Skill Learning and Skill Transfer Mediated by Cooperative Haptic Interaction

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***Abstract*— It is known that physical coupling between two subjects may be advantageous in joint tasks. However, little is known about how two people mutually exchange information to exploit the coupling. Therefore, we adopted a reversed, novel perspective to the standard one that focuses on the ability of physically coupled subjects to adapt to cooperative contexts that require negotiating a common plan: we investigated how training in pairs on a novel task affects the development of motor skills of each of the interacting partners. The task involved reaching movements in an unstable dynamic environment using a bilateral non-linear elastic tool that could be used bimanually or dyadically. The main result is that training with an expert leads to the greatest performance in the joint task. However, the performance in the individual test is strongly affected by the initial skill level of the partner. Moreover, practicing with a peer rather than an expert appears to be more advantageous for a naive; and motor skills can be transferred to a bimanual context, after training with an expert, only if the non-expert subject had prior experience of the dynamics of the novel task.**

***Index Terms*— Physical human-robot interaction, motor learning, skill learning, neural control of movement, human-human interaction.**

I. Introduction

IN RECENT years it has become evident that skilled behavior emerges from embodied cognition, namely an intimate perception-action loop, supervised by physically grounded cognitive processes. The fronto-parietal mirror neuron circuit in the cerebral cortex [1] emphasizes the unitary nature and complementarity of "Action and Action-Observation". A further step in this direction is the recognition of the unitary nature of overt and covert actions, that lead Marc Jeannerod [2] to posit that skilled behavior is part of a simulation network related to action, whose function is not only to shape the motor system for preparing an action (either overt or covert) but also to provide the self with information on the feasibility and the meaning of potential actions. A natural consequence of this approach is the notion of body schema [3] formulated as a generalization of the Equilibrium-Point Hypothesis [4] to include covert and overt actions as well as actions involving the skilled use of tools [5]. Summing up, research on embodied cognition demonstrates that individuals rely on their bodies and their individual action generation mechanisms both to improve the effectiveness of their own actions and to understand others' actions and predict their chance of success.

Nevertheless, embodied cognition, being the source of skilled behavior, would be unable to express its full potential without involving two crucial aspects: 1) the social nature of purposive action [6], namely the fact that joint actions between two or more cooperating individuals are more likely to be successful than solo actions and may be an effective channel of skill transfer; 2) the ecological permeability of skills, namely the intrinsic human capability to synch up with strong, external dynamics, rhythms, pulses or beats, a phenomenon known as entrainment [7]–[9]. These two aspects are different but, at the same time, deeply complementary. Moreover, we should consider that joint actions are conscious, in the sense that cooperating individuals may learn to share representations, predicting each other's actions, and ultimately achieving the capability to jointly plan ahead. On the other hand, physiological/psychological entrainment implies an autonomic mechanism that is largely unconscious.

The transfer of a skill from an expert to a naïve person is a typical example of social interaction. In many cases, the kind of knowledge that is transferred from the expert to the novice is to a great extent implicit, in the sense that it is hard to express it verbally but it is much more natural to exploit a physical/haptic interaction between the two actors.

Recently, there has been a great deal of interest in addressing skill learning and skill transfer during dyadic interaction. The problem is that measuring dyadic interaction during daily life activities is quite complex. For this reason, the use of robotic haptic interfaces is a very promising way to study in a detailed way the subtle aspects of dyadic interaction. In the 90's, indeed, the introduction of robotic interfaces made it possible (and quite popular) to study the human mechanism of adaptation to unknown dynamic environments by using robot generated force-fields [10]. The study of dyadic physical interaction through robotics has benefited from several notable contributions. Ganesh *et al.* [11], developed a system where the two users of a dyad are engaged in the same task (tracking independently the computer generated target) without any knowledge of each other's performance. However,

Manuscript received May 9, 2016; revised December 12, 2016; accepted March 22, 2017. Date of publication May 8, 2017; date of current version August 6, 2017. *(Corresponding author: Dalia De Santis.)*

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Digital Object Identifier 10.1109/TNSRE.2017.2700839

the two robotic manipulanda were dynamically linked by a virtual spring, a linkage of which the two individuals were unaware. In a sense, this is an example of interaction through ecological influence, namely a common haptic environment that induces a kind of haptic entrainment, in the absence of a cooperative task. In another study, van der Wel *et al*. [12] designed a simple cooperative task that consists of balancing a physical inverted pendulum through two cables operated by two individuals or by a single individual in a bimanual arrangement: the results suggest that dyads amplify their forces to generate a haptic information channel. In the same framework, Groten *et al*. [13] devised a similar task to specifically asses the mechanisms of intention integration through haptic communication: the subjects had to complete a tracking task of a virtual mass using a haptic knob and, in addition to the visual feedback of the cursor, they could receive force feedback only related to the inertia or to both the inertia and the partner's action. The results suggest that subjects could negotiate intentions through haptic communication and that the difficulty of the negotiation process was proportional to their physical effort.

In the aforementioned cases, however, the tasks faced by the interacting subjects are rather simple and not particularly challenging. In contrast, this study addresses a very challenging balancing task that somehow resembles real life problems like coordination/cooperation in minimally invasive surgery. The task is strongly unstable (reaching and stabilizing in a saddle like force field) and non-linear (the virtual tool manipulated bimanually by a single user or bilaterally by two cooperating users has a variable stiffness) and was designed in such a way to allow the user/users to adopt solutions bounded by two different limit strategies: an open loop stiffness strategy, simple but energetically expensive, or a closed loop positional strategy, complex but energetically efficient. In previous studies [14], [15] we investigated the stabilization strategies and the strategy-switching mechanisms involved by this kind of experimental setup in the case of bimanual, solo operation. In a following study [16] we presented some preliminary results of a dyadic operation in the same setup.

In this study we further expanded this research line by seeking to answer the two following questions:

1. When a novice is engaged in learning to carry out a complex task, such as controlling an unstable tool, to which extent and under which conditions a dyadic interaction with a cooperating expert partner can be beneficial for achieving an optimal performance level?
2. If the assistance of the expert is indeed effective, under which circumstances can the trained user maintain the level of performance reached during assisted training when performing solo in the same task?

The underlying issue is to find the optimal trade-off between exploration and exploitation: curiosity-driven exploration of the unknown dynamics of the task at hand by the novice, accepting low performance levels, vs. exploitation of the assisting action of the expert that may improve performance but also reduce the chance of the novice to experience a wide-range of dynamic contingencies, crucial for generalization and for a robust consolidation of the acquired skill.

II. Methods

We asked subjects to learn to jointly manipulate a virtual compliant tool under the action of an unstable force-field, rendered by a haptic bilateral interface that can be operated bimanually by a single user or bilaterally by a dyad. A single novice can become an expert user after a rather long learning process, thus incorporating in some internal model a working knowledge of the instability and non-linearity of the tool and the capability to carry out manipulation tasks with the tool using a combination of different control strategies [14], [15]. The issue, addressed by the experiments, was to ascertain if and how dyadic interaction of a novice with an expert can facilitate skill transfer, namely speed up skill acquisition. In this section we first describe the task and the setup we used for training and testing skill transfer effects. Subsequently we describe the experimental protocol and the subjects who took part in the task. Lastly, we introduce the measures of performance and the statistical methods we applied in the results section.

A. Experimental Setup and Task Description

The experimental setup (Figure 1) consists of a bimanual haptic manipulandum (BdF2, Celin srl, La Spezia, Italy, an evolution of the unimanual "Braccio di Ferro" robot [17]), used to simulate the elastic bilateral tool and emulate the dynamics of the task, and an amplifier (OTBiolab EMG-USB2+) for acquiring surface electromyographic signals using Ag/AgCl electrodes with a diameter of 26 mm. As regards BdF2, the main features are that each planar arm of the robot has a large planar workspace ($0.8\times$ 0.4 m ellipse) and is actuated by two direct-drive brushless motors resulting in a low intrinsic mechanical impedance and large range of forces. Moreover, a real-time control architecture based on 3 nested loops is implemented in a QNX machine: 1) an inner 16 kHz current loop, 2) an intermediate 1 kHz impedance control loop to render the haptics, and 3) an outer 100 Hz loop for virtual reality and data storage. The two arms are mounted in a mirror configuration on the same rigid frame with their horizontal separation computed to allow to work simultaneously with one or two subjects: the distance between the axes of the motors is 0.38 m (bimanual configuration) and 0.98 m (dyadic configuration), respectively. The recording system is used to acquire electromyographic signals from 10 relevant muscles of the arm and trunk, which are responsible for the movements of the shoulder, elbow, and wrist in the specific experiment. The selected muscles are: Upper Trapezius (UT), to detect movements in the sternoclavicular joint; Anterior Deltoid (AD), Lateral Deltoid (LD), Posterior Deltoid (PD), Pectoralis Major (PM), Infraspinatus (IS), which control the movements of the shoulder; Biceps Branchii Lateralis (BL), Triceps Lateralis (TL), responsible of elbow flexion and extension; Extensor Carpi Radialis (ER) and Flexor Carpi Radialis (FR), for analyzing the grip and the movements of the wrist. The Maximum Voluntary Contraction (MVC) for each muscle is recorded at the beginning of each experimental session. The signals are pre-amplified using a gain of 1000 or 2000 depending on the EMG amplitude

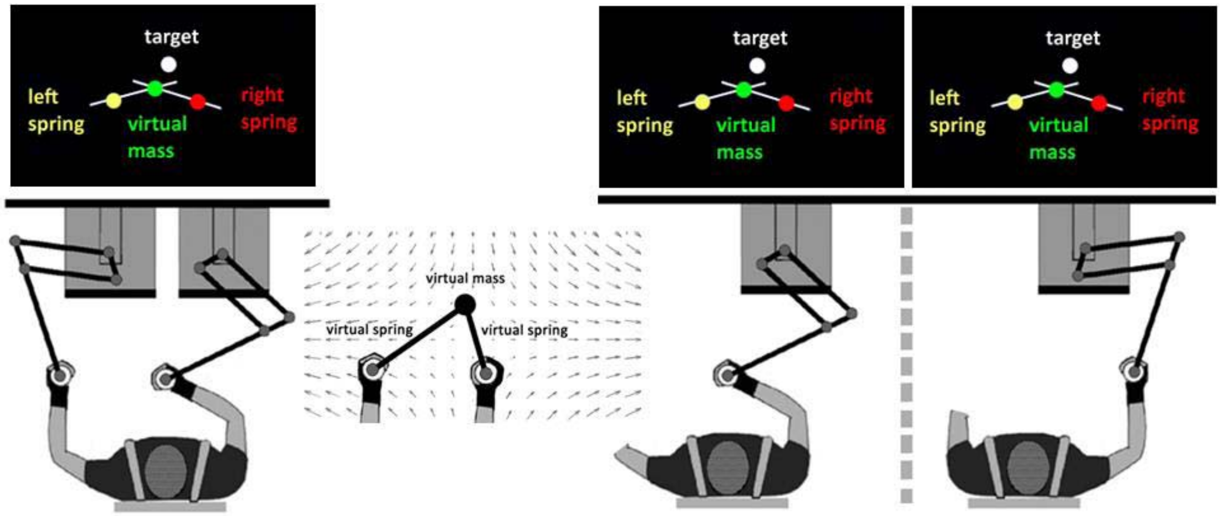

Fig. 1. Experimental robot configurations. The left part of the figure corresponds to the bimanual configuration while the right part corresponds to the dyadic one. The intermediate panel illustrates the structure of the virtual tool: two non-linear virtual springs controlling the motion of a virtual mass (the end-point of the tool), affected by a saddle-like force field. The single user, in the bimanual configuration, or the pair of users, in the dyadic configuration, all receive the same visual feedback on a computer screen: the position of the virtual mass (green circle) with respect to the target (white circle), the positions of the hand-grasped terminals of the two virtual springs (yellow circle for the left spring and red circle for the right spring, respectively), and the lines of action of the two springs (white lines). The distances between the yellow (or red) circle and the white circle are proportional to the lengths of the corresponding springs, whose magnitudes increase linearly with length.

of each subject, sampled at 2048 Hz, and band pass filtered (Fc =[10-900] Hz) in order to avoid aliasing.

The task (adopted in [14]–[16] and [18]) consists of a sequence of reaching movements performed by controlling the tip of the virtual tool (a 15 kg mass, visualized on the screen as a 1 cm diameter circle) under the action of a position dependent force-field. The targets, distributed on a circle of 10 cm diameter, are presented in randomized order. A trial includes a reaching movement to a peripheral target from the starting position (the center of the workspace), 4 s of stabilized maintenance of the virtual mass in the target area,[1] reaching back to starting position, and 4 s of stabilized maintenance of the virtual mass in the central target. The handles of the robot (and the corresponding grasping hands) are attached to the virtual mass through a couple of nonlinear virtual springs, generating two force vectors, directed from each handle to the virtual mass, whose magnitudes are computed according to the following equations:

$$\begin{cases} F_R = K_s L_R + 2\rho_s L_R^2 \\ F_L = K_s L_L + 2\rho_s L_L^2 \end{cases} \tag{1}$$

where L represents the distance between the virtual mass and the corresponding hand location, $K_s = 148N/m$ and $\rho_s = 1480N/m^2$ are the spring parameters. Moreover, the virtual mass is persistently immersed in a saddle like unstable force-field described by:

$$\vec{F}_u = \begin{bmatrix} +K_u & 0 \\ 0 & -K_u \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

where $K_u = 592N/m$ is the stiffness of the field. The force-field is centered in the origin of the workspace; the unstable manifold of the force-field is aligned with the x-axis while the stable manifold is aligned with the y-axis. The dynamics of the task can be summarized in this way:

$$M \begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} + B \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} + \vec{F}_u = \vec{F}_R + \vec{F}_L \tag{3}$$

where $B = 132N/m/s$ is the viscosity coefficient of the end-point of the virtual tool and $M = 15\ kg$ is the corresponding mass. The values of the parameters of the tool and the features of the force field were chosen to make the task challenging but solvable. Moreover, since no unique solution to the balancing task exists, the users are free to explore different coordination strategies. A detailed analysis and description of the task dynamics can be found in [14] and [15].

During the experiments we recorded kinematic and dynamic data: position and velocity of both handles and of the virtual mass; force applied by the two virtual springs to the two hands. The kinematic data was synchronized with the EMG by means of a trigger signal from the robot.

B. Subjects

Thirty young volunteers took part in the study (25.25±3.85 years of age, 64.4±11.16 kg of weight, and 171.5±8.7 cm of height). Twenty-eight of them were naïve to the task (subjects without previous knowledge of the task) and 2 were experts in the task (subjects trained and skilled in the task, following the protocol reported in [18]). The subjects were balanced as regards gender: 14 Nf (Naïve females), 14 Nm (Naïve males), 1 Ef (Expert female), and 1 Em (Expert male). All the subjects were right handed according to the Edinburgh laterality test, and did not have known neurological impairments of the upper limbs. The research conforms to the ethical standards laid down in the 1964 Declaration of Helsinki, which protects research subjects, and was approved by the ethical committee

[1] More specifically, during stabilized maintenance of a target position against the destabilizing action of the force field the virtual mass is allowed to oscillate within the target area of 2 cm diameter. The time counter for the stabilization resets every time the mass exits the area.

TABLE I
EXPERIMENTAL GROUPS AND EXPERIMENTAL PROTOCOL

Group	Naïve Subjects	Expert Subjects	**PRIMING** *Day1 6+6+3 TS*	**TRAINING** *Day2 3+ [10*	*Day3 +10+*	*Day4 10]+3 TS*	**TESTING** *Day5 6+6+3 TS*
NN	3M + 3F	-	D	D	D	D	B
NN-b	3M + 3F	-	B	D	D	D	B
NE	3M + 3F	1M + 1F	D	D	D	D	B
NE-b	3M + 3F	1M + 1F	B	D	D	D	B
BIM	2M + 2F	-	B	B	B	B	-

of Regione Liguria, Italy. Each subject signed a written consent form conforming to these guidelines. The robot training sessions were carried out at the Motor Learning, Assistive and Rehabilitation Robotics Lab of the Istituto Italiano di Tecnologia (Genoa, Italy). The 30 subjects were randomly assigned to 5 groups, characterized as follows:

- NN (naïve-naïve group): it is composed of 3 males and 3 females with no previous experience of the task. These subjects were paired to form 3 dyads.
- NN-b (naïve-naïve group with bimanual prior): also in this group there are 3 males and 3 females with no previous experience of the task, who are paired to form 3 dyads, but in this case the subjects were trained separately in the bimanual paradigm, during a preliminary priming phase.
- NE (naïve-expert group): it is composed of 3 naïve males, 3 naïve females and the 2 expert users (1 male and 1 female), who were paired to form 6 dyads, with the male expert training 4 naïve subjects (2M+2F) and the female expert training 2 (1M+1F).
- NE-b (naïve-expert group with bimanual prior): it is composed in a similar manner as the NE group, with the difference that the 6 naïve subjects were trained separately in the bimanual paradigm, during a preliminary priming phase. After this phase they were paired with the 2 expert subjects to form 6 dyads. Again, 4 subjects (2M+2F) were paired with the male expert and 2 (1M+1F) with the female expert.
- BIM: it is composed of 4 naive subjects (2 males and 2 females) who never operated in dyads.

C. Experimental Protocol

For all the experimental groups the protocol was organized into 5 days: the first day was considered a priming session, 3 days of training sessions, and 1 day of final test session. Each session included a number of target sets (TS), which were the basic module of the experimental protocol: each TS was composed of 8 trials (center-out-center sequences), one per target direction. More specifically, the session of the experimental protocol consisted of 3 phases:

PRIMING SESSION (Day 1)

1) Familiarization: 6 TS, unstable force-field off
2) Adaptation: 6 TS, unstable force-field on
3) Wash-out: 3 TS, unstable force field off

TRAINING SESSIONS (Day 2-4)

1) Familiarization: 3 TS (Day 2 only)unstable force-field off
2) Training: 10 TS, unstable force-field on
3) Wash-out: 3 TS (Days 4 only), unstable force-field off

BIMANUAL TEST SESSION (Day 5)

1) Familiarization: 6 TS, unstable force-field off
2) Adaptation: 6 TS, unstable force-field on
3) Wash-out: 3 TS, unstable force-field off

Table I summarizes the distribution of subjects into the 4 the experimental groups (NN, NN-b, NE, NE-b) and in the control group (BIM).

The experimental protocol followed by each group is detailed in the three rightmost columns. The priming session occurs on Day 1, the training session spans 3 days and bimanual test session occurs on Day 5. Each day, the subjects might perform the task either in dyads (D) or bimanually (B) according to the group. As outlined in Table I, the NN and NE groups always trained in dyads. In the NN-b and NE-b groups the naïve subjects performed alone in a bimanual way during the priming session and were exposed to dyadic interaction in the training sessions. The BIM group always performed in a bimanual way, without any dyadic interaction. The rationale of this procedure was to test for the effect of the initial skill level of the partners on skill transfer after dyadic practice.

The EMG signals of the 10 muscles listed above were collected during Day 1 to characterize the initial activation patterns, on Day 2 and Day 4 (to characterize the activation patterns at the beginning and at the end of the training sessions), and at Day 5 (bimanual test).

D. Outcome Measures

The performance of the subjects in the task was characterized by using the following metrics:

1) Effort Index (EI, [N]): it measures the total force magnitude that the two arms exert on the virtual mass. Given $\vec{F}_R$ and $\vec{F}_L$, it is computed as follows:

$$EI = \left\|\vec{F}_R\right\| + \left\|\vec{F}_L\right\|$$

This metrics is strictly related to the strategy subjects adopt to solve the balancing task. Whenever the subjects increase the stretch in the elastic elements connecting the hands and the virtual mass they increase the stiffness of the tool and therefore the responsiveness of the system to the applied forces - being either the background dynamics or the force applied by the hand at the robot handles. This control strategy, which we can define as Stiffness Stabilization Strategy, comes at the cost of a greater effort but allows a faster stabilization of the tool even at the initial stages of the learning process. Alternative strategies can be adopted, that require a much lower overall effort by the subjects. For instance, the subjects might exert a couple of forces that counteract the background disturbance by minimizing the component of the total elastic force orthogonal to the force field in each point of the tool space. This second family of strategies, or Positional Stabilization Strategies, result in a lower overall stiffness of the tool and therefore a system that has a smaller control bandwidth compared to the previous example (meaning that the response to an applied force is considerably lagged). This latter strategy takes a longer time to be mastered than the previous one, since requires a deeper understanding of the dynamics of the system but is more energy-efficient (the reader is invited to refer to [15] for more details).

In order to quantify the performance of the subjects in the task independently of their choice of the force strategy we considered the following indicator:

2) Time to Target (T2T, [s]): it measures the total trial duration from the time instant when the peripheral target appears to the instant in which the subjects achieve a complete stabilization in the central target (duration of a center-out-center sequence).

In general, the stabilization is more challenging for subjects that adopt a positional stabilization strategy than for subjects who adopt a stiffness stabilization strategy due to the greater phase-lag in the response of the system. Therefore, in the initial phases of the learning the time required to complete a trial can be greater depending on the strategy the subjects adopted.

3) Inefficiency Index (II): this index of performance combines the previous two measures of effort and reaching time independently of the specific stabilization strategy a dyad or a subject adopts. It is computed as the product of effort and reaching time in percentage with respect to the maximum effort and reaching time in the course of whole experiment:

$$II = \frac{EI \cdot T2T}{EI_{MAX} \cdot T2T_{MAX}} * 100$$

According to this index, the subjects will be most efficient (lowest score) if they are able to complete a trial in the minimum time possible using the lowest possible force to counteract the background force acting on the tool. This implies also a minimization of the interaction forces between the tool handles. The rationale is that subjects may choose to prioritize effort minimization over time minimization or time over effort [14] and Dyads may also change their strategy in time (the reader is invited to refer to Figure 1 of the Supplementary Material for more details). However, whatever strategy they adopt, there is evidence that either single subjects [15] or dyads [19] tend to minimize both effort and time to target in the course of the training. Therefore, we assume that the best performer would jointly minimize both measures in time.

4) Mutual Information (MI): it is a measure that quantifies the mutual dependence between two random variables for which a joint probability is known. In our case, we exploit the concept of Mutual Information to identify the nonlinear causal relationship between the action of the force-field on the virtual mass and the elastic force generated in each of the two spring elements attached to the virtual mass. If the two forces are highly correlated (MI is high), the action of the force-field on the mass is largely responsible for the forces that drive the motion of the tool. We can hypothesize that in this case the subject is "passive" to the action of the force-field. On the contrary, if the subject actively counteracts the divergent drive induced by the force-field and leads the motion of the tool, the elastic force generated in the spring will be virtually uncorrelated with the local direction of background perturbation acting on the mass. Let us define F_{ux} the divergent component of force-field and F_x the component of the elastic force of one spring along the unstable manifold. We can therefore compute the mutual information of the two forces as:

$$MI = \sum_{xF} \sum_{xF_u} \frac{\log(p\,(F, F_u))}{p\,(F)\,p\,(F_u)}$$

where $p(F_u,F_{ux})$ is the joint probability distribution function computed over the forces acting along x in a target set (8 trials) and $p(F_x)$ and $p(F_{ux})$ are the corresponding marginal probability density functions.

Our expectation is that when individuals performs the task bimanually both limbs will actively participate to the balancing and there will be no significant difference between the values of MI computed for the right and for the left springs. However, in dyadic actions it is likely that the balancing responsibilities are unequally distributed between the two partners [20], [21]. We therefore computed the *Mutual Information Difference* between the two partners $MI_{right}- MI_{left}$, being MI_{right} the mutual information computed for the rightward spring/subject and MI_{left} the one computed for the leftward spring/subject.

5) Average RMS (Root Mean Square Value): the RMS envelope of the EMG of a muscle. It represents the effective muscular activity during the task and it is computed as the RMS envelope of the EMG signal normalized by the maximum RMS value of the MVC:

$$RMS = \left(\frac{1}{N}\sum\nolimits_{1}^{N} EMG^2(n)\right)^{1/2}$$

More specifically, the EMG signals are band pass filtered with a Butterworth digital filter at Fc=[20-500] Hz and the RMS envelopes are calculated for each muscle on a moving window of length 100 ms over a single target set. Finally, we computed one value for each target set as the average of the RMS activation of the 10 muscles.

When a body part is destabilized by a unexpected perturbation, subjects tend to increase the stiffness of their limb co-contracting agonist and antagonist muscles [22]. This strategy provides an immediate opposition to the external force and allows maintaining movement accuracy, but comes at a high metabolic cost. Limb stiffness, however, is progressively reduced and skillfully manipulated when the subjects acquires more knowledge of the task [23], [24]. Moreover, it is likely that dyads will exert higher forces than single individuals overlap to overcome the high coordination requirements of the balancing task [12]. Therefore, we expect the average RMS of the 10 muscles to reflect both the modulation of limb stiffness throughout learning the novel task and the presence of a co-actor.

E. Data Analysis and Statistics

Data from the robot and virtual reality were collected at 1 kHz and saved at 100 Hz for subsequent analysis. Hand trajectories in Cartesian coordinates were reconstructed from the primary encoder measurements (17-bit, positional end effector resolution lower than 0.01 cm). We computed the elastic forces transmitted from the hand to the robot as in equation (1). The measures of performance were calculated for each trial separately and then averaged within the target set (8 directions).

Statistics was performed on the target set values obtained for each subjects in the force-field phase. Normality was assessed using the Kolmogorov-Smirnov test. We compared the performance measures within a same target set among groups using a one-way Analysis of Variance. When comparing the average performance along multiple sessions, we adopted a repeated measures ANOVA having time as within factor and groups as between factors. We used a paired t-test whenever comparing only two targets sets (i.e. first and last of a session). Significance level was set to 0.05. The sphericity condition for repeated measures ANOVA was assessed using the Mauchly test. When deviation from sphericity occurred, we applied the Greenhouse-Geisser correction. In this case the p-values for the statistics are reported as p_{GG}. Post-hoc comparisons were assessed using the Bonferroni correction for multiple comparisons.

III. Results

This section presents the results organized as follows. The first part of the section compares the performance of the two groups who executed the priming session always in dyads (NE and NN), with the naïve subjects having no experience of the bimanual paradigm, and the three groups where naïve subjects experienced the bimanual paradigm, at least in the priming session (BIM, NN-b, NE-b). The second part focuses on skill learning and performance during the training sessions. The third and last part presents the results of the bimanual test session to evaluate the amount of skill transfer for the naïve subjects in the four dyadic groups (NN, NN-b, NE and NE-b).

A. Priming Session

During the priming phase, the subjects practiced the stabilization task for 6 TS (48 trials). In this phase, only naïve subjects from the groups NN and NE performed the task with a partner, while the remaining naïve subjects performed the task bimanually. We are therefore interested in comparing the performance of the dyads with the performance of the individual subjects and test if any difference can be identified between conditions.

In the left part of Figure 2 is represented the evolution of the Inefficiency Index in different sessions of the experimental protocol. For the moment, let us focus on the priming session (P1-P6). From the figure we can see that naïve subjects working with an expert are the better performers both in the first TS *(NE: 1.95±0.53; NN: 10.16±6.99; NN-b: 6.37±2.54; NE-b: 9.38±5.81)* and at the end of the force-field adaptation phase of Day 1 *(NE: 1.48±0.61; NN: 3.30±2.02; NN-b: 3.98±1.18; NE-b: 3.54±1.82)*. Naïve-naïve dyads seem to represent the least favorable condition. While the subjects in both the NE and bimanual condition significantly improved their performance from P1 to P6 *(NE: $T(5) = 4.730$, $p = 0.005$; BIM+NN-b+NE-b: $T(15) = 3.011$, $p < 0.001$)*, the NN group improved to a lesser extent throughout the priming session ($T(2) = 2.342$, $p = 0.144$). Indeed, a repeated measures ANOVA conducted over the 6 TS of force-field adaptation of Day 1 supports the hypothesis that working with a skilled partner in the priming session allows to have significant performance benefits *($F(1.9,42.2) = 3.29$, $p_{GG} = 0.022$, group - target set interaction)* compared to working in a solo condition *(-3.25 [-5.76; -0.74], $p = 0.008$)* or with a peer naïve *(-3.73 [-7.41; -0.05], $p = 0.046$)*.

As regards the EMG signals, Figure 3 shows the average RMS values of the subjects in groups NN-b and NE-b (bimanual priming, panel a) and NN and NE (dyadic priming, panel b) compared to the bimanual control group throughout the sessions (force-field on phase only). If we focus our attention on the effect of the priming session (P1 - P6) in the dyadic priming condition (right panel), we can observe a tendency to decrease the overall average muscular activation in subjects who practiced with a skilled partner compared to the control condition. Conversely, subjects who trained with a less skilled subject tended to increase the overall muscular activity with respect to the bimanual condition

B. Training Sessions

In the training sessions, the dyads practiced for 240 trials over three days, corresponding to 30 target sets with perturbation in total. All the dyads showed improvement (reduction) on the Inefficiency Index (Figure 2, T1-T30) and the two groups of naïve-expert dyads improved significantly *(NE, $p = 0.002$: (T1) 1.95±0.53; (T30) 0.90±0.18; NE-b, $p = 0.003$: (T1) 1.19±0.20; (T30) 0.76±0.07)*.

In Figure 3 the RMS values of the NN and NN-b groups at the beginning of the training sessions show a decrement with respect to those of the end of the adaptation session. Moreover, the NE and NE-b groups started the training session at the same level observed at the end of the adaptation session.

A decrement in the average RMS values can be noticed in the NN and NE-b groups. This is particularly remarkable for the NE-b group at the beginning of Day 2 and at the end of Day 4 and for the NN group from Day 2 to Day 4. The values of the NE group do not present significant variations during training (Figure 3, panel b), with similar values of the NE-b group (Figure 3, panel a). Consistently

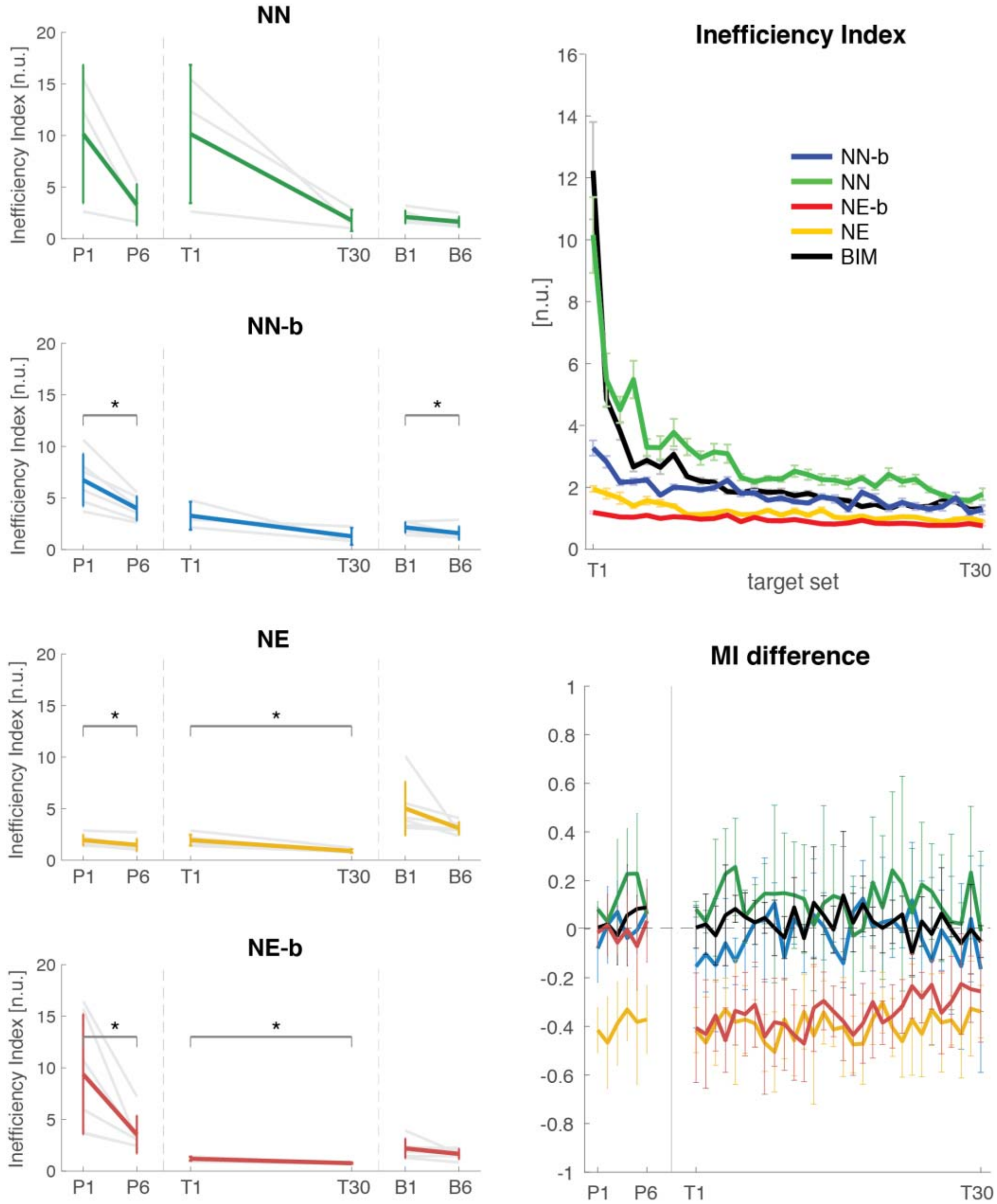

Fig. 2. Summary of performance measures. *Left panels*: Average variation of the Inefficiency Index between the first and the last training set in the three phases of the experimental protocol (P = priming; T = training; B = bimanual test), separately for the four dyadic groups (*NN-b* = naïve-naïve with bimanual prior; *NN* = naïve-naïve without bimanual prior; *NE-b* = naïve-expert with bimanual prior; *NE* = naïve expert without bimanual prior). Grey lines depict the performance of a single subject/dyad; dispersion bars represent standard deviation; asterisks denote significant differences ($p<0.05$) according to a paired t-test. *Top-right panel*: Average Inefficiency index during the 30 training sets of the training sessions. The graph reports the evolution of the different dyadic groups (blue = *NN-b*; green = *NN*; red = *NE-b*; yellow = *NE*) and the bimanual control group (black = *BIM*); vertical bars represent the standard error of the mean (n=3 for *NN-b* and *NN*; n=4 for *NE-b*, *NE*, and *BIM*). *Bottom-right panel*: difference of the average Mutual Information index between the two virtual springs of the haptic manipulandum during the priming (P) and the training (T) phase. The subjects in the BIM group always grab the two springs with both hands. The NN-b and NE-b groups grab the two springs bimanually only in the priming session, while each subject grabs only one spring during the training sessions. In the NE and NE-b groups the spring on the right side is grabbed by expert subject of the dyad and the spring on the left by the naïve subject: positive (negative) values indicate that the subject/spring on the left (right) is more responsible for compensating the instability; values close to zero indicate equal contribution from right and left subjects/springs.

with what was found in the kinematic data, the groups NE and NE-b show lower values than the NN and NN-b groups during training. However, a repeated measure ANOVA did not show any significant difference among the groups *($F(6.7,30.1)=1.507$, $p_{GG}=0.05$)* and only a mild effect of time *($F(1.7,30.1)=3.510$, $p_{GG}=0.050$)*.

The overall results of the training sessions suggested in a natural way the following question: Did the training with an expert differ from training with a naïve or in a bimanual condition in terms of performance?

In order to test if the skill level of the partner led to different performance compared to the control group during the training (Figure 2, top-right panel), we compared the Inefficiency Index of the BIM group first against NE and NE-b and then against NN and NN-b (repeated measure ANOVA, target sets as within factor). The results suggested an advantage of working

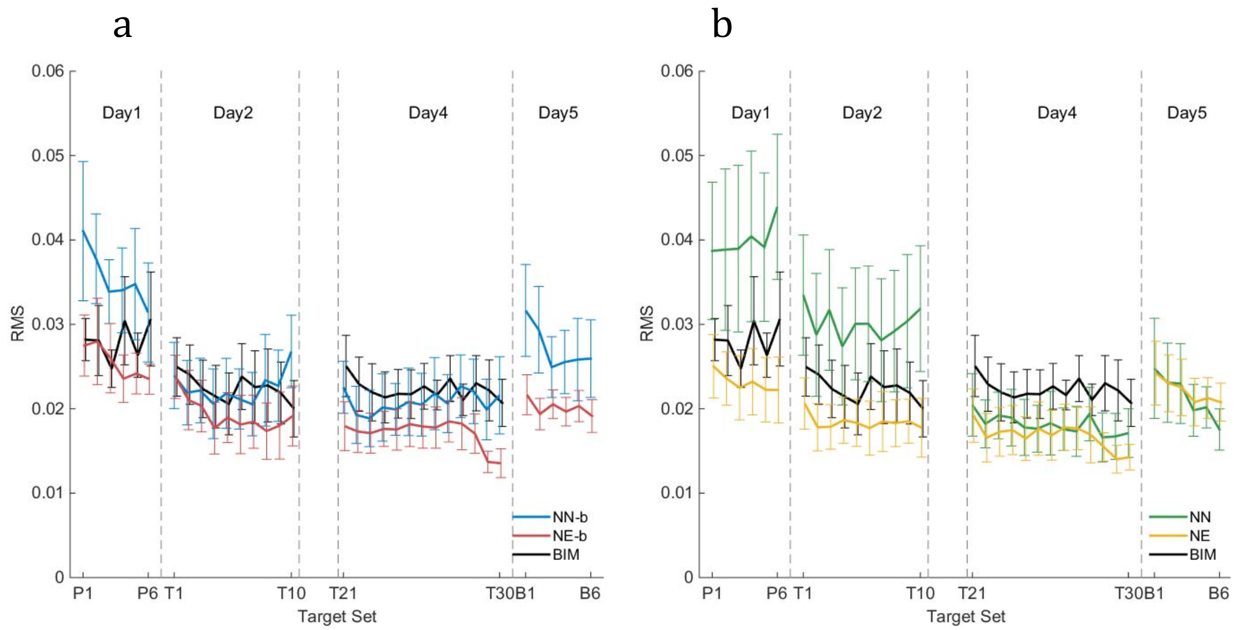

Fig. 3. Evolution of the average muscular activity index (RMS) of the different experimental groups during all the target sets of the experimental protocol. Panel a: comparison among the groups where the naive subjects could have bimanual experience of the task during the priming session (*NN-b* and *NE-b*, blue and red line respectively), with respect to the control group (*BIM*) that never operated in dyadic condition. Panel b: comparison among the dyadic groups where the naive subjects never had bimanual experience of the task (*NN* and *NE*, green and yellow line respectively), with respect to the control group (*BIM*). Each plot is divided in the 3 blocks that correspond to the experimental sessions: (P = priming; T = training; B = bimanual test). The dispersion bars represent the standard error.

with an expert over bimanual training *(F(2.5,16.5)=7.830, p_{GG}=0.003, group–target set interaction)*. No difference could be found comparing bimanual performer to naïve-naïve dyads. However, if we consider the Mutual information difference between the partners in Figure 2, we notice that in both NE and NE-b groups the expert subject has a major role in compensating for the instability. No systematic evidence of a similar separation can be found in the naïve-naïve dyads and control groups, indicating a homogeneous distribution of the balancing effort.

Moreover, the data suggested an additional question: Was there any advantage due to the bimanual experience prior to the training?

In order to answer the question, we tested if bimanual priming interfered with the early training performance in the NN-b and NE-b groups. We compared NE and NN dyads in the priming session to NE-b and NN-b dyads in the first 6 target sets of dyadic training using a repeated measure design. The groups presented significant differences in performance *(F(5.1,24) = 5.94, p_{GG}< 0.001, group–target set interaction)* having the NE-b and NE group, the best performers, being significantly different from the NN group, the worst performer *(NE-b - NN=−4.30 [−7.17; −1.42], p=0.003; NE - NN=−3.73 [−6.61; −0.86], p=0.008)*. Naïve-naïve dyads with bimanual prior were only moderately different from the subjects in the NN group *(-2.9704 [−6.29, 0.35], p=0.094)* and no difference could be found between the NE and NE-b conditions. Overall, these results suggest a positive interference effect of the skill level but no strong effect of prior bimanual experience on the dyadic performance during the first session of training.

C. Bimanual Test Session

In the last day of the experimental protocol we asked all the naïve subjects who trained in dyads to perform a session of bimanual adaptation to the force-field (6 target sets with perturbation, 48 trials). In this phase we wanted to probe if there is any evidence of skill transfer from the dyadic to the bimanual condition and if partnership (naïve vs. expert) could be a significant factor.

Our hypothesis is that if skills did transfer to the bimanual condition, the performance of the naïve in the bimanual test would differ from the bimanual controls on Day 1. Therefore, we compared the performance of the naïve subjects who trained in dyads to the performance of the control group in the priming session. We found significant differences between groups *(F(5,110)=3.847, p_{GG}=0.006 group–target set interaction)* and in particular that all the groups but NE performed significantly better than the bimanual controls. This suggests that no transfer occurred for naïve who trained with an expert and who had no previous bimanual experience of the task dynamics.

As we can notice in Figure 2, bottom-right panel, the NE dyads in the bimanual session (left panels, orange lines) did not differ from bimanual controls in the priming session in effort or in time measures (see figure 4). The NE dyads, on the contrary, benefited from the presence of the expert in minimizing the time (initial effect) and the effort throughout the session. Hence, the absence of transfer does not appear to be dependent on the absence of prior bimanual experience alone. In fact, the lack of transfer seems to depend on the combination of an expert partner and lack of bimanual experience. After comparing the Inefficiency Index

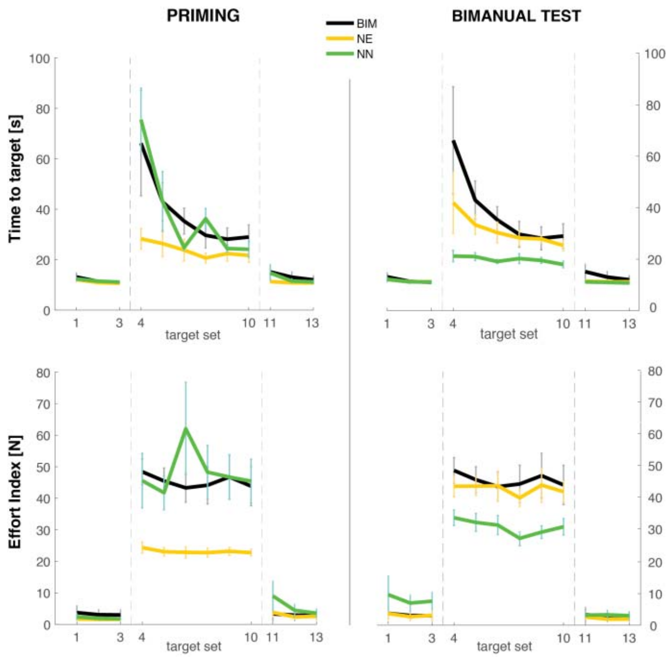

Fig. 4. Comparison of the average Time to Target (T2T) and Effort Index (EI) between the naïve subjects with no bimanual prior (*NE* = naïve-expert group, *NN* = naïve-naïve group) and the control subjects (BIM) in the priming session (P, right panels) and in the bimanual session (B, left panels); vertical bars denote standard error of the mean. Target sets from 1 to 3 correspond to the null-force condition (NF), target sets from 4 to 10 correspond to the force field condition (FF), and target sets from 11 to 13 correspond to the wash-out phase (WO).

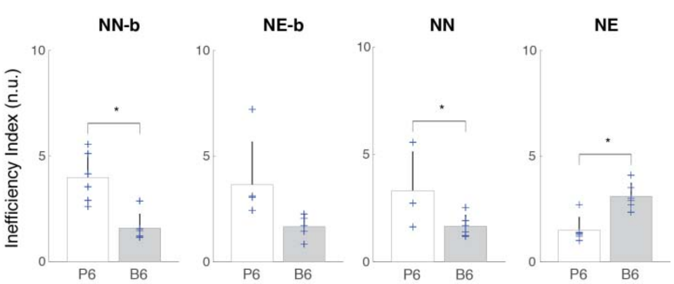

Fig. 5. Average Inefficiency Index in the end of the adaptation phase on Day 1 (priming session, P6 – white bar) and in the end of the adaptation phase in the bimanual test session on Day 5 (B6 – gray bar) for the naïve-naïve and naïve-experts dyads with and without bimanual prior. Blue markers represent the individual subjects values of the Inefficiency Index; vertical bars represent standard deviation; asterisks denote significant differences ($p<0.05$) according to a paired t-test (*NN-b*: $p = 0.013$; *NE-b* = *0.050*; *NN* = *0.099*; *NE* = *0.005*).

scores in the end of the bimanual test among groups, we found that naïve subjects who trained with an expert without bimanual prior performed significantly worse than the others when asked to perform the same task bimanually *(one-way ANOVA, F(3)=9.825, p<0.001; NE=3.096±0.616; NE-b=1.582±0.653; NN=1.645±0.514; NN-b=1.657±0.498).* Moreover, as Figure 5 shows, they performed significantly worse than in the end of the priming session when working with the expert (panel NE).

From the point of view of the EMG signals (Figure 3), the effect of switching to a bimanual condition is reflected by an initial generalized increase in the RMS. In the end of the bimanual test session, however, the values of the NN

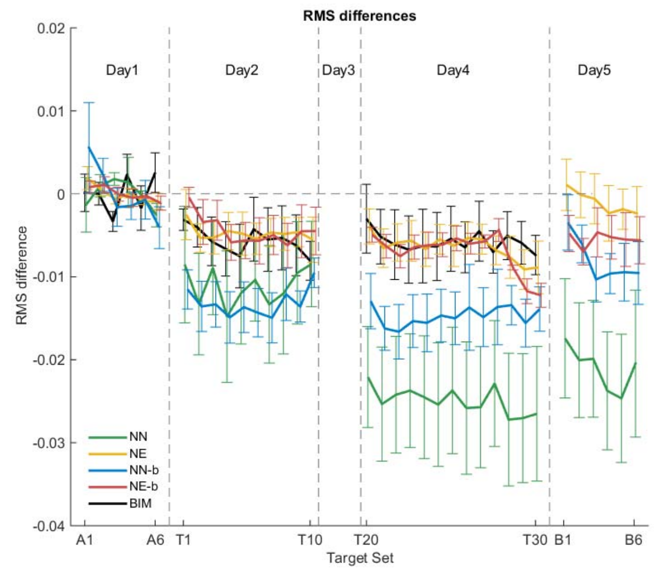

Fig. 6. Differences in the RMS values during the experiment respect to the mean value of the priming phase. The results are divided in groups, and the dispersion bars represent the standard errors.

and NN-b groups approached the same levels of the training phase. No EMG activity decrease took place in the groups that worked with an expert during training, whose RMS returned back to the initial level of the priming (Figure 6). Figure 6 emphasizes that the naïve-naïve dyads distinctively reduced the RMS session-by-session and were able to retain the improvement when switching to the bimanual condition. The statistical analysis performed for the RMS values did not show any significant differences among groups.

IV. Discussion

Previous studies reported that prior practice with a partner allows for improving the performance of the individual in the same task [11]. The main objective of this work is to understand if motor skills, acquired during dyadic practice with a cooperating partner in a challenging unstable task, could be transferred back to the solo performance in the same task. In order to test the hypothesis that training on a novel task with a peer allows for greater performance improvements [11], we trained naïve subjects to perform a challenging balancing task either jointly with a peer naïve or together with an expert subject. We assumed that prior knowledge of the task would influence the amount of skill transfer from a dyadic to a bimanual condition so that subjects who were previously exposed to the unstable dynamics would benefit more from training in pairs.

Our results seem to partially corroborate the hypothesis that greatest performance benefit comes from training with a partner with a comparable skill level, since subjects who trained with a peer performed better than subjects who trained with an expert, regardless of the initial difference in the priming session. Therefore, it seems that working with a partner with a similar skill level allows for a positive transfer to the bimanual task. On the contrary, when working with a skilled subject who has an accurate knowledge of the dynamics of the task, positive transfer occurs only if the subjects had at least some previous experience with the task dynamics, namely a chance to explore to novel task without any guidance.

Hence, there are two main aspects we should carefully consider, namely i) the influence of the expert and ii) the effect of a brief exposure of the naïve to the task dynamics (in our case the unstable force field) prior to the training.

A. Effect of Training With an Expert

The group of naïve subjects who trained with an expert without having any previous knowledge of the task dynamics displayed no skill transfer. Indeed their performance closely resembled the behavior of naïve subjects facing the task for the first time during the priming task (Figure 4).

Motor control studies report that existing knowledge can interfere with the acquisition of new motor skills [25]–[28]. In our case, prior learning with a partner may affect the subsequent learning of bimanual motor skills by the interacting subjects. This interference could either be positive, so that it facilitates subsequent adaptation to a new condition with related characteristics, or negative. In the latter case, the predictions from the consolidated motor memories collide with the actual sensorimotor experience and may result in impaired transfer of the skills to the new task condition.

Adaptation may be triggered by a change in the visual representation of the task as well as it may occur in response to a change in the dynamic characteristics of the environment [10]. Ranganathan *et al.* [29] showed that positive skill transfer between two tasks is maximized if their task spaces shared dimensionality. Whenever changing the mechanical characteristics of the environment change, e.g. introducing a force perturbation, the transfer of the dynamic model has been shown to be limited and tends to be sensitive to the limb configuration [30]–[32].

In the present work, neither the visual representation of the task nor the task dynamics per se were altered. Indeed, interference was probably due to the mismatch between the internal representation that naïve subjects built of the task dynamics during the training with an expert and the actual dynamics of the interaction with the environment. This interpretation leads us to consider the fundamental role that haptic feedback played in shaping the internal model of the joint task dynamics [13].

The mechanisms and the coding protocol underlying learning the dynamical properties of the interaction with the environment have been long debated. The traditional view posits that learning of the dynamic and kinematic properties of movement is mediated by independent mechanisms and that the brain encodes information about the limb dynamics in intrinsic coordinates [10], [26], [29]. On the other hand, there is recent evidence [30], [31] that multiple coordinate representations are involved in motor learning, a view that fully agrees with the multi-referential nature of the body-schema suggested in [3]. In particular, internal models of dynamics greatly draw on proprioceptive feedback rather than visual feedback during the task [32], [33], and haptic feedback shares the same pathways as proprioception and kinesthesia to the brain, although the ultimate criterion of success of the task (knowledge of results) is driven by exteroceptive information (visual or acoustic). Learning through exploration, as in our case, is affected by "Sensorimotor Contingencies" [34], namely causal relationships that an agent tends to attribute to his own action, as well as the perceived sensory consequences. It is therefore likely that the sensorimotor contingencies experienced by subjects in the naïve-expert condition did not reflect the primary causal role of the force field. Indeed, subjects who interacted with an expert performer, capable to partially compensate the destabilizing dynamics, experienced a completely different kind of perturbation and learnt a model that incorporated the action of the partner, but masked the true dynamics of the tool. Notably, this ambiguity was not present when the subject was interacting with a peer naïve. In this case, since neither subject could dominate the dynamics of the tool more than the disturbance, they were both exposed to a similar type of feedback to which they reacted in a similar manner and with the same amount of effort (see Figure 2, bottom-right panel). This helps explaining the absence of skill transfer experienced by the group of naïve who solely interacted with an expert, which was presented with a completely different tool dynamics from the one they learnt to manipulate.

B. Effect of Prior Exposure to a Novel Dynamics

When considering the performance of the dyads in the Day 2 of the experiment, naive subjects who experienced bimanual priming prior to training in pairs had a significant performance advantage over the other groups, regardless of the partner's skill level. Hence, there seems to be a positive transfer from the bimanual to the dyadic condition. Moreover, no distinction could be found between subjects who performed the priming session bimanually and subjects who practiced in pairs. In the previous section we saw that, although practicing with a partner with a higher skill level allowed naïve subjects to perform better than with a peer, such practice does not necessarily translate into performance benefits in the bimanual context. The factor influencing the direction of the transfer, positive or negative, seems to be the modality of the first approach with the new dynamics. When facing a novel dynamics, the development of motor skills advances through different time scales [39], [40]. Initially, a fast-learning process (within a single session) takes place and during this process subjects explore the possible motor solutions that lead to succeed in the novel task. This phase appears to be crucial for the formation of a first rough internal model of the task dynamics through feedforward trial-and-error mechanisms and relies mainly on input from the somatosensory system [41]. After a consolidation phase, a slow-learning mechanism takes place along with repetitive practice in which the internal model is progressively refined and allows for small incremental gains in performance [42], [43]. In our case, the fast learning phase coincided with the priming session. Therefore, it is likely that subjects who performed the priming session bimanually exploit the physical interaction with the virtual environment to start building a model of the tool dynamics that was unbiased by the action of a partner. Since the structure of the task did not change during training, their initial representation was sufficiently accurate to allow for a positive transfer of the consolidated initial skills to the dyadic context.

V. Conclusion

Our results show that training with an expert leads to the greatest performance in the joint task. However, the performance in the individual test is strongly affected by the initial skill level of the partner. In learning a new skill, having practiced with a peer rather than an expert appears to be more advantageous to the individual performance. After training with an expert, motor skills can be transferred to a bimanual context only if the non-expert subject has prior experience of the dynamics of the novel task.

More generally, the results also suggest a possible "didactic" approach for teaching an *expert user* to become also an *expert teacher*. The idea is that the expert teacher should intervene as little as possible, leaving enough freedom to the naïve user for exploration of the dynamics of the task. In other words, the expert teacher should provide an assistive action in an intermittent not a continuous manner. On the other hand, intermittency in the control of unstable tasks is well established, either in the stabilization of upright standing [44], [45] or in the stabilization of unstable tasks similar to the one used in this study [18], [46]. In general, the need of intermittent control is primarily driven by the destabilizing effect of sensory delay. Thus, teaching an expert to support a naïve partner in an intermittent manner is a natural aspect of master-pupil interaction. We can arrive at similar conclusions also in neuromotor rehabilitation: in this case, the expert/master is a physical therapist and the novice/pupil is a patient and the same principle applies if the expert/master is a robot: it is indeed common wisdom that the level of guidance of the robot must be as low as possible, in order to avoid the phenomenon of "slacking" [47] and induce some kind of generalization. However, our results provide a step beyond it: not only the teacher should minimize the level of guidance in general, but it should also restrain temporarily from any guidance at all leaving full freedom (and full responsibility of failure) to the pupil.

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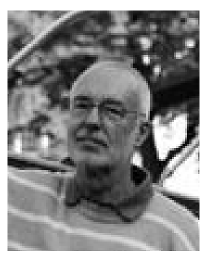

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