Force Field Adaptation Can Be Learned Using Vision in the Absence of Proprioceptive Error

Alejandro Melendez-Calderon, *Student Member, IEEE*, Lorenzo Masia, *Member, IEEE*, Roger Gassert, *Member, IEEE*, Giulio Sandini, *Member, IEEE*, and Etienne Burdet, *Member, IEEE*

***Abstract*—It has been shown that people can learn to perform a variety of motor tasks in novel dynamic environments without visual feedback, highlighting the importance of proprioceptive feedback in motor learning. However, our results show that it is possible to learn a viscous curl force field without proprioceptive error to drive adaptation, by providing visual information about the position error. Subjects performed reaching movements in a constraining channel created by a robotic interface. The force that subjects applied against the haptic channel was used to predict the unconstrained hand trajectory under a viscous curl force field. This trajectory was provided as visual feedback to the subjects during movement (virtual dynamics). Subjects were able to use this visual information (discrepant with proprioception) and gradually learned to compensate for the virtual dynamics. Unconstrained catch trials, performed without the haptic channel after learning the virtual dynamics, exhibited similar trajectories to those of subjects who learned to move in the force field in the unconstrained environment. Our results demonstrate that the internal model of the external dynamics that was formed through learning without proprioceptive error was accurate enough to allow compensation for the force field in the unconstrained environment. They suggest a method to overcome limitations in learning resulting from mechanical constraints of robotic trainers by providing suitable visual feedback, potentially enabling efficient physical training and rehabilitation using simple robotic devices with few degrees-of-freedom.**

***Index Terms*—Internal model, motor learning, proprioception, visual feedback, visuo-proprioceptive discrepancy.**

I. Introduction

ROBOTIC devices are increasingly used to repeat movements in order to improve motor performance, e.g., in sports training or for rehabilitation of stroke survivors. These devices can generate computer-controlled forces and shape the learning of different dynamic tasks [1]. Ideally, a robotic trainer would have at least six degrees-of-freedom (DOF) to perform tasks in space. However, the design, safety and cost demands increase drastically with more DOFs. Furthermore, robotic interfaces with complex designs are generally bulky and not portable, preventing their large-scale use. For these reasons, simple devices with few DOFs are often used.

Reducing the number of DOFs in a training device reduces the amount of information about the environment, modifies the dynamics of the task and prevents error-based corrections. Hence, one can expect that learning will be affected [2] or that performance gains obtained in a constrained environment may not transfer well to an unconstrained one. For example, in a recent study with the ARM Guide [3], chronic poststroke patients managed to perform functional tasks with partial support of the arm resting on a table or with the arm closer to the body after training reaching movements using this linear guide device; however, training with this device did not improve the patient's performance in free space. A plausible explanation is that the arm movement requires substantial shoulder strength, which was not trained. Therefore, if simple robotic devices are meant to be an effective tool for teaching a more complex motor task, then it is necessary to compensate for the lack of feedback information to the trainee. In this context, this paper examines whether a lack of proprioceptive error due to mechanical constraints or haptic guidance can be substituted with visual information.

Learning novel skills requires integration of different sensory modalities, in particular vision and proprioception. The importance of visual information for motor skill acquisition is illustrated by the good motor performances of neuropathy subjects (who are deprived of proprioceptive feedback) [4], [5]. Also, it has been shown that the way visual feedback is presented influences the learning of the system dynamics [6]–[8]. Likewise, the results of Scheidt *et al.* [9] showed that when visual information about the lateral deviation is removed when performing point-to-point reaching movements in a viscous curl force field (VF), compensation for the force field cannot be achieved.

Conversely, a recent study [10] demonstrated that force field adaptation depends on movement error in muscle space, suggesting a predominant influence of proprioceptive error on motor learning. Correspondingly, Scheidt *et al.* [11] found that removing position errors after adaption to a force field significantly reduced the speed of de-adaptation (when the force field was removed after learning). In fact, several studies (e.g., [12], [13]) have shown that learning of novel dynamics is not affected when visual feedback of the hand is prevented during motion.

This paper investigates whether it is possible to learn to compensate for novel dynamics without the proprioceptive error

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A. Melendez-Calderon and E. Burdet are with the Department of Bioengineering, Imperial College of Science Technology and Medicine, SW7 2AZ London, U.K. (e-mail: amelende@imperial.ac.uk; eburdet@imperial.ac.uk).

L. Masia and G. Sandini are with the Robotics, Brain and Cognitive Sciences, Italian Institute of Technology, 16163 Genova, Italy (e-mail: lorenzo.masia@iit.it; giulio.sandini@iit.it).

R. Gassert is with the Rehabilitation Engineering Lab, ETH Zurich, 8006 Zurich, Switzerland (e-mail: gassertr@ethz.ch).

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driving adaptation. To address this question, we studied goal directed arm movements in a novel dynamic environment when proprioceptive position error was removed by means of a haptic channel. Error information was provided through visual feedback based on the estimated hand position as if the channel was not present, thus creating a visuo-proprioceptive discrepancy.

The results of Mah and Mussa–Ivaldi [14] suggest that subjects may be able to form an internal model of a motor task without using proprioception, by presenting motion associated with the applied force. However, only a 1DOF task was examined in that work, and the transfer of the learned force pattern to the real movement, which requires the integration of force, vision and proprioception, was not investigated.

In our experiment, subjects were required to perform reaching movements in a haptic channel produced by a robotic interface. An estimation of how the arm would move in a viscous curl force field (VF), without the constraint, was presented as visual feedback. This was calculated from the force that the subject exerted on the channel, using a model of the subject's arm and interface dynamics. We hypothesized that subjects would learn to compensate for the external force trial by trial using the visual feedback even though there was a visuo-proprioceptive discrepancy. We examined the learning trend and after effects after training in the constrained environment through exposure to the force field in the unconstrained condition. We compared those trends with learning in the unconstrained environment (i.e., without the channel).

TABLE I
SUMMARY OF EXPERIMENT PROTOCOL

groups*		experimental phases**					
		F	L	TI	TII	W	PW
uni-directional	uVG (10)	vNF (25)	vVF (150)	vVF (20), VF (5)	vVF (20), NF (5)	NF(25)	NF (20), VF (5)
	uCG (10)	NF (25)	VF (150)	NA	VF (20), NF (5)		
multi-directional	mVG (5)	vNF (10)	vVF (30)	vVF (20), VF (5)	vVF (20), NF (5)	NF (10)	NF (20), VF (5)
	mCG (5)	NF (10)	VF (30)	NA	VF (20), NF (5)		

* the number of subjects per group is indicated in brackets
** the number of trials per direction is in brackets
NA - not applicable

- F: familiarization
- L: learning
- TI: testing I
- TII: testing II
- W: washout
- PW: post-washout

II. MATERIALS AND METHODS

A. *Experimental Setup*

Thirty right-handed subjects (26 ± 4 years old, 12 females) without reported neurological impairments participated in the study. The experiment was approved by the ethics committee of the Italian Institute of Technology (IIT, Genoa, Italy). Subjects did not have prior experience with the task and the robotic device used to perform the exercises; all subjects gave informed consent prior to participating in the experiment. Twenty subjects learned a *viscous curl force field* (VF) along a single movement away from the body (experiment 1) and ten subjects learned a VF in movements along five directions (experiment 2).

Experiments were performed at the Motor Learning and Rehabilitation Lab of IIT using the two DOF planar manipulandum, "Braccio di Ferro" (BdF) [15]. Each subject was seated comfortably on a chair in front of the robot; a seatbelt prevented trunk compensation. The BdF's end effector was positioned at the center of the workspace (start position) and the subject was asked to grasp it such that the right shoulder acromion was aligned with it. The subject's seat position was then adjusted such that the joint angles were at approximately 110° of elbow flexion and 80° of shoulder abduction. This configuration kept the distance between the handle and right-shoulder acromion within the range of 33–40 cm, depending on the subject's arm length.

Instantaneous hand position was visually represented by a 1-cm-diameter *cursor* displayed on a screen located in front of the subject. Arm movements were scaled 1:1 with respect to the screen (i.e., 1 cm movement on the robot workspace moved the cursor 1 cm on the screen). Subjects were asked to perform horizontal point-to-point movements from a 2-cm-diameter *start* circle to a 2-cm-diameter *target* circle in 0.6 ± 0.1 s. A movement was *successful* if it reached the target without overshooting and was performed in the specified time range. Trials were self-paced and movement duration was determined from the time subjects exited the start circle until the time they entered the target.

Participants were instructed to perform a certain number of trials in order to complete the experiment (see Table I). Feedback about the movement duration was provided after each trial, indicating whether it was "too slow" (target turned blue), "too fast" (target turned red) or within the required time range (in which case target the tuned green and "OK" was displayed).

The experiments involved the following environments.

- *Null force field (NF)*—No force was applied by the robot; visual feedback of the instantaneous hand position $\vec{P}$ [m] was computed from encoder reading and Jacobian of the robotic interface.
- *Viscous curl force field (VF)*—A velocity dependent force field was applied by the robot according to

$$\vec{F} = \begin{bmatrix} 0 & 25 \\ -25 & 0 \end{bmatrix} . \dot{\vec{P}} \qquad (1)$$

  where is $\vec{F}$ the force vector [N] applied on the hand and $\dot{\vec{P}}$ is the instantaneous velocity vector [m/s]; visual feedback of the hand position is provided as in the NF.
- *Virtual null force field (vNF)*—Subjects' movements were constrained by the haptic channel (stiffness 4000 N/m and damping 100 Ns/m to avoid oscillations), which allowed moving towards the target in a straight line but lateral deviations. The force exerted on the walls of the channel was used to estimate the lateral deviation during movement by solving the differential equation modeling the robot and subject arm dynamics described in the Appendix. Visual feedback combined the hand position in the channel with the estimation of lateral deviation. Note that the virtual environment created a visuo-proprioceptive discrepancy.
- *Virtual viscous force field (vVF)*—similar to vNF, however a virtual viscous force field (vVF) was added to the model's

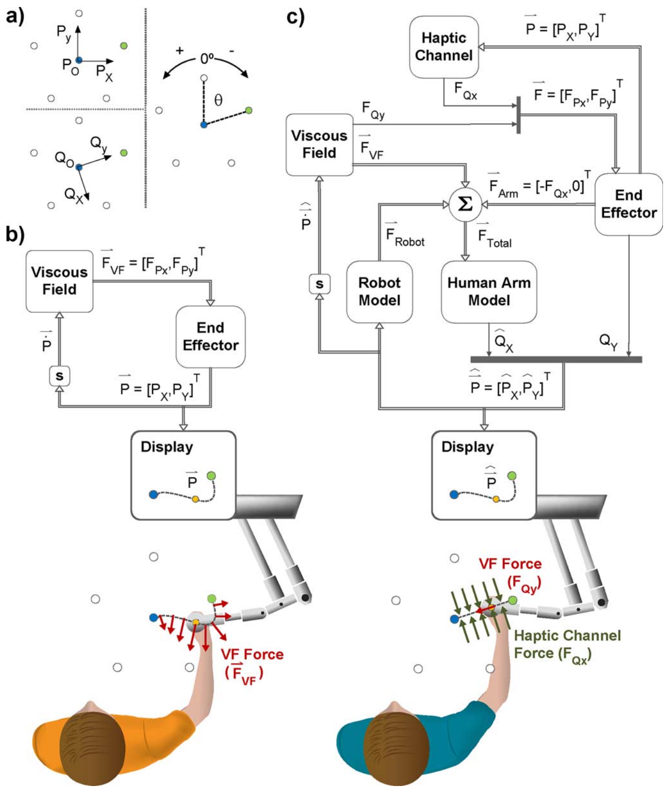

Fig. 1. (a) Coordinate systems; P is always aligned with the 0° target, while Q is aligned with respect to the current trial direction. 0° refers to targets and movements performed along the sagital plane; increasing angles are counterclockwise from this direction. Computation of visual feedback in the (b) real and (c) virtual environments.

input, which was computed using the estimated hand velocity. Hence the real time hand position performed by the subject was displayed on the screen as a curved path due to the effect of the deviating vVF. In order to correct for this deviation, the subject had to exert an appropriate lateral force pattern against the channel wall in the opposite direction to the vVF.

B. Visual Feedback

The instantaneous hand position in the virtual environments (i.e., vNF and vVF) was estimated using a subject specific arm dynamic model as shown in Fig. 1(b). Rigid body arm dynamics were modeled as in [16] and [17] using limb segment parameters based on the subjects' data as described by Winter [18], while a linear second-order model of the robot dynamics was used. The virtual arm movement was computed from the (lateral) force applied against the channel, the estimated arm dynamics, the virtual external force and the hand position along the channel, as described in the Appendix.

The position of the cursor displayed on the screen at every iteration step (k) was

$$\hat{\vec{P}}(k) = \left[\hat{P}_x(k) \quad \hat{P}_y(k)\right]^T = R_\theta^T.\hat{\vec{Q}}'(k) = R_\theta^T.\left[\hat{Q}_x(k) \quad Q_y(k)\right]^T \qquad (2)$$

where R_θ^T represents the rotation matrix of counterclockwise angle θ, corresponding to the target direction; Q_y is the real hand position along the channel (i.e., $R_{(-\theta)}^T.\vec{P} = [0\ Q_y]^T$) (see Fig. 1); $\hat{Q}_x$ is the estimated lateral deviation with respect to the straight line passing from start to end targets estimated from the model.

C. Experimental Protocols

1) Experiment 1: Unidirectional Force Field Learning: This experiment tested learning the VF along a 20-cm-long forward movement away from the body, without lateral position error. Twenty subjects participated in this experiment and were randomly assigned to the unidirectional Virtual Group (*uVG*) or to the unidirectional Control Group (*uCG*) (see Table I). Portions of this experiment were presented at the *World Congress on Medical Physics and Biomedical Engineering 2009* [19].

Subjects from *uVG* performed 25 successful movements in vNF in order to familiarize with the virtual environment (*familiarization* phase—F); then they performed 150 trials in vVF (*learning* phase—L). The trained motor movement was tested through five pseudo-randomly distributed catch trials of *VF* (*learning effect trials*) within 20 vVF trials (*testing phase*—TI), followed by five pseudo-randomly distributed catch trials of NF (*after effects trials*) within 20 vVF trials (testing phase—TII). Finally, after a session of 25 successful movements in NF (*washout phase*—W), five pseudo-randomly distributed catch trials of VF (*VF post-washout trials*) were aimed at testing the effect of VF without adaptation within 20 vVF trials (*NF post-washout trials*). We note that the effects of NF and VF without adaptation were tested after the learning phase in order to prevent subjects from experiencing the dynamics of the unconstrained environment before the virtual training, as this might interfere with it.

Subjects from the *uCG* used a similar protocol but with unconstrained movements and feedback of the real hand trajectory. i.e., the haptic channel was not active, giving rise to VF and NF instead of vNF and vVF, respectively. To compare against *learning effect trials* from uVG, we considered the last five trials performed during the learning phase.

2) Experiment 2: Multi-Directional Force Field Learning: It might not be too difficult to learn the VF without proprioceptive error in one direction, as the movement will be just either too far left or right of the target. However, when movements are performed in several directions, the movement deviations are rotated at different target directions. Thus, it was not clear whether the subjects would be able to learn the VF without proprioceptive error in multiple directions simultaneously. Therefore, we examined how subjects (who had not participated in the first experiment) would learn to perform movements in multiple directions in the constrained environment. Subjects performed 15-cm-long point-to-point movements in five directions (0°, 72°, 144°, 216°, 288°) (Fig. 1). Targets appeared in a pseudo-random sequence such that consecutive movements were always towards different targets and subjects moved towards all five targets in every block of five movements. Ten subjects participated in this experiment and were randomly assigned to the multidirectional Virtual Group (mVG) or to the multidirectional Control Group (mCG). The experiment phases are similar to the first experiment, as described in Table I.

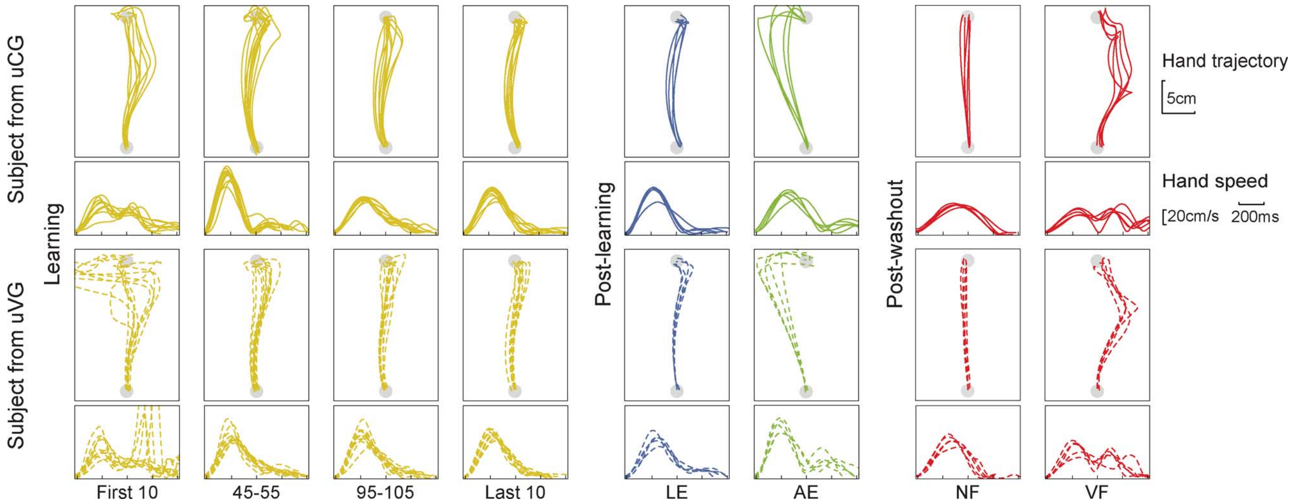

Fig. 2. Evolution of hand kinematics during learning of representative subjects from the unidirectional control group (uCG—solid line) and unidirectional virtual group (uVG—dashed line). 1) Learning phase, first 10 trials, trials 45–55, trial 95–105, and last 10 trials; hand kinematics of uVG during this phase, estimated trajectories are presented. 2) Post-learning phase, learning effects (LE) and after effects (AE). 3) Post-washout phase, Null field trials (NF) and viscous force field trials (VF).

D. Data Analysis

Hand kinematics data was recorded at 100 Hz and smoothed offline by using a second order, zero-lag, low-pass Butterworth filter with 50 Hz cutoff frequency. The subsequent analysis focuses on two aspects of movement performance: directional error and feed-forward control effort. As previously shown (e.g., [20]), if subjects learned to compensate the perturbation by developing an internal model that modifies the original motor commands, the large errors in initial trials would gradually decrease over repeated trials, while errors in the catch trials would increase as learning progresses.

The catch trials to test the learning in the virtual environment were obtained by switching off the haptic channel and vVF to unconstrained movements in VF. If the model learned in vVF was representative of the real VF dynamics, we expected the trajectories in vVF to be similar to those in the real VF, and comparable to the trajectories from unconstrained VF learning performed by the control group.

Measures of directional error during force field paradigms have been used extensively to quantify adaptation and feed-forward control (e.g., [21]–[25]). We analyzed three different measures.

1) *Aiming error at 150 ms*—computed as the angular difference between the direction of the target and that of the point of the actual trajectory at 150 ms after the initiation of movements; this measure is highly sensitive to the force field, and only lightly affected by the initial and final portions of the trajectory. We assumed movements under 150 ms to be under open-loop control. Therefore, we considered this measure as an indicator of the feedforward component of control.
2) *Aiming error at 300 ms*—computed similarly to the 150 ms aiming error. We took the 300 ms aiming error as an indicator of path curvature and lateral deviation.
3) Pearson's *correlation coefficient*—to quantify the relationship of the hand kinematics between groups. We calculated the mean trajectory performed by each subject for each set of testing trials. A Pearson's correlation coefficient (r value) between mean trajectories was computed for all possible subject combinations among groups. As the distribution of r values was skewed, the median and quartile deviation was reported.

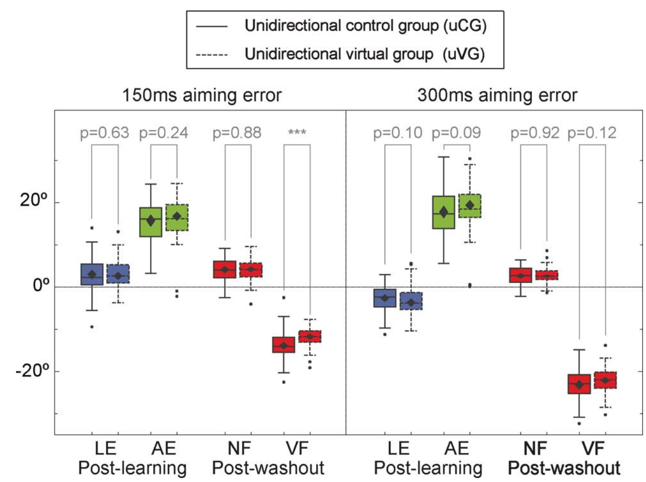

Fig. 3. Summary of the performance measures for both uCG (solid line) and uVG (dashed line). Blue and green whiskers represent learning (LE) and after (AE) effects respectively, while red whiskers represent NF and VF catch trials during the post-washout phase. To make data sets of comparable length and avoiding effects of VF catch trials, for each subject we considered only the last five NF trials that were performed at least three trials after a VF trial.

For statistical analysis, data was first checked for normality using a Shapiro–Wilk test. Then, unpaired Student-t tests were performed (p value was reported) using a 5% significance level. In the figures, one asterisk represents statistical significance at $p \leq 0.05$, two asterisks at $p \leq 0.01$ and three asterisks at $p \leq 0.001$.

Whisker box plots were chosen to examine the spread of the data. Each box shows the distance between two quartiles surrounding the median, and boundary lines indicate the range of

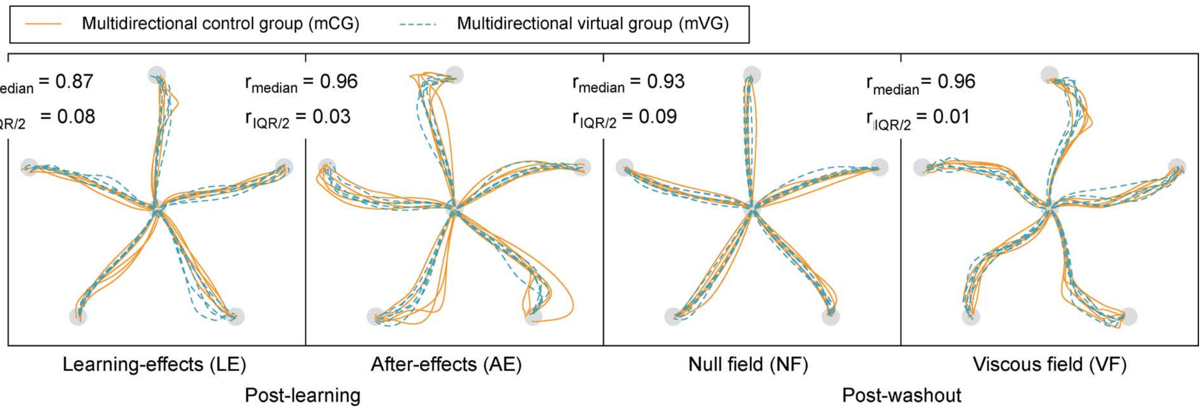

Fig. 4. Learning in multiple directions. Mean trajectories of all subjects in unconstrained (mCG—solid lines) and constrained (mVG—dashed lines) environments. Median and quartile deviation of the correlation coefficients between groups are presented.

the data set without outliers. Outliers were defined as those points beyond 1.5 times the interquartile range from the edge of the box. Outliers were removed from the data sets prior statistical tests. A "diamond" indicates the sample mean, with endpoints spanning at 95% confidence interval for the sample mean.

III. Results

A. Unidirectional Learning

Figs. 2 and 3 compare unidirectional learning of VF in the channel and in the unconstrained environment. As expected, subjects performing in the unconstrained environment during initial trials had reaching trajectories deviated by the force field, but learned to compensate for it after a few trials. *After effect* trials exhibited deviation in the opposite direction to the force, showing memorization of the compensation for this field [20].

Interestingly, similar trends could be observed in the results of subjects who trained in the channel. Using only visual feedback of the estimated hand position from the force applied on the channel, these subjects learned to compensate for the virtual force field, so that when they were tested in the unconstrained environment (i.e., no channel + VF), they produced movements similar to those of subjects who had learned the real force field $(\mathrm{r}_{\mathrm{LE}} = 0.87 \pm 0.12)$. The learned dynamics under the constrained environment also exhibited after effects similar to unconstrained learning $(\mathrm{r}_{\mathrm{AE}} = 0.91 \pm 0.05)$. Performance measures of both learning- and after-effects were not different between uVG and uCG ($\mathrm{p}_{\mathrm{LE}} > 0.10$, $\mathrm{p}_{\mathrm{AE}} > 0.09$; Fig. 3).

Performance measures of NF trials in the post-washout phase were not different $(\mathrm{p}_{\mathrm{NF(PW)}} > 0.88)$ and showed high *correlation coefficients* between groups $(\mathrm{r}_{\mathrm{NF(PW)}} = 0.94 \pm 0.06)$. VF trials during post-washout phase were highly correlated $(\mathrm{r}_{\mathrm{VF(PW)}} = 0.94 \pm 0.02)$ and the *300 ms aiming error* was not statistically different $(\mathrm{p}_{\mathrm{VF(PW)}} = 0.12)$. For those trials, the *150 ms aiming error* was smaller for the uVG, and the *absolute hand path error* values were larger, perhaps due to an incomplete washout.

We noted that large oscillations were present during the first trials of subjects from the uVG (see *learning* Fig. 2). This was expected as subjects were training in the virtual environment, so relying mainly on visual information and there was no prior knowledge of the perturbation. Subjects had to adapt to the visual disturbance using visual feedback with a typical delay between 160–200 ms [26], [27]. Changes in the direction of acceleration can be observed approximately at these intervals in the first 10 learning trials of the uVG subject in Fig. 2, corresponding perhaps to these corrective actions.

Trial after trial, subjects learned to compensate for the visual perturbation in this virtual environment without proprioceptive error. However, subjects from the uVG took longer to keep up with the time requirements of the task and they tended to slow down the movement in order to learn the dynamics by visual feedback only. After learning, both groups often produced a corrective movement at approximately 625 ms after movement onset. This happened in 40% of the trials for the uCG and in 61% for the uVG (different at $p = 0.01$). These differences probably stem from inconsistencies between the modelled and real dynamics.

Subjects from the uVG were questioned at the end of the experiment on their feelings about the visuo-proprioceptive discrepancy in the feedback. Interestingly, all subjects reported not being aware of the constraining channel. In fact, they were easily tricked and could not distinguish between trials in a constrained environment with virtual visual feedback and unconstrained trials.

B. Multidirectional Learning

All subjects who learned in the constrained environment (mVG) were able to learn to compensate for the vVF, as was indicated by a decrease in the estimated lateral deviation.

Fig. 4 shows the mean trajectories of the learning-, after-effects, NF and VF trials after washout for subjects who learned in the unconstrained vs. constrained environment. We see that mVG subjects became able, through learning in the virtual environment, to compensate for the real force (*learning effects*) and exhibited after effects similar to the subjects who learned in the unconstrained conditions.

Performance measures (Fig. 5) show that learning effects were not different between mVG and mCG $(\mathrm{p}_{\mathrm{LE}} > 0.10)$. After-effects were different for the *150 ms aiming error* but not for *300 ms aiming error* $(\mathrm{p}_{\mathrm{AE}} = 0.52)$, suggesting that subjects

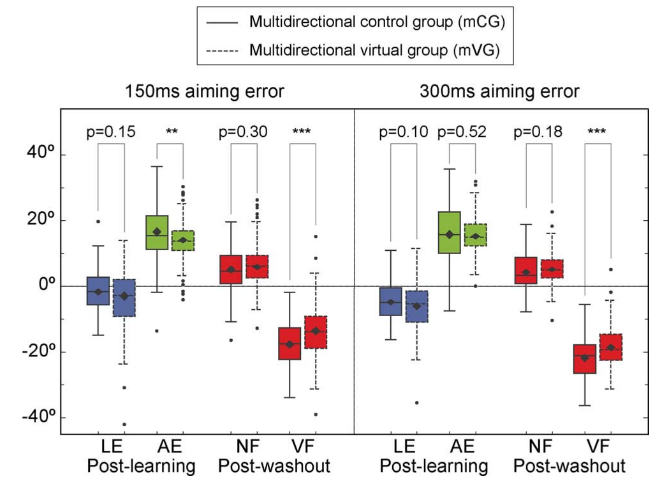

Fig. 5. Summary of the performance measures in all directions. Blue and green whiskers represent learning (LE) and after (AE) effects, respectively, while red whiskers represent NF and VF catch trials during the post-washout phase. To make data sets of comparable length, for each subject we considered only the last five NF trials on every direction that were performed at least three trials after a VF trial.

from mVG were undercompensating for the external disturbance. These differences were not found in the unidirectional case and can be attributed to incomplete learning. Nonetheless, there was a high correlation coefficient between the mean trajectories after learning in the constrained and unconstrained environments ($r_{LE} = 0.87 \pm 0.08$, $r_{AE} = 0.96 \pm 0.03$; Fig. 4). The correlation coefficients for different directions were larger than 0.83 for learning effects and larger than 0.93 for after effects, suggesting very similar kinematic patterns.

NF and VF trials were highly correlated between subjects learning in the different environments ($r_{NF(PW)} = 0.93 \pm 0.09$, $r_{VF(PW)} = 0.96 \pm 0.01$). Performance measures of NF trials indicated no difference between groups ($p_{NF(PW)} > 0.18$). Measures of VF trials for both *150 ms* and *300 ms aiming error* measures were smaller on subjects who learned in the constrained environment.

Subjects learned to compensate in every direction in less trials (30 per direction) than in the unidirectional experiment (where it took at least 50 trials for the uVG to achieve a mean *300 ms aiming error* of less than 5°). This suggests that learning to compensate for the force field was not done by rote memorization of the external forces. In contrast, an internal model of a dynamic multi-joint task was formed as subjects may have generalized the learning from other directions.

Lastly, as in the unidirectional experiment, subjects that learned in the constrained environment did not report to be aware of the constraining channel and could not detect the catch trials in the unconstrained environments.

IV. Discussion

The results of these experiments demonstrated that it is possible to learn to compensate for stable dynamics without proprioceptive error to drive the adaptation. The pattern of velocity profiles after learning, the reduced errors, and the correlation between group trajectories suggest that, using an appropriate model of the arm dynamics, it is possible to learn from visual feedback when there is reduced proprioceptive information. The final motor commands that compensate for the force field (learned in a constrained environment) are comparable to those learned in the unconstrained condition.

In the unidirectional experiment there was no difference in the learning effects between subjects training in a constrained environment and those training in unconstrained conditions. For the multidirectional experiment, the performance and correlation analysis after learning indicated that learning effects were similar between groups. Yet, there were some differences on the after effects, possibly due to incomplete learning on this more complex task. Discrepancies found in VF trials during the post-washout phase could have arisen as a result of a poor washout phase or, perhaps, indicate that learning in different environments may change the way the central nervous system (CNS) tunes the reflex gains (for vision and proprioception). This question is out of the scope of this paper, but provides an interesting avenue for further research.

Previous studies investigated the formation of a 1DOF force mapping involving no motion [14] in a virtual environment. However, learned dynamics were tested in the virtual environment rather than in the real one. Also, the main difference of our task to previous studies involving learning by vision, e.g., [7], [8], is that ours involves external forces that are actually generated at the end of the virtual training. Our results showed transfer from learning in a virtual environment to successful performance in an unconstrained environment with real dynamic interactions.

It is known that visual feedback can partially substitute for impaired proprioceptive feedback, such as in large fiber neuropathy subjects [4], [5], [28]. Sarlegna *et al.* [28] showed that a deafferented patient was able to learn to compensate for a force field without proprioception in a similar way as healthy control subjects; this results indicate that an internal representation of external dynamics can be formed on the sole basis of visual feedback. These patients may learn to successfully control movements in a similar way as was observed in our experiment. Though in our experiments, subjects were not deprived of proprioception. They had perception of their limb position in space and the setup merely prevented the perception of the proprioceptive error signal that originates from deviating from the straight line. Subjects still received feedback related to the pressure when applying force against the channel as well as tension in the corresponding muscles. The mechanisms of learning may be more related to the ones observed in recent studies [29], [30], on which amplification of the visual error from the task, rather than by physically altering movements, produce faster adaptation to a novel environment.

How could the CNS modify the feedforward command from one movement to the next by relying on visual feedback? A recent model of motor adaptation [10], [31] suggests that the CNS increases muscle activation based on muscle stretch or shortening in the previous movement. As the acquisition of the proprioceptive error was prevented by the channel, learning may have instead relied on voluntary visual corrections or visual reflexes [26], [27]. Correspondingly, when exposed to a novel environment, the CNS may combine available sensory information based on its reliability [32]. In the absence of reliable kinesthetic error information from the muscles the CNS would mainly rely on error information from vision.

Finally, the above results suggest that simple devices may be used for sport training and rehabilitation, where a complex dynamics could be learned by using visual feedback despite the limitations of the moving parts of the mechanical structure. Simplifying the devices will make them safer, cheaper and more reliable. A recent study [33] suggests that spatial abnormalities during movements of chronic post-stroke patients with hemiparesis are due to an impaired feedforward control rather than weakness, spasticity, or stereotypic muscle activation patterns. If so, appropriately designed visual feedback may allow development of effective neurorehabilitation strategies using simple robotic devices. In the same way as gravity-compensated devices can be adapted to let subjects produce more or less shoulder force, visual feedback could be used to train subjects with a planar manipulandum, to correct lateral forces in a 1DOF robot (such as ARM Guide [34] or reachMAN [35]) and to avoid compensatory movements.

Appendix

A. Human Arm Model

Human arm dynamics were modeled as in [16] and [17] and adapted to the paradigm. We assume that the central nervous system controls the arm to compensate for its dynamics, muscle visco-elasticity and reflexes produce a restoring force that can be modeled as feedback. The dynamics of the arm interacting with the environment are thus modeled as

$$H(q)\ddot{q}+C(q,\dot{q})\dot{q} = J(q)^T(F_{VF}+F_{LF}-F_{\mathrm{BDF}})+\tau_{FB} \quad (3)$$

$H(q)$ is the arm inertia matrix and is defined as

$$\begin{aligned} H(q) &= \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\ a_{11} &= J_1 + J_2 + m_1 l_{m1}^2 + m_2\left(l_1^2 + l_{m2}^2 + 2l_1 l_{m2} cos(q_2)\right) \\ a_{12} &= a_{21} = J_2 + m_2\left(l_{m2}^2 + l_1 l_{m2} cos(q_2)\right) \\ a_{22} &= J_2 m_2 l_{m2}^2 \end{aligned} \quad (4)$$

q_1 and q_2 denote the shoulder and elbow joint angles [rad] and are obtained from the inverse kinematic transformation of the arm, using $\hat{\mathrm{P}}$. l_1 and l_2 denote the segment lengths of the upper arm and forearm [m], l_{m1} and l_{m2} denote the upper arm and forearm center of mass from proximal joint in [m], m_1 and m_2 the upper arm and forearm masses [kg], and J_1 and J_2 the upper arm and forearm mass moment of inertia $[\mathrm{kg\,m^2}]$. Subject-specific parameters were estimated using the anthropometrical tables from Winter [18]

$$\begin{aligned} m_1 &= 0.028 m_{\mathrm{subject}} \\ m_2 &= 0.016 m_{\mathrm{subject}} \\ l_{m1} &= 0.436 l_1 \\ l_{m2} &= 0.430 l_2 \\ J_1 &= (0.542 l_1)^2 m_1 \\ J_2 &= (0.526 l_2)^2 m_2 \end{aligned} \quad (5)$$

$C(q,\dot{q})\dot{q}$ is the term corresponding to Coriolis and centrifugal forces and is defined as

$$C(q,\dot{q})\dot{q} = \begin{pmatrix} m_2 l_1 l_{m2}\dot{q}_2(2\dot{q}_1+\dot{q}_2)\sin(q_2) \\ m_2 l_1 l_{m2}\dot{q}_1^2\sin(q_2) \end{pmatrix}. \quad (6)$$

The Jacobian matrix transforming endpoint force into joint torque is given by

$$J(q) = \begin{pmatrix} -l_1\sin(q_1) - l_2\sin(q_1+q_2) & -l_2\sin(q_1+q_2) \\ l_1\cos(q_1)+l_2\cos(q_1+q_2) & l_2\cos(q_1+q_2) \end{pmatrix}. \quad (7)$$

The feedback

$$\tau_{FB} = \begin{cases} 0, & \dot{Q}_y < 0.1 \\ K(q_d - q) + D(\dot{q}_d - \dot{q}), & \dot{Q}_y \geq 0.1 \end{cases} \quad (8)$$

produces a restoring force toward the planned trajectory q_d, which is obtained by inverse kinematics transformation of the arm using $\vec{\mathrm{P}}$, the position of the arm along the straight line joining start and target. In order to prevent visual feedback of the hand position from converging to the straight line when the subject moves slowly, feedback is added only when the velocity in the y direction is above a threshold of 0.1 m/s. K is the mean torque-dependent joint stiffness from the subjects measured by Gomi and Osu [36]

$$K(\tau_{FF}) = \begin{pmatrix} 10.8+3.18|\tau_1| & 2.83+2.15|\tau_2| \\ 2.51+2.34|\tau_2| & 8.67+6.18|\tau_2| \end{pmatrix} \quad (9)$$

which is computed as a function of the feedforward torque τ_{FF}

$$D = (0.42/\sqrt{\dot{q}^T\dot{q}+1})K \quad (10)$$

corresponds to the viscosity in joint space, which is nonlinearly related to joint stiffness and depends on velocity [17]. F_{VF} corresponds to the force of the viscous field, F_{LF} to the lateral force applied by the subject against the channel, and F_{BDF} to the modeled friction, Coriolis and centrifugal forces as described by Casadio *et al.* [15].

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Alejandro Melendez-Calderon (S'06) received the B.Sc. degree in mechatronics and Pg.Cert in control engineering from Tecnológico de Estudios Superiores de Monterrey–Campus Estado de México (ITESM-CEM), Mexico, in 2006, and the M.Sc. degree in intelligent autonomous systems from Aalborg University, Aalborg, Denmark, in 2007. He currently is finishing his doctoral studies at the interface of rehabilitation robotics and working as Research Assistant at Imperial College London, London, U.K.

Before starting his Ph.D. studies, he worked as a Control System Engineer for General Electric, Aviation. His main research interests include human–robot interfaces and motor control/learning.

Lorenzo Masia (M'10) received the M.S. degree in mechanical engineering from the University of Rome "La Sapienza," Rome, Italy, in 2003, and the Ph.D. degree in mechanical measurement for engineering from the University of Padua, Padua, Italy, in 2007.

Currently, he holds a Team Leader position at the Robotics, Brain and Cognitive Science Department, Italian Institute of Technology (IIT), Genoa, Italy. He was a Visiting Student at the Massachusetts Institute of Technology in 2005 and 2006, working at the Newman Laboratory for Biomechanics and Human Rehabilitation. His research interests include, mechanical design, and control of dynamical systems, the development of haptic devices for robotic rehabilitation.

Roger Gassert (S'02–M'06) received the M.Sc. degree in microengineering and the Ph.D. degree in robotics and neuroscience from the Ecole Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland, in 2002 and 2006, respectively.

Since 2008 he has been Assistant Professor of Rehabilitation Engineering at ETH Zurich. He has made contributions to the field of neuroscience robotics to investigate sensorimotor control and related dysfunctions, as well as to robot-assisted assessment and therapy. His research interests are in human–machine interaction, rehabilitation robotics, assistive devices, and neuroscience.

Giulio Sandini (M'11) received the degree in electronic engineering (bioengineering) from the University of Genova, Genova, Italy, in 1976.

He is Director of Research at the Italian Institute of Technology and full Professor of Bioengineering at the University of Genoa. After his graduation in electronic engineering (bioengineering) at the University of Genova in 1976 he was Research Fellow and Assistant Professor at the Scuola Normale Superiore in Pisa until 1984. After his return to Genova as Associate Professor at the Faculty of Engineering where in 1990 he founded the LIRA-Lab (Laboratory for Integrated Advanced Robotics). Since 2006 he is leading the Department of Robotics, Brain and Cognitive Sciences at the Italian Institute of Technology. His research activities are in the fields of biological and artificial vision, computational and cognitive neuroscience and robotics with the objective of understanding the neural mechanisms of human sensory-motor coordination and cognitive development from a biological and an artificial perspective.

Etienne Burdet (S'92–M'96) received the M.S. degree in mathematics, the M.S. degree in physics, and the Ph.D. degree in robotics, all from ETH-Zurich, Zurich, Switzerland, in 1990, 1991, and 1996, respectively.

He currently is Reader at Imperial College London, London, U.K. He is doing research at the interface of robotics and bioengineering, and his main research interest is human–machine interaction. He has contributions in various fields from human motor control to VR based training systems, assistive devices, and robotics for life sciences.