Figure 6.

We than assume that, for both cursor dynamics we want a maximum lateral deviation x^{MAX} equal to 0.05 [m] assuming that the subjects do not apply any lateral force $F_s = 0$ (worst case scenario). Hence, we can rewrite Eq 2 as:

$$\dot{x} = \frac{B_{vf}}{b_1} \dot{y}_{mj} \quad (7)$$

Integrating the above expression we have:

$$x(t) = x_0 + \frac{B_{vf}}{b_1} y_{mj}(t) \quad (8)$$

where y_{mj} is the straight line path predicted with the minimum-jerk model. Therefore, the maximum lateral deviation for the viscous dynamic will be at the target coordinate $y_{mj}^{MAX} = 0.15$ m (see Figure 5). From this considerations and the above equation, we can compute the parameter b_1 as:

$$b_1 = \frac{B_{vf}}{x^{MAX}} y_{mj}^{MAX} = 42.6 \left[\frac{Ns}{m} \right] \quad (9)$$

For the elastic virtual field we assume the same maximum force F_s^{MAX} and same maximum lateral deviation x^{MAX} as previously explained. In this case we compute the stiffness of the virtual spring K neglecting the viscosity term b_2 and considering F_s applied by the subject equal to zero. Therefore, we have:

$$K \cdot x = F_v = B_{vf} \dot{y}_{mj}^{MAX} \quad (10)$$

where B_{vf} and $\dot{y}_{mj}^{MAX}$ are the same as explained above. In this condition the maximal lateral deviation corresponds to the peak of the hand velocity (Figure 4), hence:

$$K = B_{vf} \frac{\dot{y}_{mj}^{MAX}}{x^{MAX}} = 160 \left[\frac{N}{m} \right] \quad (11)$$

In the absence of the viscosity term, the noise from the load cell produces fast cursor shaking on the computer screen. Therefore, b_2 was experimentally tuned so as to filter the shaking without affecting too much the springy dynamic. We found as a good trade-off $b_2 = 11.7 \left[\frac{Ns}{m} \right]$ (which is about 14 times smaller than the stiffness $K = 160 \left[\frac{N}{m} \right]$).

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

2.4. Data Analysis

The acquired data was off-line filtered using an M-point moving average filter with M=20. To quantify motor adaptation we defined two performance indexes computed for each trial. The cursor-path error (eq. 12) is used to assess the evolution of the lateral deviations x across trials:

$$e_p = \sum_{i=1}^{N-1} x_i \cdot (y_{i+1} - y_i) \quad (12)$$

with N the number of samples acquired in a trial, x_i the lateral deviation at the sample i and y_i the coordinate of the handle at the sample i .

Due to the difference in the cursor dynamics (compare Figure 4 and 5), we believe that the integral of the lateral error along the entire trajectory allows a better comparison between the two virtual environments. Regarding the forces, as explained in sec. 2.3 both cursor dynamics are affected by the same virtual force (eq. 1) when movements are performed with the same hand-speed profile. We define the peak force error (eq. 13) as a further performance index to investigate how subjects modulate the applied force (in particular the force exerted at the peak velocity) over different trials:

$$e_f = F_{vf_i} + F_{s_i} \quad (13)$$

with i the sample number relative to the peak velocity of trial t .

For both average errors (e_p and e_f) relative to each group we fitted a trial-dependent exponential function $f(t)$ having a bias β , an amplitude A and a time constant τ (see eq.14) to further highlight the trend in term of performance during the Adaptation and the Washout phase:

$$f(t) = \beta + Ae^{(-\frac{t}{\tau})} \quad (14)$$

3. Results

Figure 7 shows the cursor paths of four representative subjects, each belonging to only one of the four different groups. For all subjects, the straight-line paths executed during the Baseline phase, presents a strong

right-curvature during the first Adaptation trials (at trial 51 the virtual force is suddenly switched on). Differently from the VS group, VV subjects present several overshoots (in proximity of the target) over the left side of the target. This difference is due to the different dynamics: while for VS subjects the virtual spring *helps* the convergence of the cursor towards the target, VV subjects have to apply a finer control of the cursor in order to stop it on the target. Another remarkable aspect is that for the VS subjects there is not so much difference between the trajectory at the beginning of the Adaptation (trials 51:55) and the trajectory at the end of the Adaptation (trials 140:150). Instead, for VV subjects there is evidence of motor adaptation although, even at the end of the Adaptation phase, the cursor paths are not completely straight but still lightly curve. The lack of motor adaptation in VS subjects is shown even during the washout trials where the after-effect is not present and the cursor paths are similar to the Baseline phase.

[Figure 7 about here.]

These results are further highlighted in Figure 8 where the cursor-path errors are plotted for each subject together with the average performance. For each group, the average performance was fitted with the exponential model (eq. 14) to obtain the trend of the adaptation. While at the beginning of the Adaptation the average cursor-path error is similar among different subjects and groups, only for the VV groups there is a decreasing trend of the error (as high-lighted by the red

curves). In particular, for subjects belonging to the SC-VS (Figure 8-a) the fitting returns a weak increasing of the error while for subjects belonging to the CC-VS (Figure 8-b) the performance is constant.

In the absence of the spring, for a dynamic completely viscous, subjects necessarily have to contrast the virtual force field (by pushing on the handle) in order to reach the target. In this case slacking behaviours would not fulfil the task. For both SC-VV and CC-VV there is an exponential decrease of the cursor-path error, however, CC-VV subjects perform remarkably better. Note that for both SC-VV and CC-VV groups, the fitted model reaches a plateau after the first 20 trials of Adaptation. The weak and the stronger adaptation for VS and VV subjects respectively, is further highlighted during the washout trials where the former group presents a weak after-effect that rapidly decreases. In contrast, VV subjects (in particular CC-VV) presents stronger after-effects that lasts several trials.

[Figure 8 about here.]

Similar analysis is shown in Figure 9. Again, while for the VS groups there is not a decreasing trend in error performance, such a trend is remarkably presents for VV subjects (especially for subjects performing with a compliant channel CC-VS). These results further suggest that the Virtual Spring dynamic does not ‘stimulate’ subjects to apply forces that counteract the effect of the virtual one. Indeed, subjects tend to react (applying counteracting forces) during the first exposure to the perturbation however, they

adopt sufficient force control just to reach the target but not to follow straight paths. Although VV subjects increase the applied force (hence they reduce the error between virtual force) during the adaptation trials, they are not capable (on average) of perfectly counter-acting the virtual force field (at the peak of velocity).

[Figure 9 about here.]

To compare the performance among the four different group we analysed the last 10 trials (140:150) of the adaptation phase. For all groups, we first used a Lilliefors test to see whether the data was normally distributed. We used the Matlab function `lillietest` using 0.05 as significance level. For the cursor-path errors and for all groups, data is normally distributed and the average errors and standard deviations are shown in Figure10. We then used a paired two-samples t-test (Matlab function `ttest2`) to compare the average of these distributions. Results were significant different at 0.05 significance level (alpha).

The same analysis, with the same results, was conducted for the peak force errors (average and standard deviations shown in Figure11).

Tables 1 and 2 show the fitting coefficients of eq.14 for all groups and for both the Adaptation and the Washout phase.

[Figure 10 about here.]

[Figure 11 about here.]

To understand why CC-VV subjects are not capable of performing straight-line path

with adaptation, nor are able to develop the same peak force as the virtual one, Figure 12 shows the evolution of the force profiles for a representative subject. When the virtual force is suddenly introduced, the subject reacts with a large delay (relying only on a feedback control strategy) and with a pattern that does not resemble the virtual ones. At the end of the adaptation phase (trials), the delay (or the distance between the subject peak force and virtual peak force) reduces and the exerted force has a bell-shaped profile similar to the virtual one. However, the subject is not capable of further reducing the delay, hence is not able to *anticipate* the virtual force. This delay in the applied force might be the reason of the lack of straight line paths for VV subjects. Indeed, in a viscous environment, the applied forces produce cursors changes that are damped and delayed by the viscosity factor. Another reason might be the responsiveness of the load cell that might slow-down the subject motor strategy.

[Figure 12 about here.]

4. Discussion

This paper presented a study on force field motor adaptation using a passive device and virtual environment. Prior studies concerning motor adaptation to virtual curl force fields used active control and robots to implement channels constraining hand motion. Channels implemented via a robot are necessarily compliant, due to limits of the robot itself. However, the effects of such a compliance on force field motor adaptation have

never been discussed, to the authors knowledge. In this paper we argue that channel stiffness plays a crucial role for motor adaptation in virtual tasks.

To disambiguate the differences in motor adaptations due to channel compliance and the virtual dynamics, we also tested a virtual viscous (VV) dynamics and a virtual springy (VS) dynamics.

Results showed that, independently of the channel compliance, the VS dynamics does not favour motor adaptation. As subjects are only required to reach the final target, subjects do not attempt to perform straight movements since the elastic component of the virtual dynamics eventually takes the cursor onto the target.

This slacking behaviour does not appear for the VV groups where, the lateral deviation is the result of the integration of the virtual force. Hence, if subjects do not apply any force, they will not be able to fulfil the task requirements (i.e. to reach the target in time and accurately).

For VV groups, where the motor adaptation has a remarkable effect (both in terms of lateral error and force compensation), results showed that channel stiffness plays an important role. In particular, a compliant channel seems to favour a better adaptation featured with less lateral errors and longer retention of the after-effect.

However, even subjects in the CC-VV group did not move along straight-line paths, nor did they fully compensate the virtual force at the end of the adaptation phase. Future studies are needed to better elucidate these phenomena.

[Table 1 about here.]

[Table 2 about here.]

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List of Figures

1	A sketch of the H-cable mechanism used to transmit the 2 DOF motions of the sensorised handle to the encoders.	14
2	The mechatronic platform and the two different channels used for the experiment. In the Stiff Channel condition the two green stops lock any lateral deviations of the handle. Instead, for the Compliant Channel condition, multiple elastic bands are added for a total lateral stiffness of the channel about $3200 \frac{N}{m}$	15
3	Sketch of the experimental setup. When the virtual force (F_{vs}) is active, the cursor is laterally displaced on the screen according to eq.2 or eq.3. The subject must apply a lateral force F_s in order to counter balance the effect of the virtual force. Note that in the case of Compliant Channel (the linear guide is compliant), the real lateral displacement of the subject's hand does not contribute to the lateral displacement x shown on the screen. Indeed, even in this, the lateral deviation of the cursor is only due to the cursor dynamic (eq.2 and eq.3)	16
4	Cursor-path predicted with the minimum-jerk model relative to the Virtual Spring dynamic and assuming a subject that does not apply any lateral force F_s	17
5	Cursor-path predicted with the minimum-jerk model relative to the Virtual Viscosity dynamic and assuming a subject that does not apply any lateral force F_s	18
6	Virtual force (F_{vf}) predicted with the minimum-jerk model.	19
7	Cursor-path for four representative subjects during the Baseline, the Adaptation and the Washout trials: (a) Stiff Channel - Virtual Spring (SC-VS), (b) Compliant Channel - Virtual Spring (CC-VS), (c) Stiff Channel - Virtual Viscosity (SC-VV), (d) Compliant Channel - Virtual Viscosity (CC-VV). . .	20
8	Cursor-path errors. Black color are the average errors (circles) between subjects belonging to the same group and their standard deviations (bars); thin gray lines are the integral errors exhibited by each subject. Dashed red lines are the result of a double exponential fitting with the average integral error. (a) Stiff Channel - Virtual Spring (SC-VS), (b) Compliant Channel - Virtual Spring (CC-VS), (c) Stiff Channel - Virtual Viscosity (SC-VV), (d) Compliant Channel - Virtual Viscosity (CC-VV).	21

9	Peak force errors computed as the sum of the force applied by subjects F_s and virtual force F_{vf} . Both forces are relative to the peak velocity of each trials. Black color are the average errors (circles) between subjects belonging to the same group and their standard deviations (bars): (a) Stiff Channel - Virtual Spring (SC-VS), (b) Compliant Channel - Virtual Spring (CC-VS), (c) Stiff Channel - Virtual Viscosity (SC-VV), (d) Compliant Channel - Virtual Viscosity (CC-VV). Thin-gray lines are the force errors relative to each subject. Continuous red lines are the result of the exponential fitting with the average error.	22
10	Average cursor-path errors and standard deviation relative to the last 10 Adaptation trials (140:150).	23
11	Average Peak force errors and standard deviation relative to the last 10 Adaptation trials (140:150).	24
12	Lateral force evolution for a representative subject belonging to the group Compliant-Channel Virtual Viscosity. Continuous lines are relative to the virtual force (F_{vf}) while dashed lines are relative to lateral force exerted by the subject. Different colors are used to highlight different trials: black color is associated with the most remote trial; light gray with the most recent. The x-axis of each plot represents a sample of 0.002 seconds.	25

Figure 1: A sketch of the H-cable mechanism used to transmit the 2 DOF motions of the sensorised handle to the encoders.

(a) Stiff Channel.

(b) Compliant Channel.

Figure 2: The mechatronic platform and the two different channels used for the experiment. In the Stiff Channel condition the two green stops lock any lateral deviations of the handle. Instead, for the Compliant Channel condition, multiple elastic bands are added for a total lateral stiffness of the channel about $3200 \frac{N}{m}$.

Figure 3: Sketch of the experimental setup. When the virtual force (F_{vs}) is active, the cursor is laterally displaced on the screen according to eq.2 or eq.3. The subject must apply a lateral force F_s in order to counter balance the effect of the virtual force. Note that in the case of Compliant Channel (the linear guide is compliant), the real lateral displacement of the subject's hand does not contribute to the lateral displacement x shown on the screen. Indeed, even in this, the lateral deviation of the cursor is only due to the cursor dynamic (eq.2 and eq.3)

Figure 4: Cursor-path predicted with the minimum-jerk model relative to the Virtual Spring dynamic and assuming a subject that does not apply any lateral force F_s .

Figure 5: Cursor-path predicted with the minimum-jerk model relative to the Virtual Viscosity dynamic and assuming a subject that does not apply any lateral force F_s .

Figure 6: Virtual force (F_{vf}) predicted with the minimum-jerk model.

(a) SC - VS

(b) CC - VS

(c) SC - VV

(d) CC - VV

20

Figure 7: Cursor-path for four representative subjects during the Baseline, the Adaptation and the Washout trials: (a) Stiff Channel - Virtual Spring (SC-VS), (b) Compliant Channel - Virtual Spring (CC-VS), (c) Stiff Channel - Virtual Viscosity (SC-VV), (d) Compliant Channel - Virtual Viscosity (CC-VV).

(a) SC - VS

(b) CC - VS

(c) SC - VV

(d) CC - VV

Figure 8: Cursor-path errors. Black color are the average errors (circles) between subjects belonging to the same group and their standard deviations (bars); thin gray lines are the integral errors exhibited by each subject. Dashed red lines are the result of a double exponential fitting with the average integral error. (a) Stiff Channel - Virtual Spring (SC-VS), (b) Compliant Channel - Virtual Spring (CC-VS), (c) Stiff Channel - Virtual Viscosity (SC-VV), (d) Compliant Channel - Virtual Viscosity (CC-VV).

Figure 9: Peak force errors computed as the sum of the force applied by subjects F_s and virtual force F_{vf} . Both forces are relative to the peak velocity of each trials. Black color are the average errors (circles) between subjects belonging to the same group and their standard deviations (bars): (a) Stiff Channel - Virtual Spring (SC-VS), (b) Compliant Channel - Virtual Spring (CC-VS), (c) Stiff Channel - Virtual Viscosity (SC-VV), (d) Compliant Channel - Virtual Viscosity (CC-VV). Thin-gray lines are the force errors relative to each subject. Continuous red lines are the result of the exponential fitting with the average error.

Figure 10: Average cursor-path errors and standard deviation relative to the last 10 Adaptation trials (140:150).

Figure 11: Average Peak force errors and standard deviation relative to the last 10 Adaptation trials (140:150).

Figure 12: Lateral force evolution for a representative subject belonging to the group Compliant-Channel Virtual Viscosity. Continuous lines are relative to the virtual force (F_{vf}) while dashed lines are relative to lateral force exerted by the subject. Different colors are used to highlight different trials: black color is associated with the most remote trial; light gray with the most recent. The x-axis of each plot represents a sample of 0.002 seconds.

List of Tables

1	Fitting coefficients for the cursor-path errors.	27
2	Fitting coefficients for the Peak force errors.	28

	Adaptation			Washout		
Group	β	A	τ	β	A	τ
SC-VS	48.3313	5.3032	-176.8015	-5.9563	-7.1084	0.0023
CC-VS	44.3378	-0.2682	-47.6263	-4.6401	-13.6956	2.3588
SC-VV	26.7672	29.4767	2.7514	-3.2623	-35.8613	1.7922
CC-VV	13.0797	38.6412	3.4384	5.6683	-30.2817	18.1066

Table 1: Fitting coefficients for the cursor-path errors.

	Adaptation			Washout		
Group	β	A	τ	β	A	τ
SC-VS	4.5588	0.0386	-66.6919	-0.8919	-1.3453	3.7475
CC-VS	3.3209	1.1870	11.7072	-0.6891	-2.1816	2.7454
SC-VV	1.1637	2.2930	36.2500	-1.5194	-3.9244	2.7633
CC-VV	0.7494	4.4882	8.1434	-0.3813	-3.3736	9.8664

Table 2: Fitting coefficients for the Peak force errors.