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Motor Learning and Motor Control Mechanisms in an Haptic Dyad

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Abstract

The word "dyad" defines the interaction between two human or cybernetic organisms. During such interaction, there is an organized flow of information between the two elements of the dyad, in a fully bidirectional manner. With this mutual knowledge they are able to understand the actual state of the dyad as well as the previous states and, in some cases, to predict a response for possible scenarios. In the studies presented in this thesis we aim to understand the kind of information exchanged during dyadic interaction and the way this information is communicated from one individual to another not only in a purely dyadic context but also in a more general social sense, namely dissemination of knowledge via physical and non-physical interpersonal interactions. More specifically, the focus of the experimental activities will be on motor learning and motor control mechanisms, in the general context of embodied motor cognition.

Solving a task promotes the creation of an internal representation of the dynamical characteristics of the working environment. An understanding of the environmental characteristics allows the subjects to become proficient in such task. We also intended to evaluate the application of such a model when it is created and applied under different conditions and using different body parts. For example, we investigated how human subjects can generalize the acquired model of a certain task, carried out by means of the wrist, in the sense of mapping the skill from the distal degrees of freedom of the wrist to the proximal degrees of freedom of the arm (elbow & shoulder), under the same dynamical conditions.

In the same line of reasoning, namely that individuals solving a certain task need to develop an internal model of the environment,

we investigated in which manner different skill levels of the two partners of a dyad interfere with the overall learning/training process. It is known indeed that internal models are essential for allowing dyadic member to apply different motor control strategies for completing the task. Previous studies have shown that the internal model created in a solo performance can be shared and exploited in a dyadic collaboration to solve the same task. In our study we went a step forward by demonstrating that learning an unstable task in a dyad propitiates the creation of a shared internal model of the task, which includes the representation of the mutual forces applied by the partners. Thus when the partners in the dyad have different knowledge levels of the task, the representation created by the less proficient partner can be mistaken since it may include the proficient partner as part of the dynamical conditions of the task instead of as the assistance helping him to complete the experiments. For this reason we implemented a dyadic learning protocol that allows the naïve subject to explore and create an accurate internal model, while exploiting, at the same time, the advantage of working with an skilled partner.

Motor Learning and Motor Control Mechanisms in an Haptic Dyad

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Introduction

Dyad is being defined as the interaction between two individuals. Such interactions are present in the everyday life of people, and it can include physical or not physical interaction. Haptic dyads are the interactions where there is a sensory feedback that guides the interchange of actions between individuals.

Lots of tasks of the daily living like moving objects or even dancing with a partner can be considered as haptic dyads, in fact it is been stated that persons are able to do more things when cooperating with other individuals than solo (van der Wel et al. 2011). Unlike the solo performance of this activities, the persons involved in the interaction cannot accurately predict the outcome of their actions, since there is an unknown action coming from the partner that can contribute to the task or can induce undesired perturbations (Reed & Peshkin 2008). Moreover, the forces exerted by the individuals allow an understanding of the mutual intentions that results in a coordinated behavior with a common goal (Groten et al. 2013).

In the last years a lot of importance has been given to the human – robot and the human – human dyads mediated by robots (Ganesh et al. 2014). The study of those dyads had shown an improvement in the task performance in comparison with a solo performance (De Santis et al. 2014; Ganesh et al. 2014). The studies of (Melendez-Calderon et al. 2015; Reed et al. 2005) showed that an advantage in the dyad performance is not always detectable without a compliant interaction, which allows the better partner to avoid following a worse partner, yet may even benefit from this interaction (Melendez-Calderon et al. 2015). The differences in the results are dependent of the experimental conditions, thus arriving to a conclusion requires deeper investigations.

Despite the differences in the aforementioned results, it is certain that humans can communicate relevant information of the task through physical interaction, and, even more, while performing as a team, the individuals have the opportunity to divide responsibilities and focus in a particular subset of actions (Reed & Peshkin 2008). This division of responsibilities can be accomplished thanks to the individual ability of using the haptic feedback channels to indirectly communicate with the partner and negotiate intentions and motions (Groten et al. 2013). The combination of motions coming from both partners lead to a single action known as a “joint action” (Masumoto & Inui 2013). Even though behavioral and neural processes underlying such joint action are still poorly understood, it is well known that humans rely in this kind of actions to complete tasks or even to learn new skills (Melendez-Calderon et al. 2015; Melendez-Calderon et al. 2011). An example of this is the interaction between a physiotherapist and a patient, where the contact between them comes together with information about the muscle tone, force and motion to the therapist, and a delivery of force and motion by the therapist (Melendez-Calderon et al. 2015; Reed et al. 2005).

In the same way that a therapist can train a patient to recover certain motions, a skilled individual can transfer the knowledge to another naïve or less skilled individual through different communication channels. For the scope of this thesis, let us focus in the process of learning a new task in either individual or dyadic configuration. The learning process is characterized by the creation of an internal model of the task, learning in a dyad propitiates the creation of a shared representation (Ganesh et al. 2014; Masumoto

& Inui 2013; Melendez-Calderon et al. 2015; van der Wel et al. 2012). During the learning, the accuracy of the internal model depends on physical and psychological factors as the sense of agency (the sensation of being in control) (van der Wel et al. 2012), and the motor adaptation involving both neural and muscular systems (Pizzamiglio et al. 2017). Although when a skilled partner assists a naïve one in the learning of a task, it is necessary to put special attention to the level of assistance provided, since a high level of assistance generate a fake sense of agency in the naïve, feeling that is in control of the task while it is the expert compensating for the performance errors (Moore & Obhi 2012). In the work presented by (van der Wel et al. 2012) the results suggest that, when both subjects in the dyad learn a task together, and when a subject learn the task alone, there is no significant difference in the senses of agency of the partners performing in dyads or solo. Instead, the sense of agency increases in the dyad subjects after they learn a task and then they perform the same task individually.

Previous experiments had shown that the internal model of an unstable task acquired in a solo training can be correctly applied in a dyad performance (De Santis et al. 2014), such study was performed in a robotic device. Working in a robotic device allows the researchers to represent novel tasks in a virtual environment and to be able to have a quantitative insight of the subjects performance by analyzing the state variables of the end effector of the device (Shakra et al. 2006), which can be modulated in a way that the motions don't interfere with the natural patients' dynamics (Krebs et al. 1998), this characteristic allows also the dyads to have a more natural interaction when the interactions is mediated by a robotic device, namely haptic mediated dyads.

In the studies discussed in this thesis, we focused first in the muscular strategies adopted by individually trained subjects while performing in haptic dyads and we managed to partially corroborate the claim that the subjects increase the limb stiffness to counteract the external disturbances during the task resolution (Pizzamiglio et al. 2017), this increment of stiffness was present as muscular co-contractions. Posterior experiments aimed to study the effects of learning a new task in a dyad configuration, where the dyads were formed by subjects with different levels of knowledge of the task. More specifically we created several groups formed by dyads in which the partners may or may not have previous experience in the resolution of the task they were required to solve, two groups were formed by couples of naïve subjects while another pair of groups were formed by couples expert – naïve (read naïve as the subject without previous knowledge of the task), for one of the naïve – naïve groups and one of the expert – naïve groups, the naïves where allowed to have an individual task familiarization session while the other groups performed directly as dyads from the first session. The results of these experiments showed the advantages and disadvantages of working with an expert partner. And in the last part of this document, we present an study in which we aim to exploit the advantages of the expert – naïve dyad while learning an unstable task, and even more we apply a protocol that in an effort for removing the disadvantages of such interaction. In the same last study we vary the experimental conditions to corroborate that an accurate internal representation can be recalled to pursuit the same objective under the same dynamical conditions but with the use of different muscle strategies

The dynamical characteristics used along our study are presented in Chapter 1, together with the general measures used to quantify the performance of the subjects. In Chapter 2 we address the identification of the differences in the muscular strategies used by expert subjects when they work dyadic or individually. The results of the experiments related to the knowledge transfer from dyad to solo are presented in Chapters 3, 4, and 5, where Chapter 3 is focused in the muscular differences found between learning with a more skilled partner and learning with a partner with the same skill level; Chapter 4 shows the generalization of the acquired knowledge (solving a different task in the same dynamical environment); and Chapter 5 presents the effects of a dyadic training when the partners have different levels of expertise in the task. In an ambitious attempt to evaluate how fast the internal representation of a task can be accurately acquired, in Chapter 6 we present the results of experiments in which the specific behaviors of the subjects where limited or encouraged in order to propitiate optimal learning conditions.

CHAPTER 1 TASK AND VIRTUAL ENVIRONMENT

To evaluate the learning process of a new skill is a challenging procedure when the studies focus in an everyday task. Previous knowledge of similar tasks can promote or have interference with the acquisition of new skills; this interference can be either physical or psychological. To avoid the influence of previous knowledge, a new unstable task had been created in order to evaluate the learning process for which a person goes through while learning a new ability. The present task considers the presence of a challenging but understandable force field that provides a completely new environment for the participants in the experiments, and it is being implemented in an haptic device capable to give to the subjects the sensation of being immersed in a virtual reality.

1.1 Haptic Scenario and Virtual tool

The subjects were trained to use a Virtual Underactuated Bimanual Tool (VUBT) as depicted in Figure 1-1: that consists of three elements: a virtual point mass and two non-linear elastic linkages, or virtual springs, which connect the virtual mass and the user(s). The general task for the user is to indirectly control the position of the tool-tip $\vec{p} = [x, y]$ in order to reach a target $\vec{p}_T = [x_T, y_T]$ in the workspace by acting on the position of the two spring terminals ($\vec{p}_R = [x_R, y_R]$ and $\vec{p}_L = [x_L, y_L]$). The users can control the position of two free extremes of the springs by operating two planar robotic arms. The tool-tip has a virtual mass M and it is under the action of the two elastic forces $\vec{F}_R$, $\vec{F}_L$ generated by the

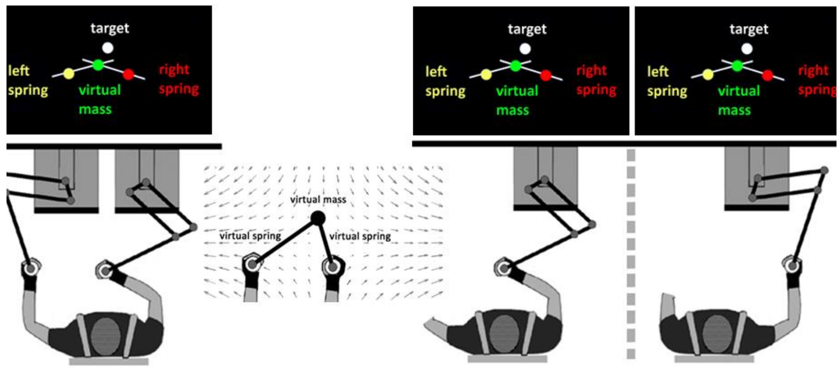


Figure 1-1: Experimental robot configurations. The left part of the figure corresponds to the bimanual configuration while the right part corresponds to the dyadic one. The intermediate panel illustrates the structure of the virtual tool: two non-linear virtual springs controlling the motion of a virtual 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.

two springs and the destabilizing force $\vec{F}_u$, due to a position-dependent force-field with saddle-type instability in the origin $[x_0, y_0]$. The overall dynamics of the virtual tool is then characterized by the following equation, where $\vec{p}$ is the controlled variable and $\vec{p}_R, \vec{p}_L$ are the two control variables:

$$M\frac{d^2\vec{p}}{dt^2} + B\frac{d\vec{p}}{dt} = \overrightarrow{F_u}(\vec{p}) + \overrightarrow{F_R}(\vec{p}, \overrightarrow{p_R}) + \overrightarrow{F_L}(\vec{p}, \overrightarrow{p_L}) \tag{1.1}$$

$$\begin{cases} \overrightarrow{F_u} = \begin{bmatrix} +K_u & 0 \\ 0 & -K_u \end{bmatrix} \begin{bmatrix} x - x_0 \\ y - y_0 \end{bmatrix} \\ \vec{F}_R = (K_s L_R + \rho_s L_R^2)\vec{v}_R \quad L_R = |\vec{p}_R - \vec{p}|;\ \vec{v}_R = (\vec{p}_R - p)/L_R \\ \vec{F}_L = (K_s L_L + \rho_s L_L^2)\vec{v}_L \quad L_L = |\vec{p}_L - \vec{p}|;\ \vec{v}_L = (\vec{p}_L - p)/L_L \end{cases} \tag{1.2}$$

The *x*-axis of the workspace is aligned medio-laterally and is the unstable manifold of the field; the *y*-axis is aligned in a posterior-anterior way and it is the stable manifold of the field. A viscous field (characterized by the parameter B) carries out a damping action. L_R, L_L are the lengths of the two springs; K_s, ρ_s are the spring parameters.

1.2 Motion of the tool under the effect of the force-field

The action of the unstable saddle-type force-field in the workspace can be decomposed in two vector fields that act on the mass along two manifolds; a stable manifold parallel to the y-axis induced by a convergent force-field towards the origin and an unstable manifold oriented along the x-axis induced by the divergent component of the force-field:

$$\begin{cases} M_{\ddot{x}} + B_{\dot{x}} - K_u x = 0 \\ M_{\ddot{y}} + B_{\dot{y}} + K_u y = 0 \end{cases} \tag{1.3}$$

The motion along the stable manifold is a damped oscillation with natural frequency ω_n and damping factor ζ. The motion along the unstable manifold is characterized by two exponentials, one with a negative time constant and the other with a positive (unstable) time constant τ_u. These three coefficients are related to the parameters of the virtual tool by the following equations:

$$
\begin{cases}
\omega_n = \sqrt{\dfrac{K_u}{M}} \\
\zeta = \dfrac{B}{2\omega_n M} \\
\tau_u = \dfrac{2M}{-B + \sqrt{B^2 + 4MK_u}}
\end{cases}
\tag{1.4}
$$

1.3 Stiffness of the virtual tool

The interaction between the mass and the environment can be characterized computing the overall stiffness of the virtual tool as:

$$
K_{VUBT} = \begin{bmatrix} K_{xx} & K_{xy} \\ K_{yx} & K_{yy} \end{bmatrix} = \frac{\partial \vec{F}}{\partial \vec{p}}
\tag{1.5}
$$

where $\vec{F}$ is the resultant of the external forces applied to the virtual mass in the absence of perturbation. The four elements of the stiffness matrix explicitly depend on the coefficients of elasticity (K_s, ρ_s) and the positions of the two hands with respect to the tool-tip. Therefore, the subject can indirectly determine the size and orientation of the stiffness ellipse of the tool in order to achieve equilibrium and/or stability. If we define $\Delta x_R = x_R - x$; $\Delta y_R = y_R - y$; $\Delta x_L = x_L - x$; $\Delta y_L = y_L - y$ we can derive the analytical expression of the stiffness matrix coefficients:

$$
\begin{cases}
K_{xx} = [Z_1 + Z_2] - \rho_s \left[\dfrac{\Delta y_1^2}{L_1} + \dfrac{\Delta y_2^2}{L_2} \right] \\
K_{yy} = [Z_1 + Z_2] - \rho_s \left[\dfrac{\Delta x_1^2}{L_1} + \dfrac{\Delta x_2^2}{L_2} \right] \\
K_{xy} = K_{yx} = \rho_s \left(\dfrac{\Delta x_1 \Delta y_1}{L_1} + \dfrac{\Delta x_2 \Delta y_2}{L_2} \right)
\end{cases}
\tag{1.6}
$$

Whenever the tool is affected by the position-dependent force-field, the user has to manipulate the tool stiffness in order to stabilize it in the space. In particular, the critical element for the stabilization is the component of stiffness aligned with the x-axis. This can be easily seen If we linearize equation (2.1) in the neighborhood $\left[\delta_x, \delta_y\right]$ of an equilibrium state $[x_e, y_e]$:

$$M\begin{bmatrix}\delta\ddot{x}\\ \delta\ddot{y}\end{bmatrix} + B\begin{bmatrix}\delta\dot{x}\\ \delta\dot{y}\end{bmatrix} + \begin{bmatrix}(K_{xx}-K_u) & K_{xy}\\ K_{yx} & \left(K_{yy}+K_u\right)\end{bmatrix}\begin{bmatrix}\delta x\\ \delta y\end{bmatrix} = 0 \qquad (1.7)$$

A necessary and sufficient condition for the asymptotic stability of the equilibrium point is for the eigenvalues of the elastic matrix to be negative, hence, $K_{xx} > K_u$. We can therefore define $K_{xx} = K_u$ as the condition of 'marginal (asymptotic) stability'. By acting on the configuration of the springs relative to the tool-tip, the user can orient and scale the ellipse associated to the stiffness matrix of the tool.

As it can be noted in equation (2.2), the two elastic elements are non-linear. In particular, the stiffness of each elastic linkage grows linearly with the degree of stretch:

$$\begin{cases} Z_1 = K_s + 2\rho_s L_1 \\ Z_2 = K_s + 2\rho_s L_2 \end{cases} \qquad (1.8)$$

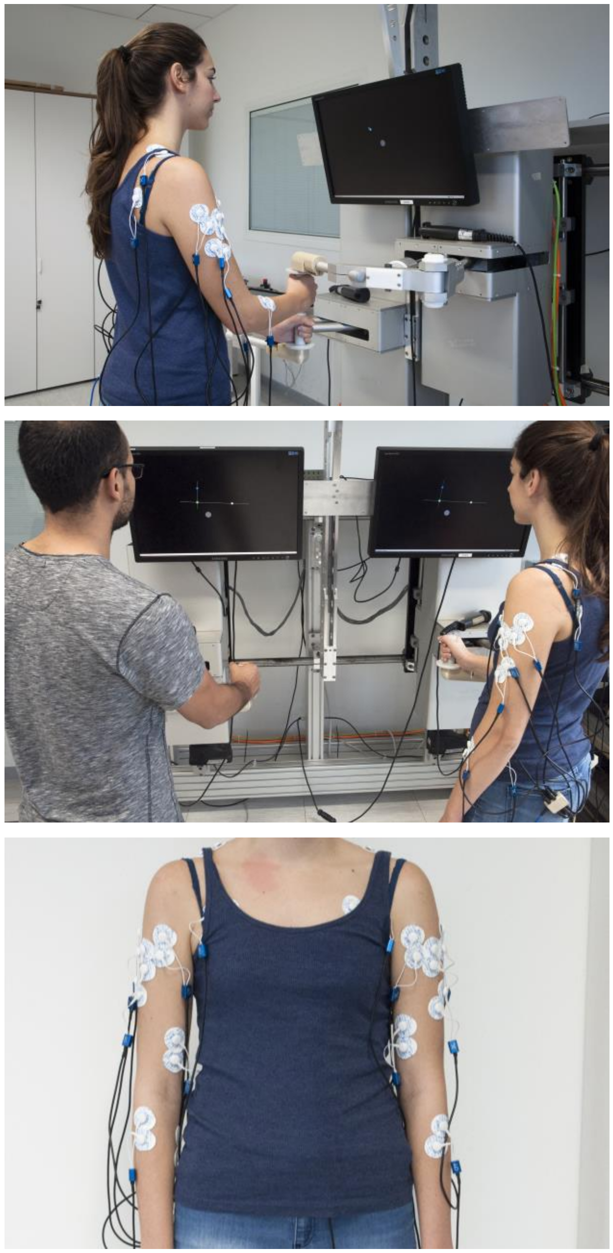
The choice of nonlinear springs against linear springs has several advantages. From the point of view of the task, springs that increase the stiffness linearly with the strain allow the subjects to exert enough force to stabilize the tool at the extremes of the task space (that is where the force-field is maximum, 50N) while keeping the robot arm within its operative workspace. Moreover, the values for the minimal stiffness were computed to be insufficient to provide asymptotic stability of the tool-tip, which oscillates around the equilibrium position. Therefore, from the point of view of the control strategies, such nonlinear springs allow the users to manipulate the magnitude and orientation of the stiffness of the tool in multiple ways. For instance, they add a higher cost to the control strategy that aims at a generalized increase in the stiffness of the tool to counteract the background force-field, pushing subjects to explore other solutions to the balancing tasks that are less energetically expensive. On the other side, for low strains, the spring stiffness increases less than linearly, challenging the subjects to accurately predict the time response of the system in different positions of the space.

1.4 Rationale for the haptic environment

Divergent force-fields have been extensively adopted in motor control studies to analyze how the sensorimotor system adapts to novel dynamic environments and responds to perturbations (i.e. modulating limb stiffness). The haptic environment in equation (2.2) represents a divergent force-field that pushes the state of the system away from an unstable equilibrium point along the x-axis. This choice allows replicating the dynamics of an inverted pendulum that oscillates along the x-axis while the force-field along the y-axis tends to attract the pendulum to the equilibrium point. This particular choice allowed us to mimic an ecologically inspired environment similar to upright bipedal stance. In order to balance the pendulum, subjects can in principle adopt two stabilization mechanisms: i) increasing the overall stiffness of the tool (and therefore the arms) virtually eliminating the effect of the instability or ii) exploit the sensory feedback to implement an intermittent control strategy that injects forces in the system at specific time instants through a predictive control. Moreover, the presence of a convergent vector field superimposed to a divergent one sets the conditions for subjects to choose to differentially modulate the magnitude and orientation of the tool impedance. In one case, subjects might primarily increase the tool stiffness along the x dimension to compensate for the instability and move the tool as if only under the action of the convergent component of the force-field. In another case, they might reorient the stiffness ellipse to counteract the force-field locally. We can call the first category of strategies Stiffness Stabilization Strategies (SSS) and the second one Positional Stabilization Strategies (PSS) (Morasso et al. 2014).

1.5 Experimental setup

The experimental setup (Figure 1-2) consists of a bimanual haptic manipulandum (BdF2, Celin srl, La Spezia, Italy, an evolution of the unimanual “Braccio di Ferro” robot (Casadio et al. 2006)), 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 (Figure 1-2 C). As regards BdF2, the main features are that each planar arm of the robot has a large planar workspace (0.8x0.4 m ellipse) and they are 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 working simultaneously with one or two subjects: the distance between the axes of the motors is 0.38 m (bimanual configuration, Figure 1-2 A) and 0.98 m (dyadic configuration, Figure 1-2 B), respectively.



A)

B)

C)

Figure 1-2: Experimental set up for the unstable stabilization experiments. A) Bimanual configuration. The subject is able to control both handles of the BdF2 robot and complete the task. B) Dyad configuration. The handles of the BdF2 robot are manipulated by a couple of subjects who solve the task in a collaborative way. C) Placement of the Ag/AgCl electrodes for the recording of the EMG signals.

The recording system is used to acquire electromyographic signals from the 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 for the first part of the study are:

Anterior Deltoid (AD), Medial Deltoid (MD), Posterior Deltoid (PD), Biceps Brachii (BL), Triceps Brachii Lateral Head (TL), Triceps Brachii Long Head (TM), Pectoralis Major (TM), Infraspinatus (IS), Latisimus Dorsi (LD), Brachioradialis (BR), Flexor Carpi Radialis (FR), Extensor Carpi Ulnaris (EU), and Extensor Carpi Radialis (ER). After the analysis of the muscular activity, and the relevance of the acquired information, the selected muscles for the rest of the experiments 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 Brachii 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 sampled at 2048Hz, and band pass filtered (Fc = [10-900] Hz) in order to avoid aliasing.

1.6 The unstable task

The task (adopted in (Zenzeri et al. 2011; Saha & Morasso 2012; Zenzeri et al. 2014; De Santis et al. 2015)) 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 (Figure 1-3), 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:

$$\begin{cases} \vec{F}_R = (K_s L_R + \rho_s L_R^2)\vec{v}_R \\ \vec{F}_L = (K_s L_L + \rho_s L_L^2)\vec{v}_L \end{cases} \tag{1.9}$$

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

$$\vec{F}_u = \begin{bmatrix} +K_u & 0 \\ 0 & -K_u \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{1.10}$$

where $K_u = 592\,N/m$ 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. From equation (2.1), the dynamics of the task can be summarized in this way:

$$M \begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} + B \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} + \vec{F}_u = \overrightarrow{F_R} + \overrightarrow{F_L} \tag{1.11}$$

[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.*

where $B = 132\,N/m\,/s$ 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 (Saha & Morasso 2012; Zenzeri et al. 2014).

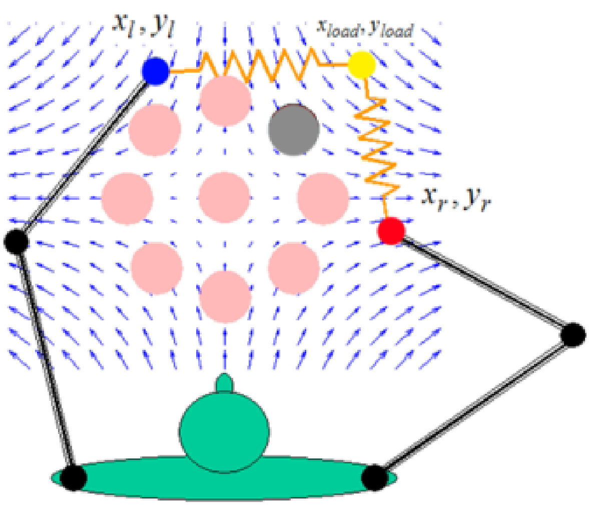


Figure 1-3: Representation of the distribution of the targets in the unstable force field. Blue and red dots represent left and right handles of the robot respectively, the yellow dot represents the virtual mass, and the orange lines are the virtual springs used by the subject to control the virtual tool. The hidden targets are presented as pink circles and the active target is presented with a gray circle. The blue arrows represent the direction and intensity of the force field for every position of the workspace.

In order to stabilize the virtual tool in a specific location, the subject has to control the intensity and orientation of the stiffness matrix of the tool by modulating the degree of stretch of the two elastic linkages and adjusting the position of the hands in space. In particular, the subject can choose between two ‘optimal’ strategies previously described and presented in (Saha & Morasso 2012): (i) the Stiffness Stabilization Strategy, SSS, and (ii) Positional Stabilization Strategy, PSS. The first strategy optimizes the stability of the system providing a faster response to perturbation, the second strategy optimizes the mechanical effort at a cost of a reduced control bandwidth. Depending of the experiment or the phase of the experiment, the subjects are constrained to use one of the two aforementioned strategies, or free to choose the one they consider the best option (Zenzeri et al. 2011). Visual feedback of the target, the tool position, the hand positions and the elastic linkages connecting the hands to the tool were displayed at 60 Hz on a 24.5" LCD monitor positioned in front of each subject at a distance of 30 cm from the center of the workspace (Figure 1-2).

The experiments are organized into target sets. Each target set includes a series of at least 16 stabilizations, 8 in the central target and 8 in each one of the peripheral targets with an out-center-out sequence. The peripheral targets are presented randomly.

1.7 Main outcome indexes

The completion of the task is characterized by several metrics that can describe either the kinematic or the muscular performance of the subjects during the resolution of the task. The most general metrics are:

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 represents the sum of the norms of the elastic forces between the virtual mass and the handle of each manipulandum is computed as follows:

$$EI = \|\vec{F}_R\| + \|\vec{F}_L\| \tag{1.12}$$

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 (SSS) 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 (PSS) results 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 (Zenzeri et al. 2014) 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:

Time to target (TT, [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.

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:

$$II = \frac{EI \cdot TT}{EI_{MAX} \cdot TT_{MAX}} * 100 \tag{1.13}$$

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 (Saha & Morasso 2012) and Dyads may also change their strategy in time. However, whatever strategy they adopt, there is evidence that either single subjects (Zenzeri et al. 2014) or dyads (Iandolo et al. 2015) 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.

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:

$$RMS = \left(\frac{1}{N}\sum_{1}^{N} EMG^2(n)\right)^{1/2} \tag{1.14}$$

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 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 (Shemmell et al. 2010). 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 (Balasubramanian et al. 2009; Ethienne Burdet et al. 2001). Moreover, it is likely that dyads will exert higher forces than single individuals overlap to overcome the high coordination requirements of the balancing task (van der Wel et al. 2011).

This metrics are able to describe the general behavior of the subjects while performing the unstable task, the particulars are explained by special metrics presented in their corresponding analysis for every experiment are presented.

The experimental protocol changed during the different experiments we performed along our studies. With exception of our last experiment, the task was performed entirely in the BdF2 robot (Casadio et al. 2006) For the last experiment, one group of subjects completed the task using the BdF synchronized with the Wristbot (WB) (Masia et al. 2009) when the subjects were working in dyads, and the bimanual configuration of the BdF when the subjects where working individually (further details can be found in Chapter 6).

CHAPTER 2 MUSCULAR AND KINEMATIC STRATEGIES OF EXPERT SUBJECTS DURING UNSTABLE TASKS

Several studies have shown that, when dealing with instabilities in a bimanual manipulation paradigm, humans modulate the stiffness of the arms according to feedforward or feedback mechanisms as a function of the dynamics of the task. In the case of human-human interaction, the haptic sensory feedback plays a primary role in the construction of a shared motor plan, being the channel for the mutual sharing of intentions. This chapter aims to complement these results getting insights on how the central nervous system controls the muscles to achieve the aforementioned control strategies in a solo performance, and the strategy selection in contexts in which instability is arising both from the environment and from the interaction with a partner. Results suggest the existence of an intermittent muscle ensemble recruitment that follows two distinct activation patterns, namely synchronous co-contractions and independent activations. The observed EMG patterns were independent of the motor control strategy applied in the task. These findings therefore suggest the existence of separate control strategies for the tool stabilization and the control of hand movements at the muscular level during a balancing task in the presence of a disturbing force-field.

Unstable tasks are very common in activities of daily living such as screwing/unscrewing, drilling, inserting a peg in a hole, chiseling, balancing a pole etc. These tasks are difficult to carry out because they are sensitive to different initial conditions and factors as neuromotor noise and external perturbations that can cause an unpredictable and unsuccessful performance. Since any small internal or external perturbation can lead to unpredictable behaviors and unsuccessful performances, careful integration of feedback information is fundamental. These peculiarities make them suitable for investigating kinematic strategies used by humans to solve problems of stabilization. On a higher level of complexity, during the interaction with another person, it is required a predictive response to the behavior of the partner which requires a certain level of mutual understanding of intentions (Groten et al. 2013). Moreover, the dynamics of the interaction may drive the two partners to explore new strategies that allow them to comply with or take advantage of the constraints posed by the dyadic interaction (Ganesh et al. 2014).

A biomechanical system that comprises muscles, dynamics of the human body and environment is unstable if starting from an equilibrium configuration any small perturbation is generally capable to induce boundless growth of state variables. By using a combination of control strategies (Lakie et al. 2003; Etienne Burdet et al. 2001), the Central Nervous System (CNS) is able to compensate the biomechanical instability and bring the controlled system to stability, such as asymptotic, meta or bounded stability. As mentioned in Chapter 1, several studies have shown that in the control of a bimanual unstable tool emerges the existence of 2 main strategies (Saha & Morasso 2012): the Stiffness Stabilization Strategy (SSS), a feedforward mechanism where the subject uses high levels of effort to accomplish the task, and the Positional Stabilization Strategy (PSS) characterized by low levels of effort and a feedback mechanism. After the demonstration of the existence of the two strategies it has been proven that naïve subjects can be trained to become expert in both strategies and to be able to switch from one to the other in a natural way (Zenzeri et al. 2014). Even so, the mechanisms that simultaneously accommodate kinematics and muscular aspects to achieve stability still remain unclear. To look into this interrelation we performed the analysis of the kinematic and electromyographic data from the so called "experts", which allowed the characterization of the two strategies from a kinematic point of view. The aim of this chapter is to explore the intrinsic characteristics of the muscle control during a bimanual stabilization task in an unstable dynamic.

2.1 Description of the experiments

For the experiments of this study we used the experimental setup and the task described in Chapter 1. We divided the experiments in target sets and each target set included 24 stabilizations, 12 in the central target and 12 in the peripheral ones. The subjects completed 6 target sets, alternating the SSS and PSS strategy, and they were allowed to rest between sets.

During the task, surface EMG signals were collected from 13 muscles for each arm. The signals were recorded and processed as described in Chapter 1, and later they were segmented in pairs of targets (peripheral-center). RMS envelopes of the raw signals where acquired using a window of 100 ms. In the stabilization phase the raw signals were normalized with the MVC while the RMS envelope was normalized with the envelope of the MVC. Due to the ECG contamination in both Pectoralis and the left Infraspinatus and Latisimus Dorsi, the entropy of the raw signals for every trial was estimated using a window length of 128 ms and a step of 8 ms, as proposed in (Zhang & Zhou 2012).

SampEn (Sample Entropy (Zhang & Zhou 2012)) is calculated along the EMG signals to facilitate highlighting the muscle information when the ECG peaks are present:

$$SampEn(x, m, r) = -\ln\left(\frac{A^m(r)}{B^m(r)}\right) \tag{2.1}$$

where m is the dimension of the expected vector and r is the tolerance; $A^m(r)$ and $B^m(r)$ are probability matrixes; and x is the original signal. The probability $B^m(r)$ that two vectors match for m points is then computed by counting the average number of vector pairs, without self-matching allowed. The match of two vectors is defined as their distance lower than a tolerance r. Similarly, the other probability $A^{m+1}(r)$ can also be computed for $m+1$ points. We used: $r = 0.20*\sigma(\text{trial})$ and $m = 2$.

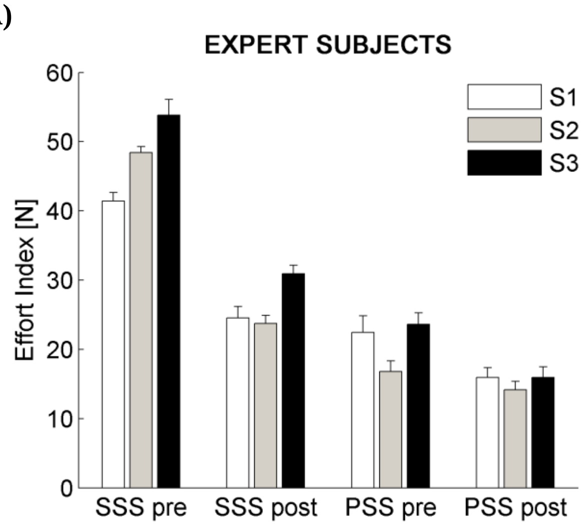
The SampEn values were estimated for each muscle and used to represent the intensity of the EMG contractions. After the computation of the correlation among each muscle, we averaged the result in each trial in order to find the global correlations of all the muscles during the experiment. Moreover, we can define co-activation as the level of synchronous activation of the muscles inside the considered timeframe.

In order to better understand how the CNS selects an appropriate strategy to deal with environmental instabilities, two concurrent experiments were performed:

- In the first experiment (*Experiment 1: Bimanual Training*) three subjects (1F, 2M; 29 ± 1 years, 2 right-handed, 1 left-handed), previously trained to become expert users of the virtual tool, were monitored while performing the balancing task.
- In the second experiment (*Experiment 2: Dyadic cooperation*), the EMG and kinematic data were recorded while the same three subjects repeated the task acting in

cooperation 2 by 2. Each subject grasped the

A)



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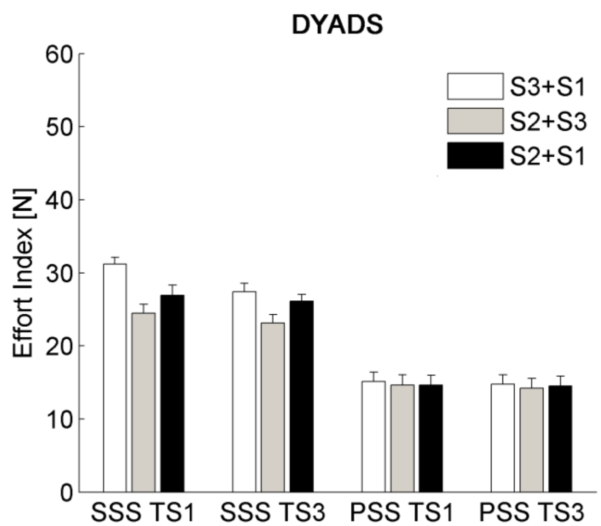


Figure 2-1: Summary of the performance of the expert subjects when performing individually compared to the dyadic condition. A) Effort index at the beginning and at the end of the bimanual training sessions of the individual subjects; **B)** Effort index computed for the dyadic combinations of the three expert subjects in the first and in the last target set.

manipulandum with their right hand. The dyads where formed as:

- Dyad 1: S3 – S1.
- Dyad 2: S2 – S1.
- Dyad 3: S2 – S3.

One experimental session consisted of 3 target sets. Subjects first performed Experiment 1 and subsequently Experiment 2 in the following order: S1, S2, S3 for Experiment 1; S3+S1, S2+S3, S2+S1 in Experiment 2, where the first subject handled the left arm of the manipulandum and the second one the right arm.

2.2 Muscular and kinematic performance of the expert subjects

Kinematic results show that when comparing the performance of the three dyads with the performance of the three expert subjects executing the task bimanually, and despite the subjects not having followed a training phase as dyads, they employ on average a comparable or lower time to complete a single trial in both stabilization strategies in the shared configuration (*Experts*: SSS = 6.03 ± 0.59 s, PSS = 7.41 ± 0.62 s, *Dyads*: SSS = 6.29 ± 0.49 s, PSS = 6.90 ± 0.61 s) (Figure 2-2). Moreover, consistently with our previous work (De Santis et al. 2014), the three dyads are able to minimize the average total employed effort to a greater extent than in the bimanual task (*Experts*: SSS = 27.14 ± 3.4 N, PSS = 15.25 ± 0.78 N, *Dyads*: SSS = 26.32 ± 2.29 N, PSS = 14.67 ± 0.39 N) (Figure 2-1 B).

In the analysis of the time to target we can observe that the dyad performance resembles the performance of an expert working bimanually. As can be seen in Figure 2-2, with the level of dexterity presented by our subjects, the reaching time and, by default, the ability to stabilize the virtual tool in the different targets depends only on the imposed kinematic strategy and not in the interaction with the partner.

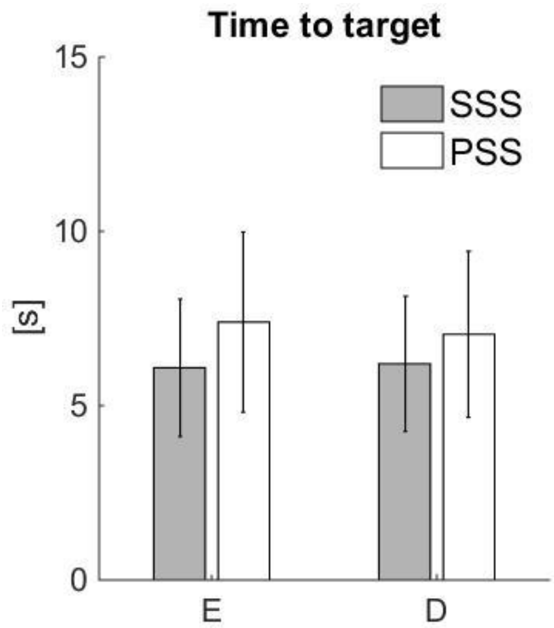
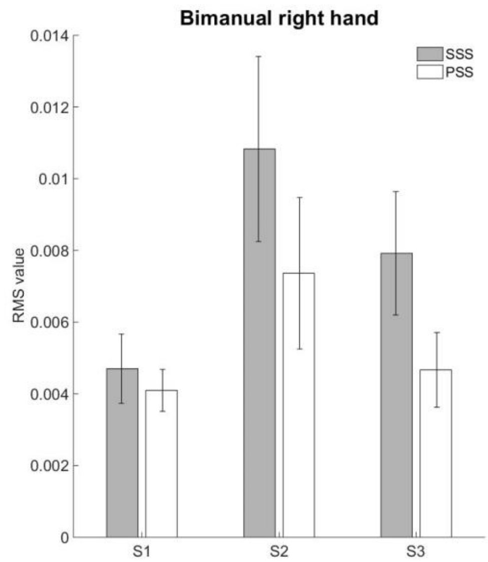


Figure 2-2: Average time to target during the experiment for both kinematic strategies: SSS in gray and PSS in white. The time consumed in the resolution of the task with the PSS is longer independently if the expert (E) subject is working solo or if the subjects are working as dyads (D).

In line with the behavior presented by the effor index, the muscular activity during the bimanual resolution of the task is higher for the SSS than it is for the PSS (Figure 2-3 A). On the other hand, dyads do not minimize the the muscular activity as a function of the kinematic strategy, there is no evidence that during the dyadic performance the muscular activity is linked to a specific kinematic strategy. When the subjects were working in a dyad, the levels of muscular activity are similar for both kinematic strategies and the variability of such levels is low compared with the variability during the bimanual part of the experiment (Figure 2-3 B).

A)



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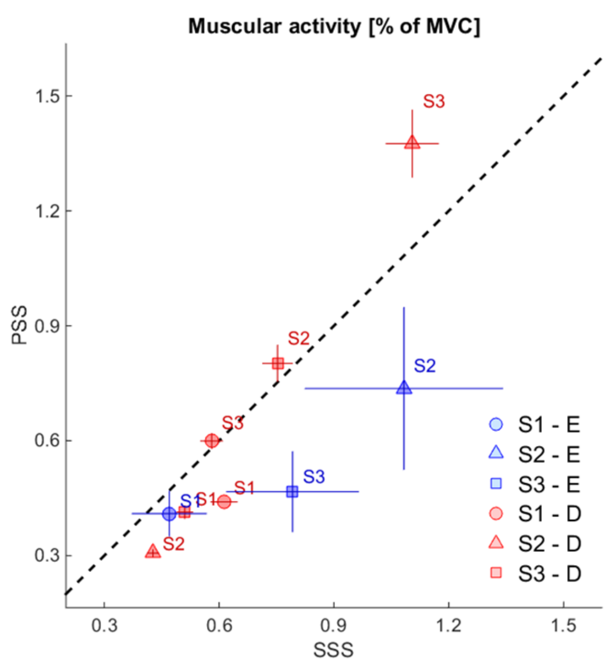
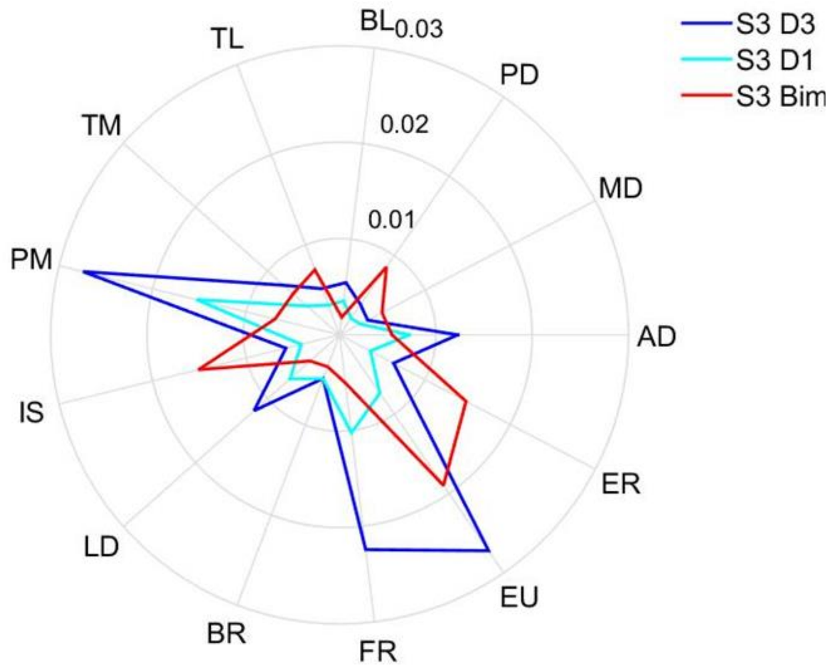


Figure 2-3: Muscular activity of the PSS and SSS during the task. A) Mean RMS values and standard error by single subject during the whole experiment for the SSS (grey) and the PSS (white). B) Mean muscular activity (SampEnt) and standard error by subject (blue) and by dyad (red) during the whole experiment as a percentage of the maximum voluntary contractions.,

A) SSS



B) PSS

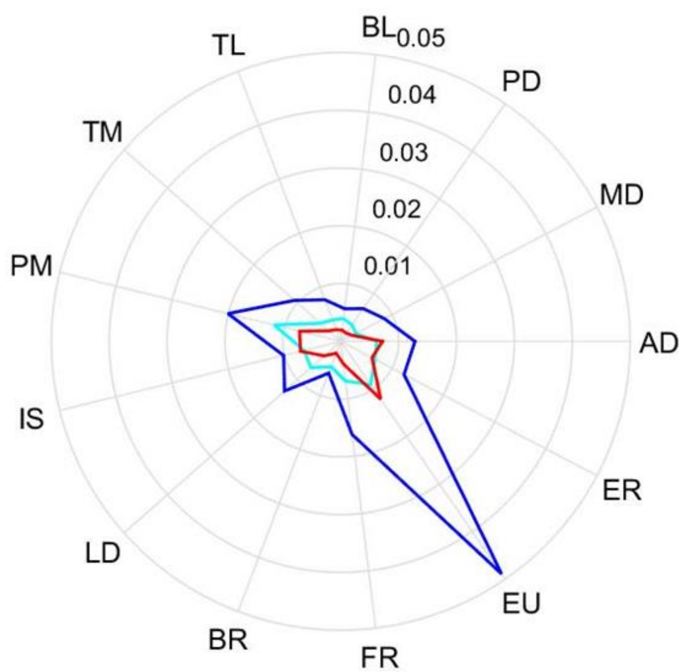
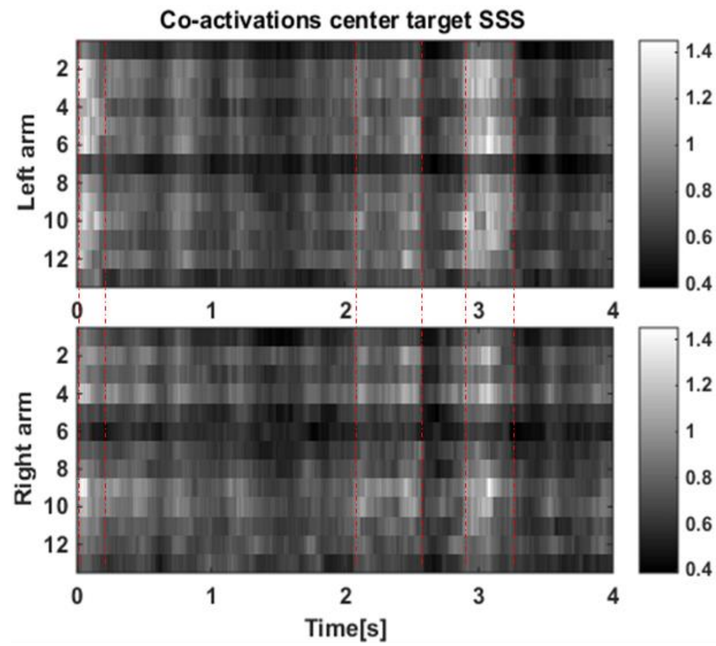


Figure 2-4: Influence of the partnership in the RMS values of the muscular activation in subject 3. It is shown the performance during the Dyad 3 (blue), Dyad 1(magenta), and bimanual. A) Muscular activity during the SSS. B) Muscular activity during the PSS.

However the partnership in dyads has a detectable influence detectable in the RMS values. Either changing the partner during the dyadic performance or else during the bimanual performance, the dominant activation of different muscles can be apreciated independently of the kinematic strategy used to solve the task. Also, the In Figure 2-4 we present the RMS correspondent to the most representative subject (subject 3), here we can see that the difference in the RMS values when the subject 3 is working together with subject subject 1 (Dyad 1) are similar to the ones of the bimanual performance, moreover while working with subject 2 (Dyad 3) there is an general increment in the activation of the muscles, mainly observable in the pectoralis (PM) and the extensor ulnaris (EU).

Despite of the lack of evidence of the existence of a muscular strategy correspondent to each kinematic strategy, the EMG data reveal the existence of two different mechanisms at the muscular level. The first muscular strategy is presented in the performance of subject 1, where we observed the presence of high co-contractions of all the muscles in both arms during the SSS and the PSS. Figure 2-5 shows a color map where it can be noted that co-activations are present in a synchronous way in both arms, which resulted in high correlation coefficients when calculating the correlation among muscles of each arm with a Lag = 0. The second muscular strategy is showed in Figure 2-6, and it was used mainly by subject 2 during both kinematic strategies, in this strategy we can find independent contractions of the muscles and there are not correlation peaks among muscles.

A)



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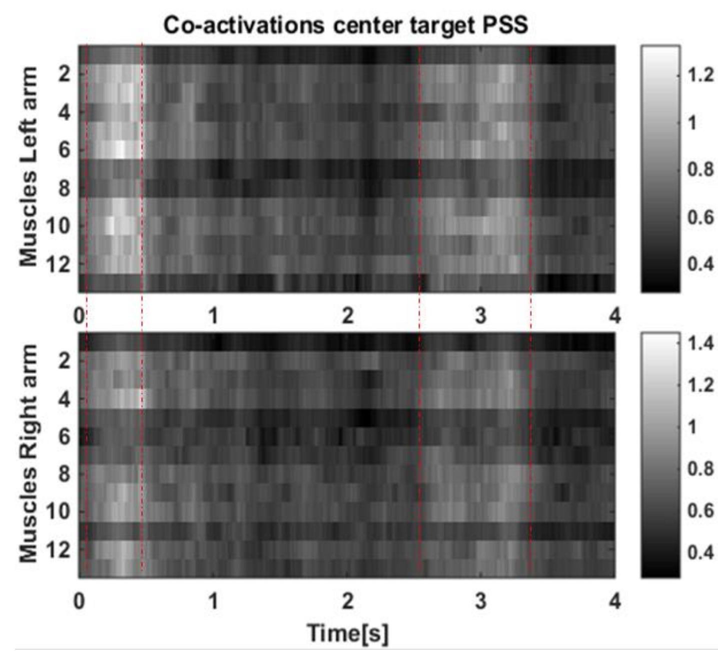


Figure 2-5: Color map of the co-activation muscular strategy used by the subject 1 for both kinematic strategies during the 4 seconds of stabilization in the center target. A) Co-activation strategy while solving the center targets using the SSS. B) Co-activation strategy used to solve the center targets for the PSS.

A)

B)

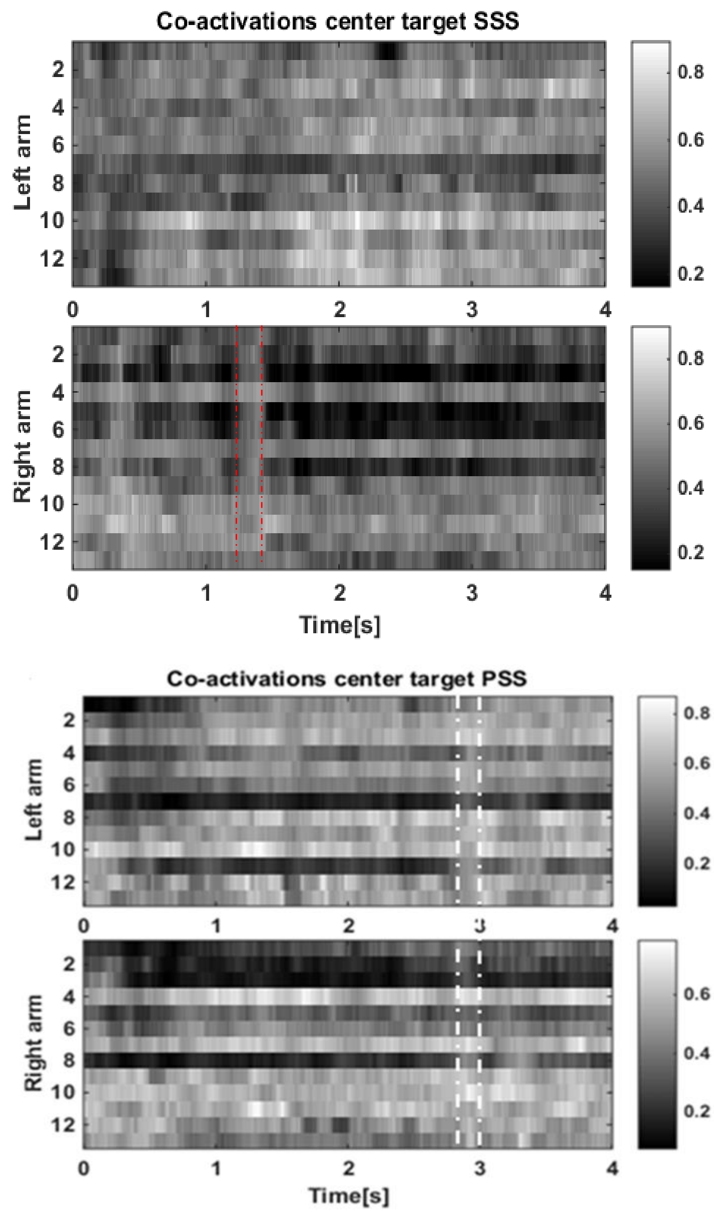
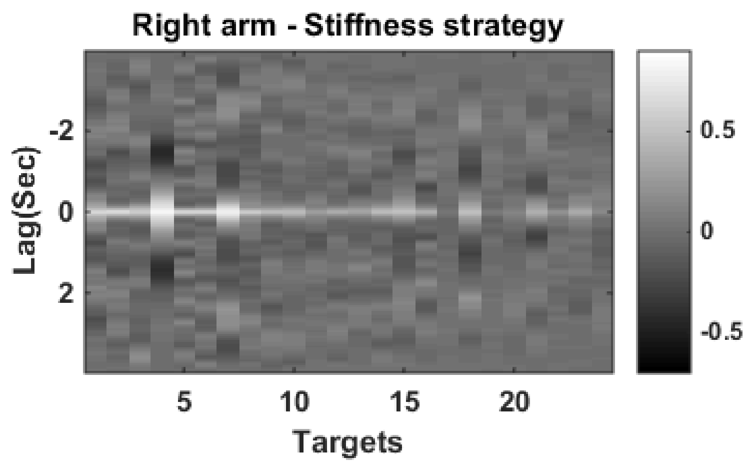


Figure 2-6: Color map of the muscular strategy used by the subject 2 for both kinematic strategies during the 4 seconds of stabilization in the center target. A) Independent contractions strategy while solving the center targets using the SSS. B) Independent contractions strategy used to solve the center targets for the PSS.

Figure 2-7 shows the values of the average correlations of all the muscles of the right arm of Subject 1 along 24 targets ordered chronologically. As can be observed in the color map in Figure 2-7 A, the correlation among muscles activations decreased with time. In Figure 2-7 B, the linear regression shows a decrement of 60% in the peaks of the correlation values after 24 targets. Such decrement indicates a change in the muscular strategy, allowing the subject to complete the task in a more efficient way. This is suggested by the decrease in the average RMS values calculated for each target set that is mirrored by a reduction of the estimated effort applied by the subject (Figure 2-9).

A)



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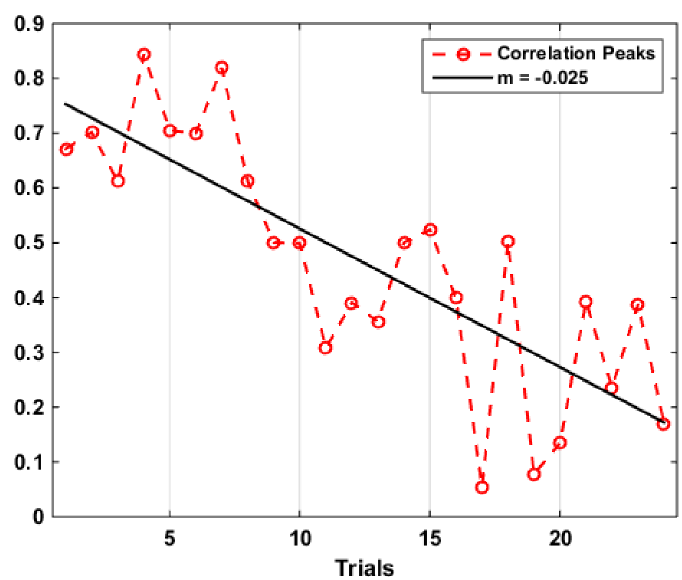
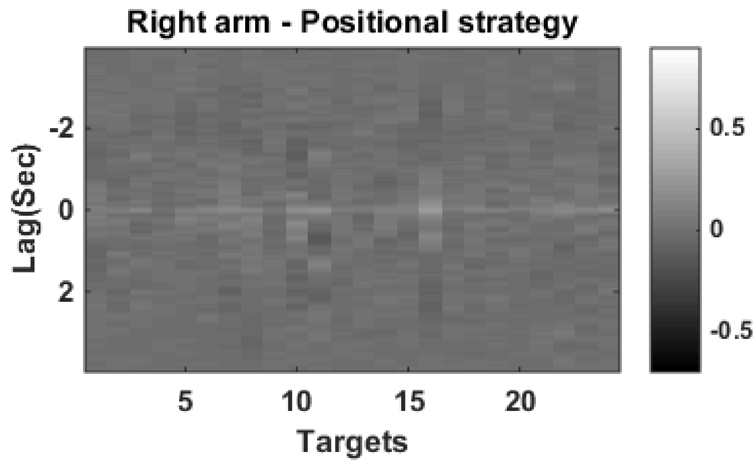


Figure 2-7: Average correlations of the muscle contractions during 24 consecutive stabilization phases on the center target. A) Subject 1 during SSS: Color map showing a decrement in the muscle correlations. B) S1 during SSS: Peaks of the average correlations from the top figure and their linear regression, with $R^2 = 0.635$.

A)



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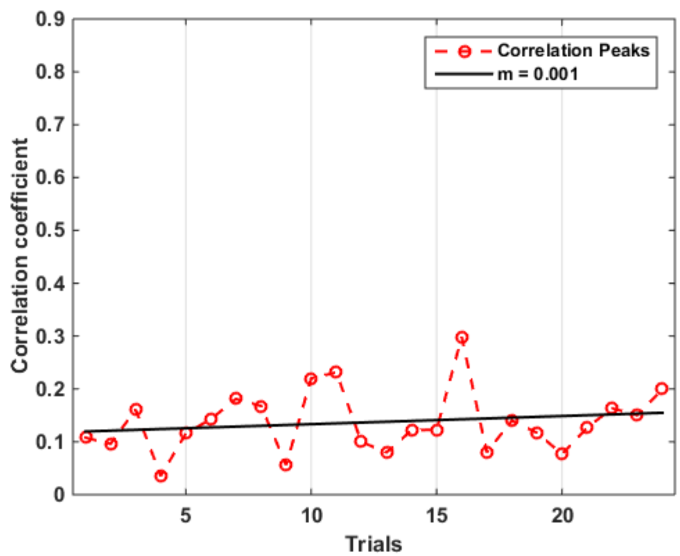


Figure 2-8: Average correlations of the muscle contractions during 24 consecutive stabilization phases on the center target. A) Subject 2 during PSS: Color map showing low correlations. B) Subject 2 during PSS: Peaks of the average correlations from the top figure and their linear regression, with $R^2 = 0.033$.

On the other hand, Subject 2 exhibited a very low correlation among muscles activities during the whole experiment (Figure 2-8 A). Figure 2-8 shows that subject 2 choosed the strategy of low correlation since the beginning of the experiment. In the linear regression in Figure 2-8 B, it can be observed that the correlation peaks maintain a value below 0.2, even if at the end of the experiment the peak value increased by 2.4%. Lastly, the behavior of Subject 3 during the experiments is characterized by the presence of both muscular strategies with no direct link to the kinematic strategy being used.

It is important to observe that all the subjects were experts in the task, and were able to solve it in a similar kinematic way, despite using completely different muscular strategies.

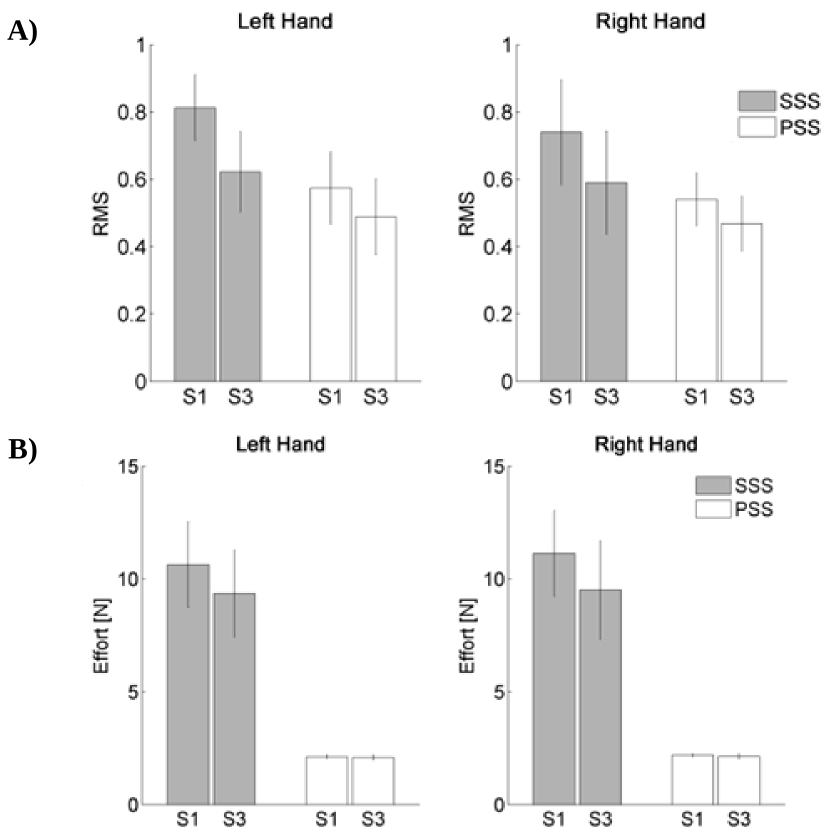


Figure 2-9: RMS contraction (A) and kinematic effort (B) in the first (S1) and last target set (S3) of each of the two strategies (grey bar->SSS and white bars->PSS). Each bars represents average across muscles and subjects (mean±SD).

2.3 The lack of correlation between muscular and kinematic strategies in unstable tasks.

The results presented in this chapter suggest that in unstable dynamic environments that allow for multiple control strategies, subjects adopt two different neuromuscular stabilization strategies. Moreover, the choice of the control strategy at the muscular level seems not to depend on the specific bimanual coordination strategy used.

In particular, at the task level, expert subjects can solve the balancing problem manipulating the stiffness of the virtual tool so as to apply a mainly feedforward control strategy or a feedback control strategy (Morasso et al. 2014). At the muscular level, the control of the hand position can be achieved in two ways: i) a muscular recruitment strategy equivalent to a stiffness strategy that makes use of co-contraction patterns, ii) a strategy in which different muscles can be recruited independently one from the other. However, when it comes to stabilizing an unstable load, both strategies make use of intermittent muscular activation patterns in time.

This result is consistent with previous works supporting the existence of intermittent feedback response mediated by discontinuous muscular activation in postural unstable tasks such as human standing (Loram et al. 2011; Vieira et al. 2012), as well as the statements that the performance is prioritized over the energy used to solve the task (Balasubramanian et al. 2009) and that the impedance of the limb gets optimized after achieving a skillful level of performance (Ethienne Burdet et al. 2001). In addition, the observation that in low stiffness conditions the behavior of the muscles is not necessarily related to the mechanics of the load appears to be in close relationship with the finding that, in the maintenance of posture, the modulation of intrinsic stiffness acts as a decoupling mechanism between muscle and the body (Lakie et al. 2003).

As in the case of the two bimanual coordination strategies, also the two muscular coordination strategies are characterized by different levels of effort. As easily predictable, the co-contraction scheme is characterized by higher levels of muscular energy compared to the independent contraction one. The latter control paradigm is therefore advantageous when the stabilization task has to be performed for a longer time. Our results suggest that independent muscular recruitment is preferred over the synchronous muscle activation when the stabilization task has to be performed for a longer time.

CHAPTER 3 TRANSFERRING KNOWLEDGE DURING THE DYADIC INTERACTION: THE ROLE OF THE EXPERT IN THE LEARNING PROCESS

The enhanced performance of the dyads respect to the individuals has been the center of interest of many studies. However, the factors that result in this higher performance are still poorly understood. The aim of this chapter is to investigate how the learning of a stabilization task gets affected by the difference in skill levels when one of the participants in the dyad is already an expert in that task. For the experiments conducted for this study, twelve subjects, divided in two groups, trained in couples in a joint stabilization task. In the first group the couples were composed of two naive, while in the second a naive was trained together with an expert. Results show that training with an expert result in the greatest performance in the joint task. However, this benefit is not transferred to the individual when performing the same task bimanually. A distinctive feature that makes joint actions in a haptic task particularly interesting, is their capacity to induce an increment in the sense of agency (i.e. experience of being in control of an action) proportional to the performance of the interacting subjects (van der Wel et al. 2012). Let us make an insight on the main findings presented previously about this topic.

On one side, physical coupling between two subjects has shown to be an advantageous solution in many cooperative contexts (Masumoto & Inui 2015; van der Wel et al. 2011; Ganesh et al. 2014; Masumoto & Inui 2013). However, the behavior and performance was strongly dependent on the individual capabilities of the two partners. For instance, interacting with a partner that is more skilled would result in an improvement respect to the individual performance. Interestingly though, when it comes to a novel task, the interaction between partners with a similar skill level leads to better performance than the interaction with a more skilled partner (Ganesh et al. 2014).

On the other side, little is known about how two people mutually exchange information to exploit the coupling. Some findings suggest that dyads may adopt “force amplification” as a possible strategy to improve their performance especially in contexts that are challenging from the point of view of coordination (Melendez-Calderon et al. 2015; van der Wel et al. 2011). Some other studies have shown that dyads may have a disadvantage in coping under the presence of noise or unforeseen disturbances (Reed & Peshkin 2008).

We have previously observed that complex balancing skills can be transferred from a bimanual to a dyadic paradigm and that dyadic training or simple dyadic practice brings to an improvement in performance when the subjects have a similar skill level (De Santis et al. 2015; De Santis et al. 2014).

For the study presented in this chapter, we were interested in testing how the presence of an expert partner affects the skill learning process of a naive in a challenging dyadic stabilization task. In particular, we focused our attention on how learning develops in a context where training of a novel skill occurs in pairs. We asked subjects to learn to jointly manipulate a compliant tool under the action of an unstable force-field, rendered by a haptic bimanual interface. The dynamics of the tool allowed the dyads to select multiple control strategies to accomplish the task.

In order to characterize the learning process, we compared the case of two interacting individuals to one alone. Ten naïve subjects were trained in the unstable task presented in Chapter 1 for 5 days. The first day served as familiarization whiles the fifth one for the ability evaluation of each naive to perform the task in a solo condition. Our objective was to evaluate whether the shared internal representation of the task built during the interactive period could be sufficiently accurate to allow for a solo execution. Both skilled subjects previously trained for 10 sessions according to the protocol presented in (Zenzeri et al. 2011). The analyses were conducted on the end-effector kinematics and the electromyographic signals from 10 relevant muscles of the arm and trunk.

3.1 Experimental setup

The experiments where conducted using the task and the experimental setup previously described in Chapter 1. In this study the target sets where considered as a sequence of 16 stabilizations in out – center – out sequence. The experiment was divided in 5 sessions having an approximate duration of 2.5 hours. Sessions from 1 to 4 were the training sessions, while session 5 was considered as the assessment session. Every session was divided into a variable number of target sets (TS). The complete protocol was structured as follows:

1. Session 1:
   i) Familiarization: 6 TS, unstable force-field off.
   ii) Adaptation: 6 TS, unstable force-field on.
   iii) Wash-out: 3 TS, unstable force field off.
2. Session 2-3:
   i) Training: 10 TS, unstable force-field on.
3. Session 4:

i) Training: 10 TS, unstable force-field on.
ii) Wash-out: 3 TS, unstable force field off.

4. Session 5:
   i) Familiarization: 6 TS, unstable force-field off.
   ii) Adaptation: 6 TS, unstable force-field on.
   iii) Wash-out: 3 TS, unstable force-field off.

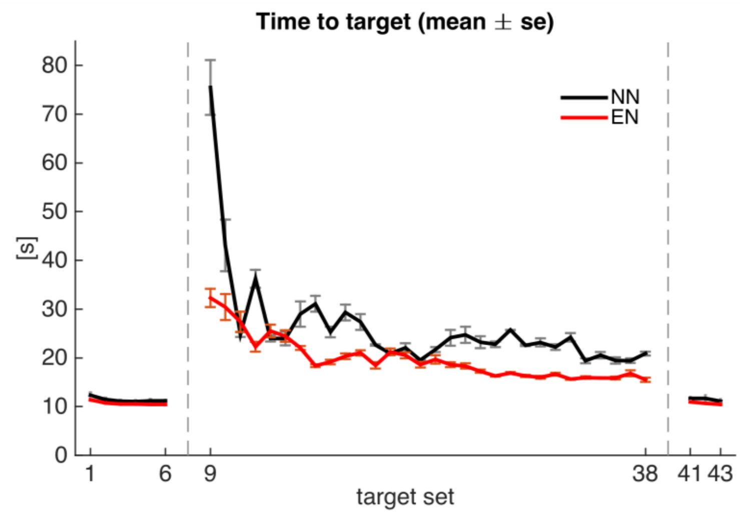
Twelve right-handed (according to the Edinburgh test) subjects took part in the experiment (26±4 year-old): 5 male and 5 female naïve in the stabilization task, and 1 skilled male and 1 skilled female. We called these skilled subjects "expert" (a subject that completed the learning process described in (Saha & Morasso 2012; Zenzeri et al. 2014) previous to the experiment. The subjects were divided in 2 different groups. In the Naïve – Naïve group (N-N) each dyad was made by 2 subjects with no experience in the task. The dyads in the Expert – Naïve group (E-N) were formed by an expert, and a naïve subject. The subjects were assigned to each group upon their gender: 3 naïve males and 3 naïve females were selected to be part of the N-N group (dyad 1: female-female, dyad 2: male-male, dyad 3: male-female) and the remaining subjects were assigned to the N-E group (dyad 1: expert female-naïve female, dyad 2: expert female-naïve male, dyad 3: expert male-naïve female, dyad 4: expert male-naïve male).

During the sessions 1, 2, 4, and 5, surface EMG signals were recorded from 10 relevant muscles from the arm and the trunk (see Chapter 1.). The recorded EMG signals were band pass filtered within 20-500 Hz, and separated in targets. For this analysis, only the stabilization phases of the peripheral targets were considered. The segmented signals were grouped according to the position of the corresponding outer target. In the post-processing of the EMG signals, the raw signals were normalized with the maximum values of the MVC recordings. Then, the normalized signals were rectified and low-pass filtered at 10 Hz. We also computed a ***Principal Component Analysis (PCA)*** on the enveloped EMG signals to understand which muscles contribute mostly to the corrective movements produced in the stabilization phases of the task.

3.2 The expert – naïve and the naïve – naïve learning difference

As shown in Figure 3-1, both groups of subjects were able to complete the training and significantly improve their performance at the end of Session 3. The N-N group in particular reduced the time to target faster and more consistently than the E-N group troughout the target sets. Moreover, the E-N group employed a much lower effort than 2 over 3 N-N dyads since the first session. As the training proceeded, however, the N-N dyads greatly decreased the overall effort compared to the initial phases of the training. The great initial difference in the effort values for the two groups could be accounted for by the adopted strategy of stabilization. The N-N dyads employed more effort by stretching the springs much more than the E-N group with the objective of increasing the overall stiffness of the hand-mass-hand system. Indeed, by amplifying the forces acting on the mass, the system was less compliant and more stable in face of unforseen perturbations coming from the force-field or from the partner’s motion. The E-N dyads, instead, tended to adopt a feedback strategy to compensate for the perturbations, exerting a total force oriented mainly in the direction of the force-field. This strategy required more coordination among the partners but resulted in the reduction of the overall effort.

A)



B)

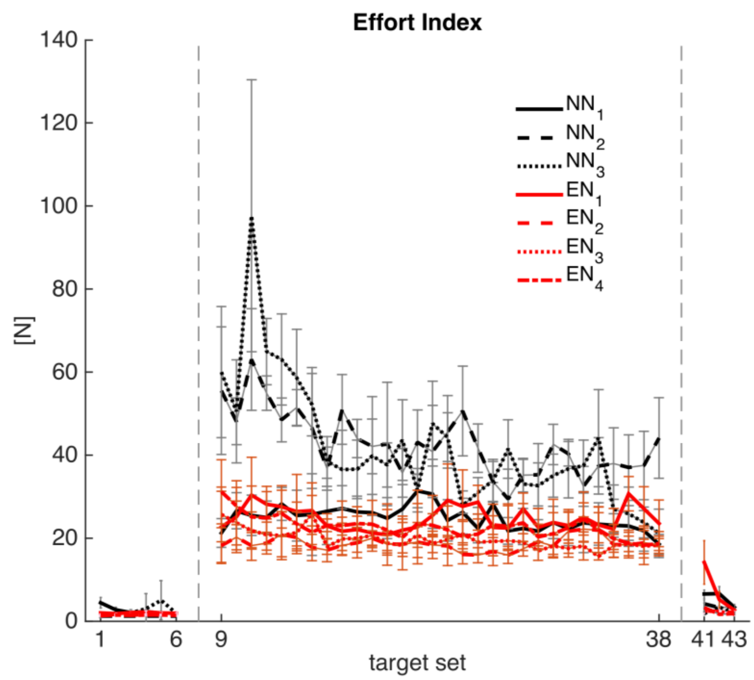


Figure 3-1: Average performance during the training for the N-N and E-N groups. The N-N group is shown in black, while the E-N group in red. A) The solid line represents the mean over the dyads and the deviation stands for the corresponding standard error along the target sets. A) Mean and standard deviation of the effort index in the 7 dyads. Trials 1-6 correspond to unstable force-field off condition; trial 9-38 corresponds to the unstable force-field on condition and the final 3 trials correspond to the wash-out phase.

Figure 3-2 depicts the performance of the subjects during the exposure to the force-field in the bimanual task. Since the very first target set the 6 subjects in the N-N group has been able to reach the

8 targets within half of the time needed to the 4 naive subjects of the E-N group (N-N: 21.2 ± 2.2 s; E-N: 48.6 ± 14.4 s). The N-N subjects did not achieve this performance at the cost of a greater effort. In fact, both at the beginning and at the end of the assessment phase, with the unstable force-field on, they employed a much lower effort than the naive subjects who trained with the experts (N-N7: 41.5 ± 3.8 N; E-N7: 33.5 ± 2.4 N; N-N12: 39.1 ± 2.3 N; E-N12: 30.6 ± 2.6 N). Moreover, in the solo condition the N-N naive were actually able to apply less effort than when interacting with a partner. The behavior of the naïve subjects in the E-N group was more etherogeneous, with the tendency to apply a greater effort compared to the N-N group and almost double the effort they employed in the training. It is interesting to notice that, despite not reducing the effort index, they were able to accomplish the stabilization within much less time since the very beginning of the session. This result was consistent with the evidence that the Central Nervous System tends to first optimize the performance and later the effort (Balasubramanian et al. 2009). An explanation for the observed difference among groups could be that the E-N naive were subject to an ‘interference effect’ of the previuos training with an expert, while the N-N naives experienced a positive transfer of the acquired skills.

In order to find a possible explanation for the observed kinematic performance, we conducted further analysis on the EMG data during the stabilization phase for the task. A PCA was used in order to identify the muscles that could account more for the observed corrective actions during the stabilization interval inside the target area. The PCA reconstructions in Figure 3-3 represent the muscles for which the variation in the EMG signal envelope accounts for at least 80% of the total variability of the signal in a group of representative subjects when reaching the target number 5

(180 deg, which was the most representative among the group of targets solved during the task). In general, the E-N group showed concurrent activation of synergistic muscles for flexion or extension of the arm (i.e. IS+ER, PM+FR+AD) rather than couples of antagonistic muscles (i.e. ER+FR, IS+PM, TL+LD). The N-N group showed more co-contraction of agonist and antagonist muscles, at least in the initial phases of the training. This observation was consistent with the higher effort index in this group during the training. Nevertheless, whilst the E-N subjects seemed to settle on a characteristic muscular pattern (PM+FR) since the first one or two sessions, subjects in the N-N group tended to explore diverse combinations. This difference in exploration during the training phase may have favored the N-N subjects over the E-N during the assessment phase, since the expert partner may have restricted the exploration of disadvantageous (in terms of effort) configurations.

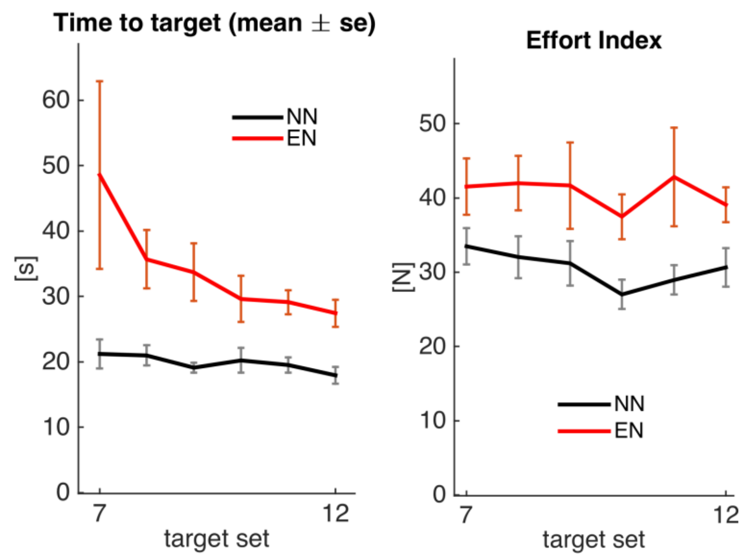
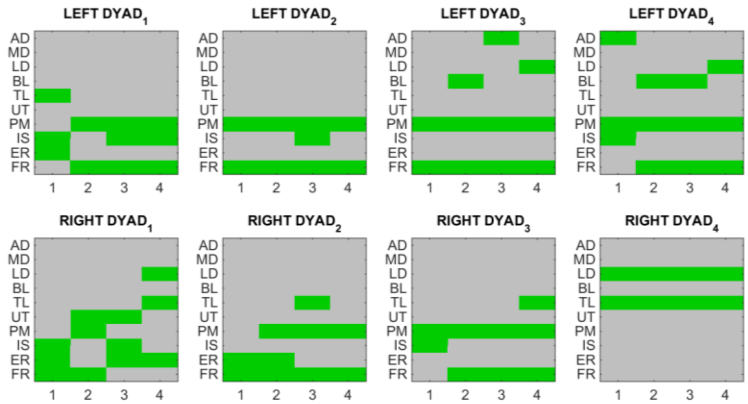


Figure 3-2: Average performance during the bimanual test for the naïve subjects. The subjects who trained in the N-N group are shown in black, while the E-N group is in red. The solid line represents the mean over the dyads and the deviation stands for the corresponding standard error along the target sets.



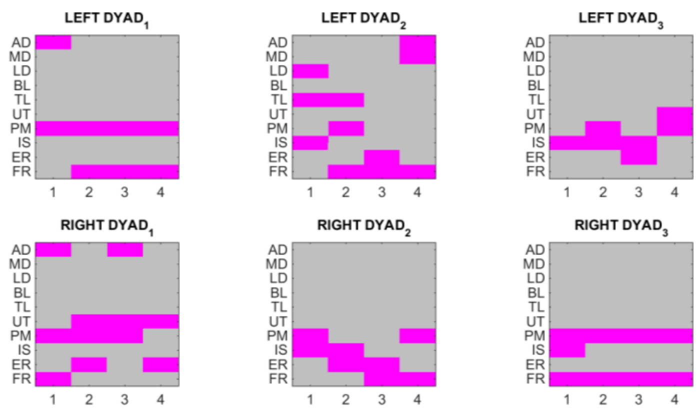


Figure 3-3: Reconstruction of the muscle activation in the projection of the first 3 Principal Components for the N-N group (top two rows) and 3 representative subjects of the E-N group (bottom two rows). The muscles whose projection over the first 3 components was greater or equal to the 80% is shown in magenta and in green, respectively. In each group of panels the top row shows the subject manipulating the left arm and the bottom row the subject on the right.

The main findings of the present work can be summarized as follows: dyads are not only susceptible to adaptation, but can also quickly learn new skills in a shared context; the amount of knowledge that can be transferred from a dyadic to an individual condition is limited by the interaction itself. Therefore, in addition to what already stated in the introduction, physical interactions are not always beneficial to the individual performance of the interacting partners.

Our results suggest that the initial level of the performers has a strong impact on the learning of a context-independent representation of the dynamics of the task. In particular, the interaction with an expert can be detrimental in this sense. While interacting with an expert brought to a greater advantage over working with a pair, it partially manipulated the dynamics that the naïve perceived. As a consequence, the naïve subjects may have learnt how to cope with a leading expert rather than to master the background task.

In general, the results of the experiments show that the protocols of haptic interaction can influence critically the capability of skill acquisition and skill transfer, in a subtle manner. As a consequence, specific interaction protocols are likely to be necessary in different applications as in surgery or rehabilitation.

CHAPTER 4 MOTOR KNOWLEDGE GENERALIZATION AFTER ROBOT – MEDIATED DYADIC TRAINING

Several studies have investigated how the interaction between two people or between a person and a robot can be harnessed to improve the skills of the partners. Indeed, solving a task as a dyad can lead the individual to perform better than by himself. The goal of this work is to investigate how the skill level of the partner and different interactive conditions affect learning of a novel task. In particular we considered the case of partners with different initial skill level (naïve or experts) and the influence of prior individual practice. Twenty two subjects trained in a joint stabilization task for 4 days. On the last day we tested their ability to perform the same task individually. The results show that training with a skilled partner, despite bringing to a faster learning in the joint task, does not facilitate skill transfer in the absence of individual prior practice. This suggests that the physical coupling with an expert partner may interfere with learning due to the formation of a non-veridical internal representation of the task.

In our previous works we studied skill transfer from a bimanual to a dyadic paradigm. Furthermore, we showed that a dyadic training can help partners with similar skill levels to improve their performance in complex stabilization tasks (De Santis et al. 2015; De Santis et al. 2014).

In this chapter we further expand our study on the transfer of skills from the dyadic to the bimanual paradigm but we mainly focus our attention on the generalization abilities of the subjects after the training. The training consisted of solving a stabilization task under different conditions of interaction. These conditions included the training in dyads with a partner with the same skill level or with a partner proficient in the task and the acquisition of an a priori knowledge of the task itself. The ultimate goal was to evaluate whether the shared internal representation of the task built during the interactive period could be sufficiently accurate to allow for a solo execution. Kinematic and electromyographic data have been used to evaluate the performance of the subjects.

4.1 Methods

The subjects solved the task described in detail in Chapter 1 using both configurations of the BdF2 during the different stages of the experiments. In addition to the measures presented in Chapter 1, we also calculated the ***Tracking Error***, which measures the average distance between the mass and the moving target during each repetition of one trajectory (explained below).

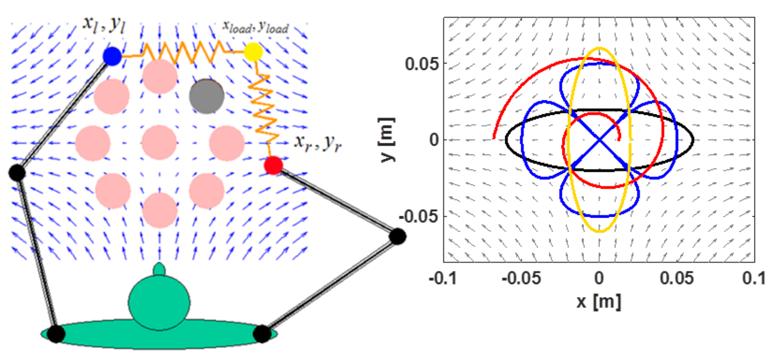


Figure 4-1: Task diagram. *Left panel:* Distribution of the targets for the stabilization task during the training and the bimanual evaluation. *Right panel:* Trajectories followed for the moving target during the generalization phase: Horizontal Ellipse (HE, black), Vertical Ellipse (VE, yellow), Clover (C, blue), and Spiral (S, red).

The protocol was divided in three different stages. The first stage (training) consisted in the stabilization of the virtual mass in 9 different target locations for 4 seconds. The targets were equally distributed around a circle of 10 cm of diameter (Figure 4-1, *left panel*) and were presented in a random order in an out–center–out schema. A target set (TS) consisted of 16 different stabilization trials. The training stage lasted 3 sessions, during which the subjects had to complete a sequence of 3 TS of familiarization with the tool in the absence of instability ($\boldsymbol{F_u} = 0$), 30 TS (10 per day) of stabilization in the presence of the instability, and 3 TS of washout, again in the absence of instability.

In the second stage of the experiment (tracking), the subjects had to control the virtual tool while tracking a moving target along 4 different trajectories, as represented in Figure 4-1 (*right panel, horizontal ellipse, vertical ellipse, clover, and spiral*)**.** Each trajectory was repeated three times, the first of which in the absence of the unstable force-field. The objective of the task was to test how well the skills acquired during the balancing task could be generalized to a novel task that shared the same intrinsic dynamics as the trained task.

In the last stage of the experiment all the subjects had to bimanually solve the balancing task. The protocol was the same as in the training stage with the difference that the subjects had to complete only 6 TS in the presence of the unstable force-field. This stage was used to evaluate whether the internal model developed during the training phase was sufficiently accurate to allow for a bimanual execution.

The subjects (22 persons, 25.7 ± 3.8 years old, all right handed according to the Edinburgh test, from which 2 of them were experts in the task (Zenzeri et al. 2014; Zenzeri et al. 2011)) were separated in 4 different groups, as depicted in Figure 4-2. In two of these groups subjects trained together with an expert (NE and NE-a) while the other subjects trained in pairs of naïve (NN and NN-a). In order to test the effect of prior individual experience of the task in both dyadic conditions, subjects in the NN-a and NE-a groups performed an additional stage before training in pairs. Each subject performed a session of adaptation to the force field using a protocol identical to the last stage of bimanual evaluation.

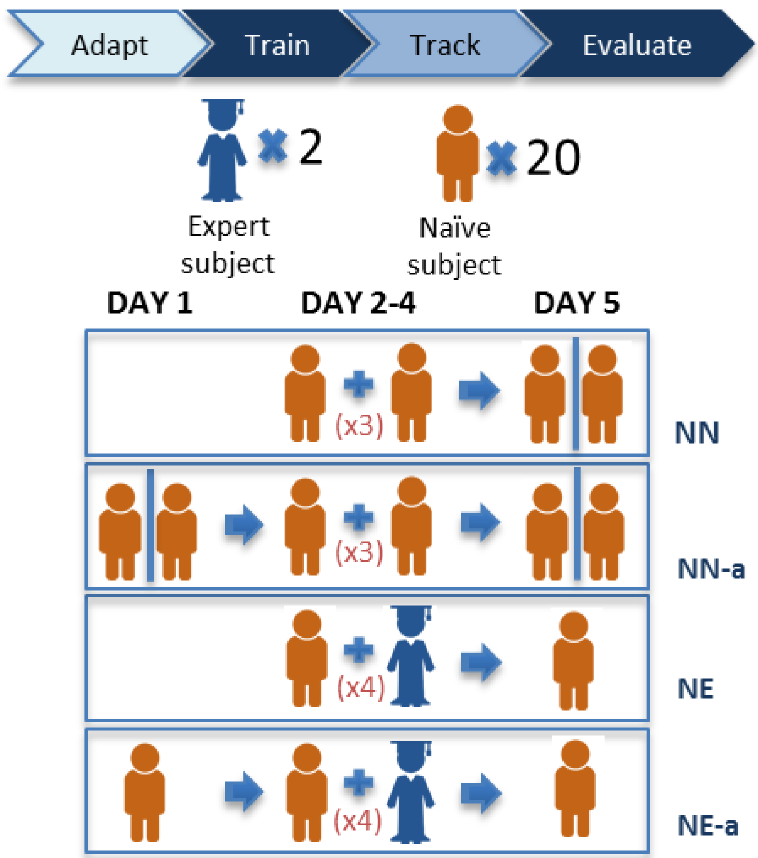


Figure 4-2: Four groups were formed to evaluate motor learning under different conditions. NN: 3 couples formed by 2 naïve subjects that complete the training working always in a dyadic configuration. NN-a: 3 couples of naïve subjects with one session of bimanual experience before the training. NE: 4 couples naïve – expert which completed the training in a dyadic configuration. NE-a: 4 naïve – expert couples where the naïve subjects had one session of bimanual experience previous to the dyad training.

The kinematic data of the robots and of the virtual tool were recorded at 100Hz. Moreover, surface EMG signals of 10 muscles responsible for the movement of the shoulder, elbow, and wrist were recorded and processed as explained in Chapter 1. The RMS envelopes of these signals were used to analyze the muscular activity of the subjects.

4.2 Generalization of the acquired skills

The Figure 4-3 summarizes both kinematic and electromyographic measures during the tracking phase of the experiment. Figure 4-2 A shows the average kinematic performance by group for every trajectory of the moving target. Compared to the bimanual control group, the NE-a group was the best performer, while the NN-a group committed the greatest error in all figures. The NN group, instead, performed worse only in the easier figures (ellipses). One may expect that the groups with a higher tracking error also present higher levels of muscular activity, related to the difficulty in solving the task. Interestingly, the above observation is true only for the NN-a group. Indeed, the RMS values of the NN-a group are considerably higher than NE, NE-a, and NN groups. An opposite tendency can be observed for the bimanual control group that displayed a high average RMS value but committed small tracking errors. Unfortunately the tracking average RMS value over the muscles is affected by a big variability, making considerations relative to the muscular activity for every single group difficult.

Figure 4-4 shows the effects of training on the activity of individual muscles for representative subjects in groups NN, NN-a, NE, and NE-a. The effect of the different interaction conditions can be seen during the bimanual evaluation of the task (blue areas). From the muscular point of view, it can be detected a difference among the groups in which the expert subject is present in the dyad and the groups in which is not. In Figure 4-4 A) the first session of training presents higher muscular activity than the last one. Figure 4-4 B) shows that, for subjects who trained with a peer with previous experience of the task (NN-a), the muscular activity is quite low since the first day of training These levels decrease considerably the last day of training and did not increase in the bimanual evaluation. On the contrary, the muscular strategy adopted by the NN group during the bimanual test is similar to the one used during the first day of training, it requires the intervention of the same muscles but with different levels of intensity.

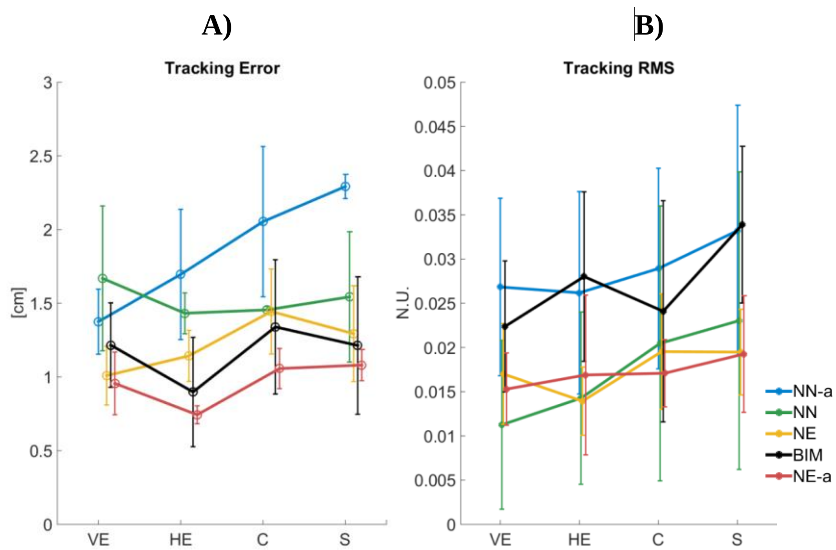


Figure 4-3: Kinematic and EMG results of the generalization task. *a)* Average tracking error for each group in every trajectory of the moving target. *b)* Average RMS (Normalized Units, N.U.) during the performance of the tracking task. VE = Vertical Ellipse; HE = Horizontal Ellipse; C = Clover; S = Spiral.

The polar plots presented in Figure 4-4 C) and D) show the evolution of the muscular activity for the subjects of group NE and NE-a respectively. The presence of the expert since the beginning of the training in the group NE helps the naïve subject to “optimize” the muscular activity. By the end of the training, the naïve subject shows an increment in solving the RMS values, meaning a higher muscular contribution in the task. However, this subject increased the muscular activation during the bimanual evaluation. We can also observe that the muscular contribution to the movement is different for every stage represented in the polar graphs.

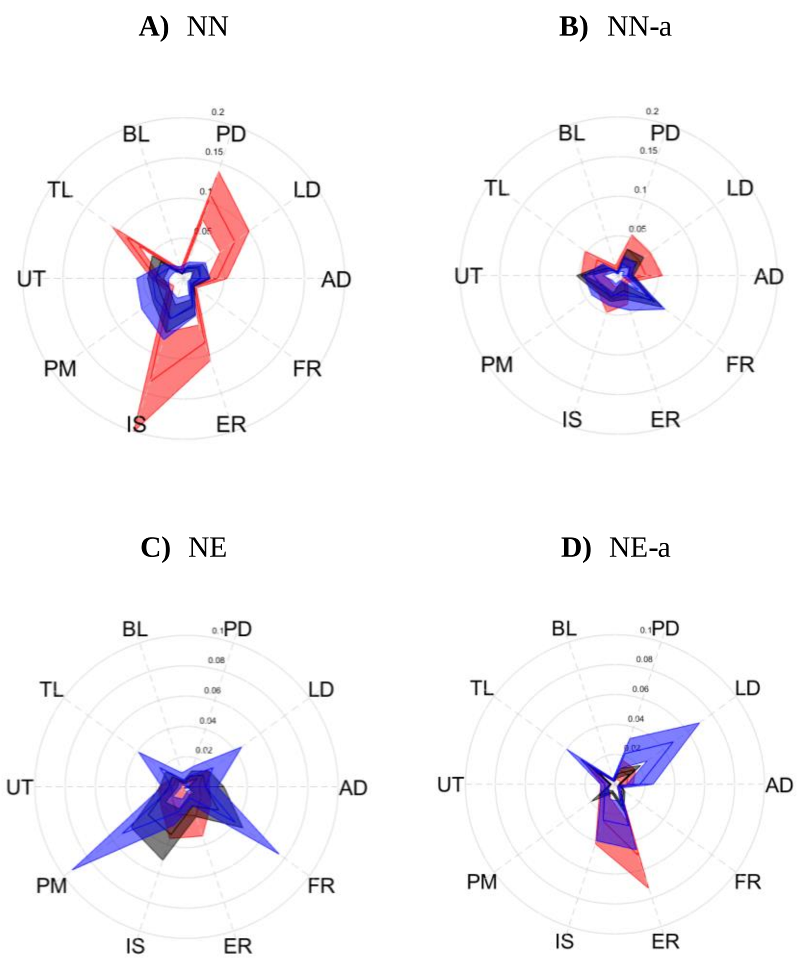


Figure 4-4: Average RMS (by muscle) of the most representative subjects of the dyad groups during the first day of training (*red*), during the last day of training (*black*), and during the bimanual evaluation (*blue*). *a)* Muscular activity of the subject from NN group. *b)* Corresponds to the subject of the NN-a group. *c)* Shows the muscular activity of one of the naïve subjects in group NE. *d)* Muscular activity of a naïve subject from group NE-a.

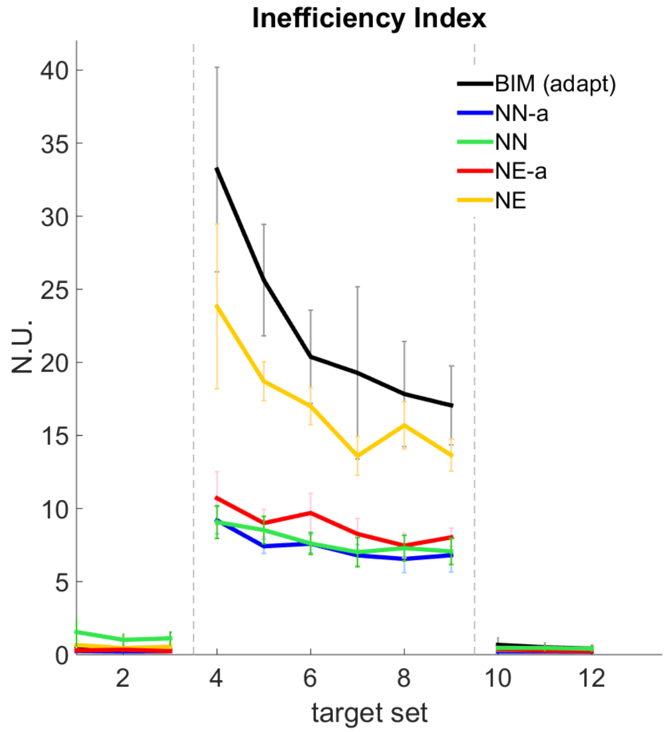


Figure 4-5: Inefficiency index values to measure the kinematic performance during the bimanual evaluation. At difference of the rest of the data, the data corresponding to the BIM group were taken from the first day of training.

The analysis of the kinematic data can give us a wider view of the impact of the expert in the dyadic training. In Figure 4-5 we can see the comparison of the Inefficiency Index from the bimanual evaluation of the NN, NN-a, NE, and NE-a groups against the adaptation phase of the BIM group. Here it is important to notice that while the Inefficiency Index values of the NN-a, NN, and NE-a groups are low and similar to each other, the values of NE group are much closer to the ones of the BIM (adapt) ones (The data corresponds to a group where the subjects performed the whole training and generalization of the task in a bimanual configuration, the adaptation phase was considered as illustration of the Inefficiency Index evolution when the task is novel to the subjects. Further details are presented in Chapter 5). Despite having been training for several days, the subjects of NE group seem to progress into the adaptation as if the task was novel to them.

4.3 Expert stablished limitations in the Knowledge transfer

The overall results of the training confirm the theory that the presence of the expert in the dyad helps to improve the performance while solving the task. The kinematic results of the experiment show a better performance for the dyads in which the expert was present, even if the naïve subject did not have any previous experience in the task. In both tracking and training stages of the experiment, the muscular activity seems to be lower in the NE and NE-a groups, suggesting that the contribution of the expert in solving the task helps optimizing the muscular strategy needed to complete the experiment. Apart from the bimanual control group, the common condition in the groups with the lowest tracking error is the presence of the expert in the dyad. One of the reasons for the bigger error in the NN and NN-a groups can be the perception of the partner as an extra perturbation. In fact, in the NE and NE-a groups the expert was probably responsible for compensating the perturbations coming from the naïve subject.

On the other side, both kinematic and electromyographic data of the bimanual evaluation stage show how the subjects from NN and NN-a groups were able to generalize the acquired knowledge from the dyadic to the bimanual condition. At the same time, the naïve subjects from the NE-a group improved their performance (decreased the muscular activity) with respect to the first session of training but, differently of what happened with the NN and NN-a groups, the muscles contributing to the movement were different in both the first and the last session. In this case the naïve subjects of the NE-a group were able to generalize the kinematic strategy but not the muscular one (Avila-Mireles et al. 2015). On the other side, NE subjects were not able to transfer either the kinematic skills or the muscular skills learnt during the interaction with the expert to the bimanual condition. In this case, the presence of the expert constrains the exploration from the naïve of the virtual environment and imposes a sort of bias on the force field. The expert subjects have a wide knowledge of the task and are able to correct the perturbations from both the naïve subject and the virtual environment, and this forces the naïve subject to create an erroneous internal model of the conditions of the task due to a distorted perception of the virtual environment. As a consequence, the naïve subject cannot learn to handle the perturbations coming from the unstable force field alone.

The results show how the interaction of two subjects mediated by a haptic interface can be helpful in the knowledge transfer and skill acquisition. However, it is necessary to be careful during the design of any dyadic protocol, since a wrong interaction condition can be of no advantage or even counterproductive.

CHAPTER 5 *SKILL LEARNING AND SKILL TRANSFER MEDIATED BY COOPERATIVE HAPTIC INTERACTION*

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.

In the 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 (Rizzolatti et al. 1997) 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 (Jeannerod 2001) 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 (Morasso et al. 2015) formulated as a generalization of the Equilibrium-Point Hypothesis (Mussa Ivaldi et al. 1988) to include covert and overt actions as well as actions involving the skilled use of tools (Maravita & Iriki 2004). 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 (Knoblich & Sebanz 2006), 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 (Keller 2008; Keller & Appel 2010; Clayton 2012). These two aspects are different but deeply complementary at the same time. 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 and this is the reason for which 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 (Shadmehr & Mussa-Ivaldi 1994). The study of dyadic physical interaction through robotics has benefited from several notable contributions. Ganesh et al. (Ganesh et al. 2014), 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, 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. (van der Wel et al. 2011) designed a simple cooperative tasks 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. (Groten et al. 2013) 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, the study presented in this chapter 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 the studies of (Saha & Morasso 2012; Zenzeri et al. 2014) it was presented an investigation of 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 some preliminary results of a dyadic operation in the same setup were presented (De Santis et al. 2015).

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.

5.1 *Organization and implementation of the experimental methodology*

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 (Saha & Morasso 2012; Zenzeri et al. 2014). 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. The experimental setup, the task description, and the details of the virtual environment used for this study have been described in detail in Chapter 1 together with the specifics of the muscular and kinematic data recorded.

5.1.1 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 (Zenzeri et al. 2011)). 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 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.

5.1.2 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 5-1 summarizes the distribution of subjects into the 4 the experimental groups (NN, NN-b, NE, NE-b) and in the control group (BIM).

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	-

Table 5-1: Experimental groups and experimental protocol

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 5-1, 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).

The kinematic and EMG performance of the subject was analyzed using the measures detailed described in Chapter 1. For this study we also included the ***Mutual Information (MI)***, which 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:

$$MI = \sum_{xF} \sum_{xF_u} \frac{\log(p(F, F_u))}{p(F)p(F_u)} \tag{5.1}$$

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 perform 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 (Reed et al. 2005; Stefanov et al. 2009). 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.

5.1.3 Data Analysis and statistics

Data from the robot and virtual reality were collected at 1kHz and saved at 100Hz 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 (1.9):

$$\begin{cases} \vec{F}_R = (K_s L_R + \rho_s L_R^2)\vec{v}_R \\ \vec{F}_L = (K_s L_L + \rho_s L_L^2)\vec{v}_L \end{cases}$$

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.

5.2 How does the skill level of the partner conditions the skill learning?

The first part of this section compares the performance of the two groups who executed the priming session always in dyads (NE and NN), without any experience of the naïve subjects 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).

5.2.1 PART 1: 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-b and NE-b 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 5-1 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).

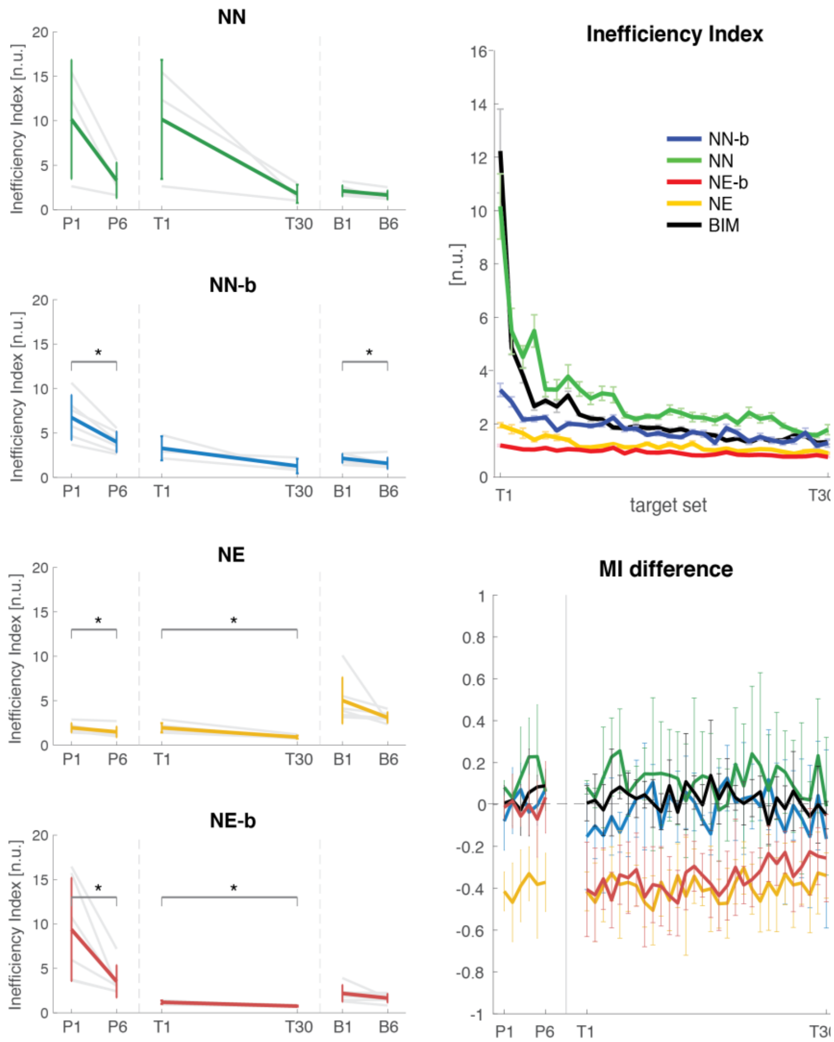
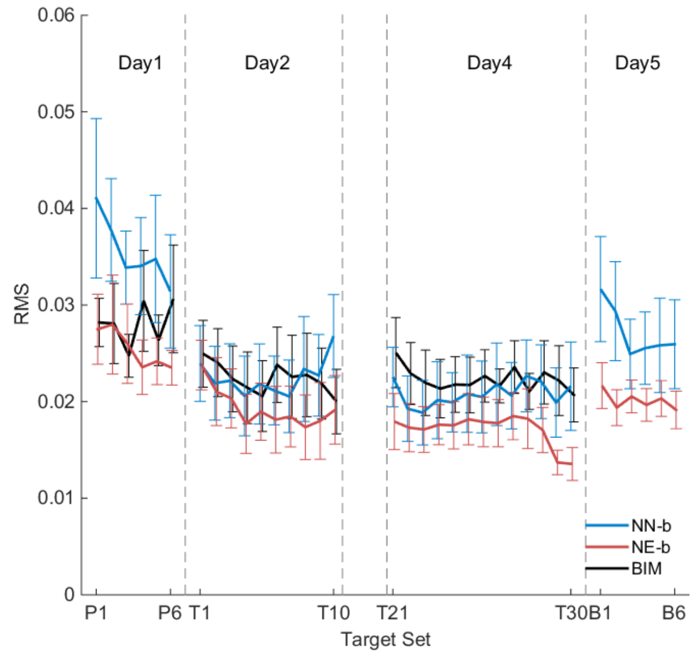


Figure 5-1: Summary of performance measures. *Left panels*: Average variation of the Inefficiency Index between the first and the last training set in the three phases of the experimental protocol (P = priming; T = training; B = bimanual test), separately for the four dyadic groups (*NN-b*; *NN*; *NE-b*; *NE*). 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. 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.

A)



B)

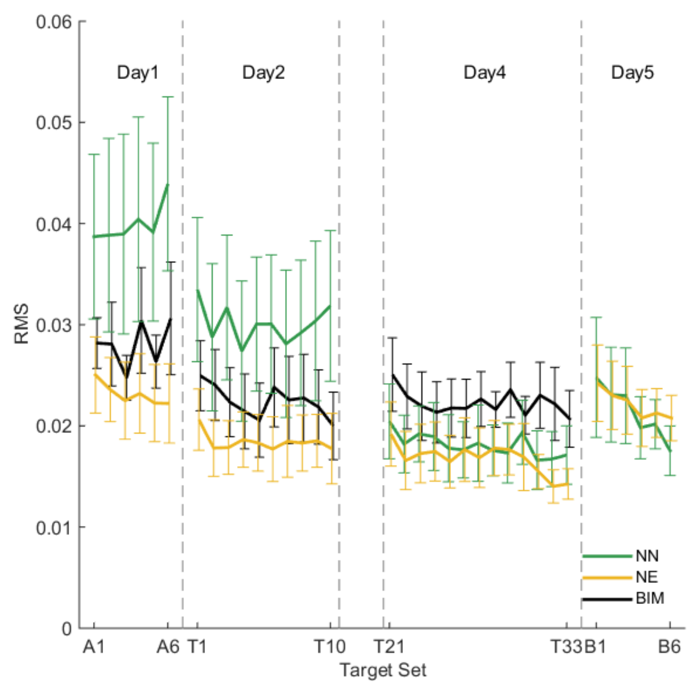


Figure 5-2: Evolution of the average muscular activity index (RMS) of the different experimental groups during all the target sets of the experimental protocol. A): Comparison among the groups where the naive subjects could have bimanual experience of the task during the priming session (*NN-b* and *NE-b*, blue and red line respectively), with respect to the control group (*BIM*) that never operated in dyadic condition. 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.

As regards the EMG signals, Figure 5-2 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

5.2.2 PART 2: 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 5-1, 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 5-2 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 5-2 B), with similar values of the NE-b group (Figure 5-2 A). Consistently 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 5-1, 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 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 5-1, 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 suggest and 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.

5.2.3 PART 3: 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 naive 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.

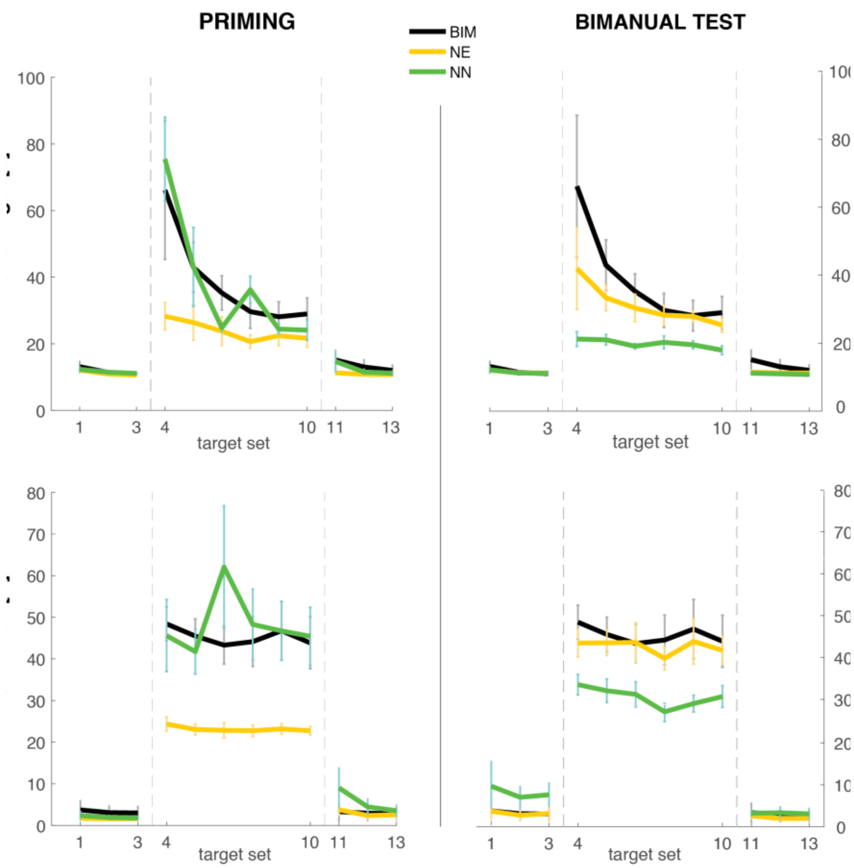


Figure 5-3: Comparison of the average Time to Target (T2T) and Effort Index (EI) between the naïve subjects with no bimanual prior (*NE* = naïve-expert group, *NN* = naïve-naïve group) and the control subjects (BIM) in the priming session (P, right panels) and in the bimanual session (B, left panels); 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).

As we can notice in Figure 5-1, 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 5-3). 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 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 5-4 shows, they performed significantly worse than in the end of the priming session when working with the expert (panel *NE*).

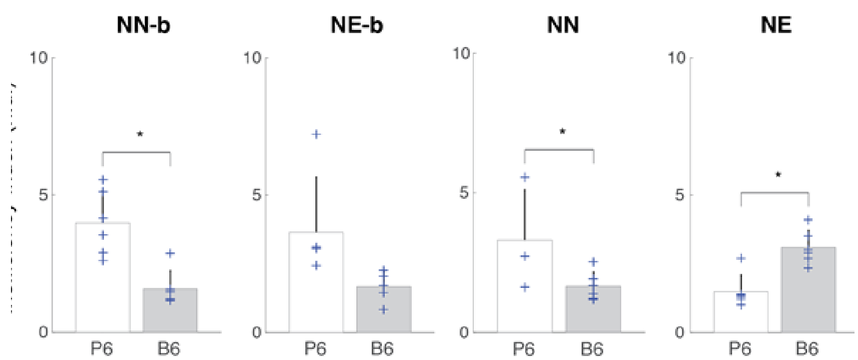


Figure 5-4: Average Inefficiency Index in the end of the adaptation phase on Day 1 (priming session, P6 – white bar) and in the end of the adaptation phase in the bimanual test session on Day 5 (B6 – gray bar) for the naïve-naïve and naïve-experts dyads with and without bimanual prior. Blue markers represent 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*).

From the point of view of the EMG signals (Figure 5-2), 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* 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 5-5). Figure 5-5 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.

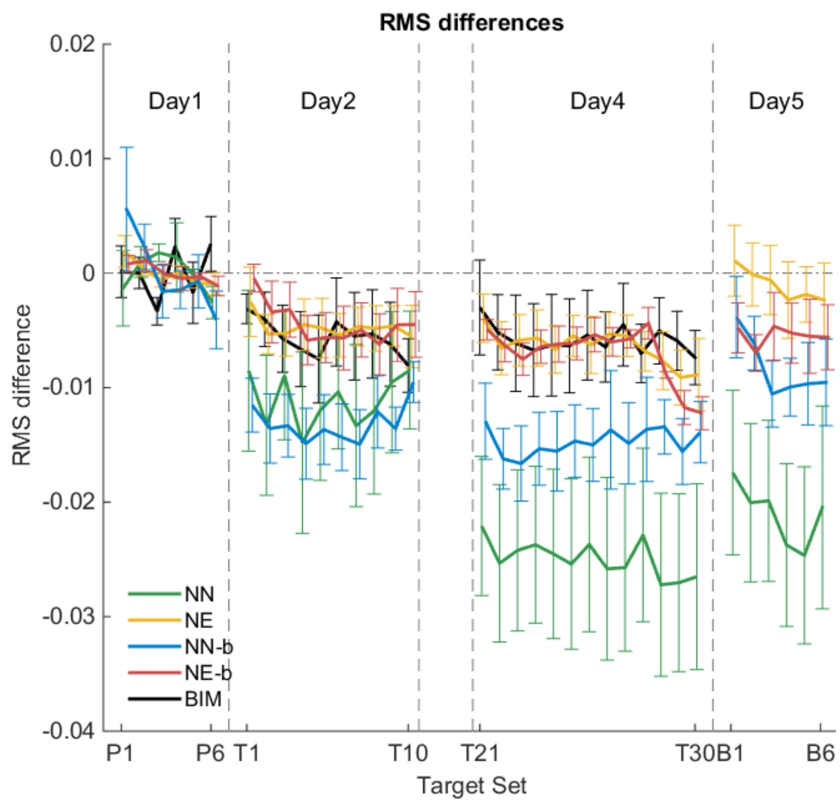


Figure 5-5: Differences in the RMS values during the experiment respect to the mean value of the priming phase. The results are divided in groups, and the dispersion bars represent the standard errors.

The statistical analysis performed for the RMS values did not show any significant differences among groups.

5.3 Understanding the advantages and disadvantages of working with a skilled partner

Previous studies reported that prior practice with a partner allows for improving the performance of the individual in the same task

(Ganesh et al. 2014). 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 (Ganesh et al. 2014), 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.

5.3.1 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 5-3).

Motor control studies report that existing knowledge can interfere with the acquisition of new motor skills (Berniker, Mirzaei, et al. 2014; Schweighofer et al. 2011; Boutin & Blandin 2010; Pauwels et al. 2014). 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 (Shadmehr & Mussa-Ivaldi 1994). Ranganathan et al. (Ranganathan et al. 2014) 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 (Krakauer et al. 1999; Malfait et al. 2005; Malfait et al. 2002).

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 (Groten et al. 2013).

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 (Shadmehr & Mussa-Ivaldi 1994), (Schweighofer et al. 2011), (Ranganathan et al. 2014). On the other hand, there is recent evidence (Krakauer et al. 1999), (Malfait et al. 2005) 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 (Morasso et al. 2015). In particular, internal models of dynamics greatly draw on proprioceptive feedback rather than visual feedback during the task (Malfait et al. 2002), (Wang & Sainburg 2004), 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" (Berniker, Franklin, et al. 2014), namely causal relationships that an agent tends to attribute to his own action, as well as and 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, who partially compensated the destabilizing dynamics experienced a completely different kind of perturbation and learnt a model that incorporated the action of the partner, thus masking 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 5-1, 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.

5.3.2 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 (Kim et al. 2015), (Hirano et al. 2015). 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 (Bernardi et al. 2015). 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 (Dayan & Cohen 2011), (Karni et al. 1998). 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.

In synthesis, 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 (Bottaro et al. 2005; Asai et al. 2009) or in the stabilization of unstable tasks similar to the one used in this study (Morasso et al. 2014; Zenzeri et al. 2011). 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” (Reinkensmeyer et al. 2009) 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.

CHAPTER 6 KNOWLEDGE TRANSFER AND MOTOR MEMORY OVERLAP

We had shown in previous studies that, when the subjects work in couples, it is advantageous to work with a more skilled partner (Avila-Mireles et al. 2017; Avila-Mireles et al. 2016) but only when the less skilled subject has the chance to explore the task by himself before coupling with the skilled partner. This has been demonstrated by (Galofaro et al. 2017) in a work in which was enough to limit the contribution of the expert subject to allow the more naïve to explore the task and let him/her perform almost at the same level than the expert after a relatively short training.

The studies presented by (De Santis et al. 2015; De Santis et al. 2014) the results show the effectiveness of the knowledge transfer from an individual performance to a dyadic collaboration. The opposite direction of the knowledge transfer was analyzed in (Avila-Mireles et al. 2016; Avila-Mireles et al. 2017; Avila-mireles et al. 2016) where the subjects passed from a dyad collaboration to an individual performance. In both paradigms there were results showing that the learning experimented by the subjects went beyond the tactile stimulation received during the experiment.

In this chapter we studied an experimental condition in which the training and the testing of the subjects share the same dynamical properties but differ in the way in which the task is performed. The subjects were separated in 2 groups that followed the dyadic to bimanual paradigm, with the difference that one of these groups was trained to perform the task using the wrist while the other one was trained to use the muscles of the elbow and shoulder. At the end both groups where tested in the performance of the task using the muscles of the elbow shoulder. The kinematic data was analyzed to evaluate if the internal representation of the task created during training is enough to be able to develop the necessary skills to transfer the knowledge from the wrist to the elbow – shoulder.

Figure 6-1: Experimental setup Braccio di Ferro – WristBot. The left handle of the Braccio di Ferro was substituted by the WristBot, in this way the subjects can share the same virtual reality while working in different haptic devices.

6.1 Experimental protocol

The task used for the experiment is a direct evolution of the exercise presented in (Zenzeri et al. 2014; De Santis et al. 2014) with the addition of the modifications implemented by (Galofaro et al. 2017). For this study the task was completed using the Braccio di Ferro (BdF2) (Casadio et al. 2006) synchronized with the WristBot (WB) (Masia et al. 2009) when the subjects were working in dyads (Figure 6-1), and the bimanual configuration of the BdF2 when the subjects where working by themselves (Figure 1-2 A). The task used in this experiment is the one described in Chapter 1, and in this case the target set was considered as a serial of 16 stabilizations in the out – center – out sequence. The experiment was divided in two stages. During the first stage the subjects work in dyads, one of the subjects (considered as the expert) takes control of the right spring using the BdF2 while the other one (considered as the naïve subject) takes control of the left spring using the WB. For the second stage the naïve subject works bimanually using only the BdF2 robot (Figure 1-2 A).

6.1.1 WB – BdF Synchronization Protocol:

The two devices used for this study have different characteristics in both software and hardware. For such reason it was necessary to develop a protocol capable of stablish a communication stable enough to let the subjects work on the same task simultaneously. The BdF system is programmed on a Windows XP operative system using the Simulink tool box from Matlab, while the WB runs over a C++ platform implemented over Linux Mint 18. Both devices have a Sensoray Acquisition Board (826 model for the WB and 626 model for the BdF) that allowed us to send and receive data from both devices. We took advantage of this and managed to establish a direct electrical connection between the two cards. We used the 48 digital channels of each card in parallel for continuous broadcast/reading of the dynamical states of both devices with a rate of 1KHz (which is the minimum refresh rate required for force control and haptic algorithms); 24 channels were used to broadcast information and 24 were used to read the data broadcasted for the other device. At the same time, for each 24 bits, 12 bits were used for the x values and 12 more for the y values.

The WB's CPU was used only as slave terminal and its function was to read the encoder positions for the degrees of freedom corresponding to the x and y axis, to broadcast them to the BdF, and to read and apply the force values received from the BdF to the motors. On the other side, BdF's CPU was in charge of the main processing of the task, it read and used the positions broadcasted by the WB to complete the haptic calculations, broadcasted the updated force values to the WB, and then displayed the virtual reality using the information from both robots.

Because of the mechanical differences between the 2 devices, and as consequence the difference in the workspaces, the position values coming from the WB to the BdF where adjusted as:

$$x_L = \alpha x_{wb} \qquad\qquad y_L = \beta y_{wb} \tag{6.1}$$

where x_{wb} and y_{wb} are the coordinates of the end effector in the WB's workspace position, x_L and y_L are the corresponding BdF workspace coordinates values of the left manipulanda (see Chapter 1.1 for details), and α and β are the constant transformation factors from WB to BdF workspaces.

The x_L and y_L values were used as parameters for the haptic algorithm and the force $\vec{F}_L$ (from equation 1.9 in Chapter 1.6) corresponding to the left spring was sent back to the WB. $\vec{F}_L$ consisted in 2 components: $\vec{F}_{Lx}$ and $\vec{F}_{Ly}$ which were adjusted to be coherent with the WB's mechanical characteristics, and scaled to compensate the difference in the muscle strength between the wrist and the elbow – shoulder. The conversion was made as:

$$\tau_x = \left({F_{Lx}}/{2}\right) r \qquad \qquad \tau_y = \left({F_{Ly}}/{2}\right) r \qquad (6.2)$$

where τ_x and τ_y are the torques applied to the end effector of the WB; and r stands for the rotation ratio of the WB's degrees of freedom correspondent to flexion – extension and adduction – abduction.

6.1.2 Experimental protocol:

For this experiment, 21 subjects (25±5 years old, 175±7.4 cm tall), all right handed according to the Edinburgh test, were recruited. Two of these subjects were considered experts in the task after been completed the protocol described in (Zenzeri et al. 2014), the rest of the participants were completely novel to the task and were considered as naïve subjects. The naïve subjects were separated in 2 groups, known as Control Group and Test Group. Both groups followed the same protocol but under different experimental conditions.

The experiment was organized in a way that the subjects had to complete 16 stabilizations of the virtual mass, 8 in the peripheral targets and 8 in the central target, each group of 16 stabilizations is called a target set (TS). Each naïve subject was requested to complete a full session consisting in 2 stages, a training stage and a testing stage.

- ***Stage 1 (Training):*** The naïve subject works together with an expert subject as dyads completing a total of 10 TS. In all the cases the expert subject was manipulating the right spring while the naïve subject manipulates the left spring. In the control group, both subjects used the BdF in a dyad configuration, while in the Test Group the naïve subjects used the WB and the expert used the BdF in bimanual configuration. In both cases the expert subject takes control of the right spring of the virtual reality, and in order to give the same contribution in the two group, the expert has to maintain a constant length in the spring, stablished at 7±1 cm with which the contribution from the expert is around 18N. As visual help for the expert, the color of the spring was changed every time the length of the spring was out of the optimal range (Figure 6-2).

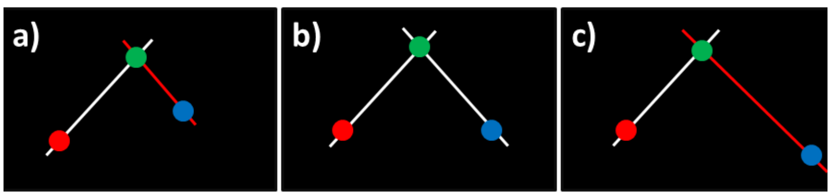


Figure 6-2: Visual Feedback for the expert subject implemented on the virtual tool. a) L_r< 6 cm, right spring becomes red; b) : **6 cm <** L_r< 8 cm, right spring remains white; c): L_r>8 cm, right spring becomes red.

- ***Stage 2 (Testing):*** Immediately after the Training, the naïve subjects complete a series of 3 TS in which they have to work with the BdF in a bimanual configuration. For this case the visual assistance of the right spring is removed and the subject has to control both right and left springs.

6.1.3 Analysis:

To the measures described in Chapter 1, we added the following:

Stiffness Size Index (SSI): It is a dimensionless parameter that identifies the stabilization strategy used to solve the task: Stiffness Stabilization Strategy (SSS when SSI>1) or Positional Stabilization Strategy (PSS when SSI<1).

Bimanual Separation Index (BSI): $BSI = |\overrightarrow{p_R} - \overrightarrow{p_L}|$ (cm). This index tends to be small in the PSS, with low levels of effort and almost round stiffness ellipses. It measures the separation between the virtual representations of the end effectors of the haptic devices used for the task.

The rationale and the detailed description of these measures can be found in (Zenzeri et al. 2014).

6.2 Data analysis of the training and the test stages

In the first part of this section, we present the results of the Training stage of the experiment, and the second section corresponds to the results of the Testing stage. It is important to remember that, for the Training stage, the naïve subjects in the Test Group solve the task using the WB and subsequently they were tested by using the BdF. This means that they are being trained to solve a task using the wrist muscles while being assisted by an expert, while the test is completed using the muscles correspondent to the shoulder and elbow of both arms without any assistance, but using only the knowledge recently acquired.

6.2.1 Training stage

Because of its dynamical characteristics, the SSS allows the naïve subjects to be capable of solving the unstable task in a shorter time respect to the PSS. The naïve subjects where trained by the experts to become proficient in the SSS. Giving the visual assistance during the training session, the experts where capable to give the same assistance to all the subjects by keeping a constant separation between the extremes of the virtual springs, and to assure that the kinematic strategy used is correspondent to the objective of the experiment (Control BSI = 0.1005 ±0.0049 cm; Test BSI = 0.0916 ±0.01 cm) (Figure 6-3). Even if during the training of the control group the SSI values slightly tend to be in the values correspondent to the PSS (Control SSI = 0.9009 ±0.0164), the difference with the Test group made them valid since the Test group is in the limit or under the limit values of the separation of the two kinematic strategies (Test SSI = 0.9932 ±0.0461) (Figure 6-4).

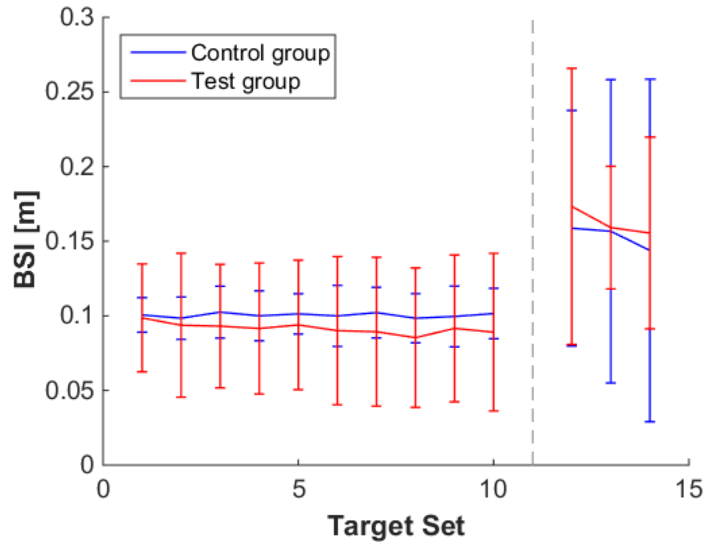


Figure 6-3: Bimanual Separation Index of the control group (blue) and the test group (red). Thanks to the visual assistance given to the expert subjects both groups are able to maintain the same separation between the ends of the springs during the training stage. The separation of the springs and its variability increase during the testing stage of the experiment.

As it is been said before, the Effort Index depends of the longitude of the virtual springs, for this reason the separation between the ends of such springs, measured by the BSI, is directly related to the effort exerted by the subjects. It was expected the controlled assistance of the expert given during the training to limit the effort applied by the naïve subject and hence the total effort applied by the dyad to solve the task, resulting in a low variation and very similar Effort Index for both groups (Control EI = 29.4974 ±1.2085 N; Test EI = 28.4093 ±2.3252) (Figure 6-5 A). Moreover, despite the fact that the change in the values of the EI from the first to the last Target Set of the training stage is small, we can observe how the time to target decreases along the experiment. Even if during the whole training the Control group takes less time to complete each target, the Test group tend to decrease the difference between groups from 7.92 s at the first TS of the training to 0.95 at the last TS of the same stage (Control T2T = 10.5 ±1.1 s first TS, T2T = 7.76 ±0.44 s last TS; Test T2T = 18.43 ±4.93 s first TS, T2T = 8.72 ±1.15 s last TS)(Figure 6-5 B).

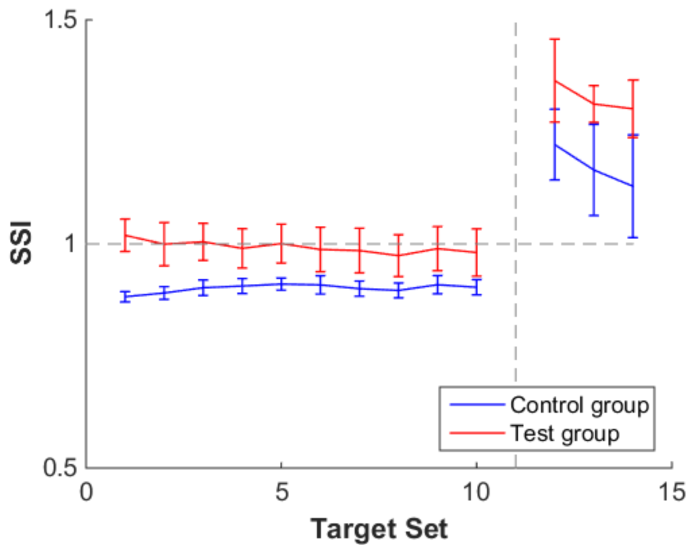
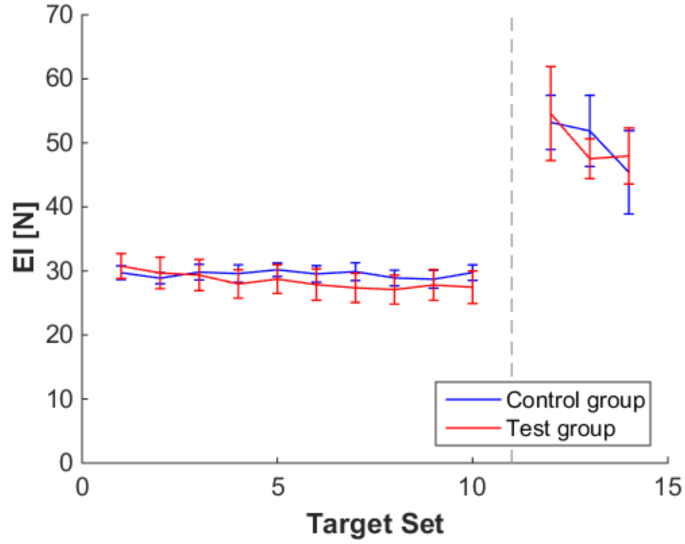


Figure 6-4: Stiffness Size Index values for the for both control group (blue), and test group (red). During the training stage the values of the SSI are not determinant in the differentiation between the SSS and the PSS. For the test stage it is noticeable the use of a SSS for the resolution of the unstable task.

The fact that the values of the EI are similar in both groups leaves the T2T as the variable dictating the behavior of the Inefficiency Index, and this can be observed in the graphic presented in Figure 6-6. The II reflects an improvement in the task performance along the target sets of the Training stage. Since the EI is limited by the expert subjects, the naïve subjects show their understanding of the task by solving it faster, which also guides to lower levels of inefficiency in the last TS(Control II = 0.912 ±0.0513; Test II = 0.9848 ±0.2049).

A)



B)

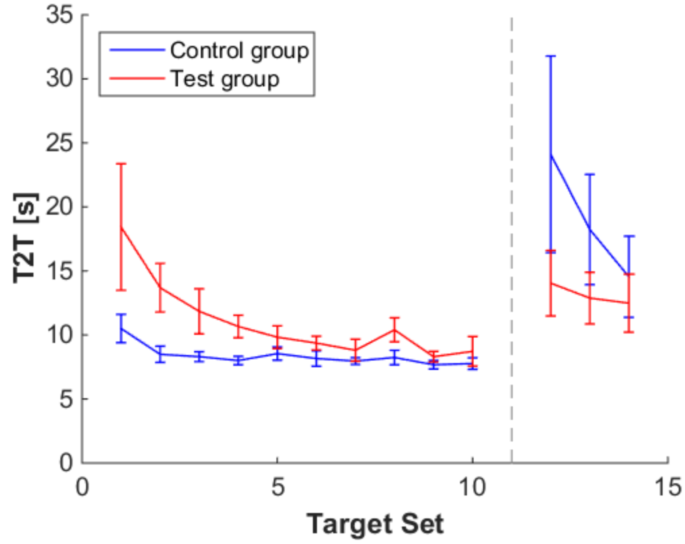


Figure 6-5: Time to Target and Effort Index values for the control (blue) and the test (red) groups. A) The effort index remains in similar levels for both groups in both stages of the experiment. B) In general during the training stage the subjects on the control group were able to solve the task faster, instead during the testing stage the subjects of the test group solved the task in shorter times than their counterparts in the control group.

6.2.2 Testing stage

Unlike the training stage, during the testing stage all the subjects of both groups perform the experiments under the exact same conditions. Moreover for the subjects in the test group it was their first time using the BdF2 robot and the relation from the wrist to the elbow – shoulder motion had to be explained to avoid confusion.

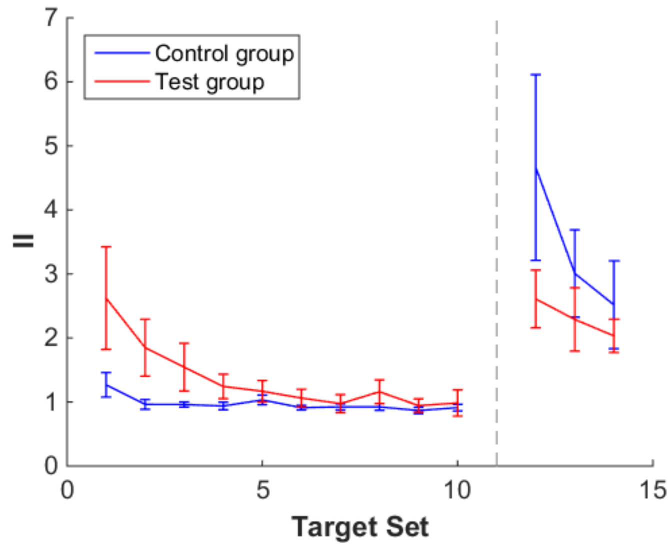


Figure 6-6: Inefficiency index of the control group (blue) and the test group (red). At the beginning of the training session the global performance of the test group was higher than the performance of the control group, this behavior was maintained along the target sets even if at the end of the training stage the difference is almost unnoticeable. Opposite to what happens on the training stage, during the testing stage the subjects in the test group perform generally better than the control subjects.

From the beginning of the testing stage it was noticeable the increment in the ends of the spring's separation, and because of the lack of limitation from the expert also the variability in the separation increased. Despite of the increments in the mean and the standard error of the BSI, the values for both groups remained similar even during the testing stage (in average: Control BSI = 0.1531 ±0.0165 m; Test BSI = 0.1626 ±0.0149) (Figure 6-3). As mentioned in the previous section the subjects were trained to perform using the SSS but during the training stage it was not possible to distinguish the use of SSS over PSS by analyzing the

SSI values, instead during the testing stage the values of the SSI let no doubt about which kinematic strategy is being used for the subjects to solve the task (in average: Control SSI = 1.1718 ±0.0984; Test SSI = 1.3261±0.0659) (Figure 6-4).

The similarity found in the BSI and SSI values was reflected in the EI. In Figure 6-5 A we can observe how the effort applied by the subjects of both groups is similar, even more we can observe a decrement in the values of the EI along the 3 TS of the testing stage (Control EI = 53.2041 ± 4.2355 N first TS, EI = 45.4059 ± 6.5072 N last TS; Test EI = 54.5795 ± 7.3416 N first TS, EI = 47.96 ± 4.3727 N last TS). This can be interpreted as the beginning of an optimization of the kinematic strategy used to solve the task. This optimization is more clear in the time that takes the subjects complete the targets, in the case of the T2T the decrements in both groups show an understanding of the dynamical characteristics of the task. Surprisingly the subjects of the Test group were generally faster as solving the task than their peers in the control group (Control T2T = 10.5 ±1.1 s first TS, T2T = 7.76 ±0.44 s last TS; Test T2T = 18.43 ±4.93 s first TS, T2T = 8.72 ±1.15 s last TS) (Figure 6-5 B). In the same way that happens during the first stage, the differences in the general performance were determined by the time to target, since the effort exerted by the subjects was similar for both groups. The EI show a better overall performance of the task during the testing stage of the experiment (Control II = 4.6629 ±1.4498 first TS, II = 2.5185 ±0.686 last TS; Test II = 2.6096 ± 0.4506 first TS, II = 2.0335 ±0.2596 last TS) (Figure 6-6), suggesting higher proficiency and better understanding of the force field and virtual tool from the subjects trained using the WB even if they had to change device to be evaluated, changing device also meant to change the muscle strategy used to complete the task.

6.3 Insight of the joint learning

In the study presented in this chapter groups were trained under different conditions; the control group was trained using the dyadic configuration of the BdF2, while the test group was trained using the WristBot. After a short training constrained by the expert subjects, all the subjects were evaluated using the bimanual configuration of the BdF2.

The measures used to quantify the proficiency of the subjects during the whole experiment showed an equivalent performance for both groups during the training stage, making valid the further comparison between groups during the testing stage. The only difference between groups was present in the time spend by the subjects to complete the task, which difference became inconsiderable at the end of the tenth TS. It was expected to find considerable differences among subjects of the two groups. Controversially the evaluation of the subjects during the testing stage showed a similitude among subjects that was only distinguishable by the time they took to solve the task. The overall performance suggests a better learning of the task from the subjects in the test group than the ones in the control group.

The test groups was able to perform better than the control group even when they were trained in a different experimental condition, which force them to transfer the knowledge acquired from the muscles of the wrist to the muscles of the elbow – shoulder. This adaptation to the task dynamics is achievable only if the internal model of the task created by the subject is accurate enough and unrelated to the muscular strategy applied during the experiment. In previous studies the naïve subjects had shown problems to transfer the knowledge acquired after training with an expert partner from a dyad to a bimanual configuration (Avila-Mireles et al. 2017). In the other side, solving different tasks under the same dynamical conditions is better performed while the naïve subject is still collaborating with the expert (Avila-mireles et al. 2016). In our current study the naïve subjects were able to apply the knowledge acquire as dyads in the bimanual configuration even when they were working with an expert subject since the beginning of the training. The constrains intentionally induced by the expert subjects during training propitiate this adaptation to the different conditions (Galofaro et al. 2017). Even with this constrains, it remains unclear how a subject trained with the wrist is able to solve the task with the elbow – shoulder. The work of (Hirashima & Nozaki 2012) suggest the learning of novel movements perturbed by force fields as the learning of primitive joint kinematics to achieve the desired movement. In our experiment the subjects may not be aware of specific movements to counteract the effects of the force field, but instead they may have the visual perception and the understanding of how to reach the equilibrium points on the different targets together with a blurry notion of the force field directions and intensities in such positions (Morasso et al. 2015; Kuo et al. 2010; Gribble & Ostry 2000). This basic understanding of the task may be enough to allow the subjects to use a combination of feed forward control and feedback control, and adapt them to achieve the stabilization of the virtual tool in the different targets in a different configuration (Doya et al. 2001; Shadmehr & Mussa-Ivaldi 1994).

In summary our results suggest that the ability of the naïve subjects to create an internal representation of the task goes beyond the tactile feedback that they can get from the haptic devices. Instead we observed that the motor learning of an unstable task is more dependent of the understanding of the dynamical conditions of the environment in which the task is taking place.

CHAPTER 7 CONCLUSIONS

The word "dyad" defines the interaction between two people or two things. During such interaction, there is a variable amount of data flowing from/to the individuals of the dyad. With this information they are able to understand the actual and previous states of the interaction and, in some cases, to predict a response for possible scenarios.

Recently, great attention has been given to the studies focused in physical interaction of human – human dyads and human – robot dyads. In general these studies show that show that, in general, the human – human dyads perform better than the human – robot dyads even if the human partner is perceived as a hindrance (Reed & Peshkin 2008). The main objective of the studies presented in this thesis was to understand the kind of information exchanged during the dyadic interaction and the way that this information is communicated from one individual to another in order to achieve that advantageous performance.

Solving a task as an individual promotes the creation of an internal representation of the dynamical characteristics of the working environment. And understanding the dynamical characteristics of the environment allows the subject to become proficient in such task. It has been proved that individuals are able to project this representation to a dyad configuration (De Santis et al. 2014). Taking this as reference, our second objective was to evaluate if a dyadic training can promote a shared internal representation of the task accurate enough to allow the subjects for a solo execution.

We performed a sequence of experiments using variations of the task outlined in Chapter 1. Firstly we trained several subjects to make them become experts in the task, working individually. In the next experiment those subjects were asked to work in dyads, and we analyzed the muscular strategies corresponding to two specific kinematic strategies. Once these strategies were identified we recruited 5 groups of naïve subjects to be trained by the experts, each group was trained under different experimental conditions and they were free to use any kinematic strategy. Posterior to this we included a reinforcement learning algorithm and it was tested in 2 more groups. To this point, all the experiments were performed exclusively in the BdF robot. In the last study presented in this thesis the naïve subjects were trained by the experts, who were provided of visual assistance in order to increase the amount and quality of knowledge transferred to their naïve dyad partners.

Around 70 subjects have taken part in our experiments along this project, they were placed in several groups which followed different protocols based on the results of the preliminary experiments and focused on getting closer to our objectives. The common characteristic of the protocols was the transition from dyad to bimanual paradigm during the experiment.

In the preliminary experiments we found that together with the two main kinematic strategies used to solve the unstable task proposed for this project (Stiffness Stabilization Strategy, SSS; and Positional Stabilization Strategy, PSS) (Zenzeri et al. 2014), there are also two muscular strategies that seems to be independent of the kinematic strategies (Avila-Mireles et al. 2015). One of the muscular strategies found shows a correlated contraction of the arm muscles, the analysis showed a series of contraction and relaxation periods that seem to be followed by all the muscles at the same time. The main characteristic of the second muscular strategy is the absence of correlation among the muscular contractions. It is important to mention that all the subjects on this experiment were considered experts in the task after completing the training specified in (De Santis et al. 2014).

For our main study we put together five different groups of naïve subjects which completed a sequence of training, generalization (subjects work in dyads for these two stages) and evaluation (subjects work bimanually) stages of the experiment. The protocol for each group was slightly different, this differences allowed us to study the effect of coupling in a dyad with an expert partner or with a partner with similar skill level. In addition to this, the subjects of a couple of groups had the chance to try by themselves the task before coupling with their respective partner. To start with the analysis of all these groups we first focused our attention in the groups last mentioned in which the subjects were working in dyads formed by a couple of naïve subjects (NN-b) or by a naïve and an expert (NE-b). During the training stage of the experiments these groups show the advantages of training with an expert partner, even if during the evaluation stage the subjects in the NE-b group had a rough start, they quickly adapted to the new condition in the task (Avila-Mireles et al. 2016).

After finding the main differences of the NN-b and the NE-b groups, we proceed to include the groups without previous experience before the dyad training, namely NN and NE. We also include a control group whose subjects completed all the stages of the experiment working always as individuals (BIM). EMG signals from each subject were recorded along the experiment. However, it was in the kinematic data that we found the most relevant results. We designed the so called Inefficiency Index which considers the effort applied by the subjects to solve the task and they take from the completion of one target to the next one.

We compared the performance of the naïve subjects who trained in dyads to the performance of control group in the adaptation session. We found significant differences between groups and in particular that all the groups but NE performed significantly better than the bimanual controls. This suggests that no knowledge transfer occurred for naive who trained with an expert and that had no previous bimanual experience of the task dynamics. The absence of knowledge transfer does not appear to be dependent on the absence of prior bimanual experience alone. In fact, the lack of transfer seems to result from the combination of the presence of an expert and lack of bimanual experience. Moreover they performed significantly worse than in the end of the adaptation session when working with the expert.

From the point of view of the EMG signals, 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 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 the training (Avila-Mireles et al. 2017).

The analysis of the generalization stage of the training gave us an insight of how the knowledge acquired during the training stage can be applied in a different task where some of the dynamical characteristics remain the same. In this case the task consisted in tracking a moving target inside of the same force field used for the stabilization task. Interestingly the group that showed the highest error during the tracking was NN-b, giving us the idea of a competition between the subjects who are aware of the force field but which internal representation of it was acquired separately, opposite case to what happens with the NN group in which the internal representation of the task was created in collaboration with the partner (Avila-Mireles et al. 2016).

With these results we can sustain the claim that the knowledge acquired during a dyad interaction, while solving an unstable task, is solid enough to allow the individuals to perform solo in the same task. In the last study presented in this thesis we test the ability of subjects who were trained to perform the unstable task using the wrist to use the acquired internal representation of the task to solve it with the elbow – shoulder. Surprisingly the subjects who tried this particular protocol performed better than the subjects who got trained and evaluated solving the task with the elbow – shoulder.

In general, our results partially corroborate the hypothesis that the best performance in a novel task comes from training with a partner with a similar skill level. It can be posit that working with a peer partner allows for a positive knowledge transfer to the bimanual task. On the contrary, when working with a partner who has an accurate knowledge of the dynamics of the task, positive transfer occurs only if the naïve has at least some solo experience with the task dynamics. Another way to promote the transfer is by limiting the contribution of the expert to the task, avoiding over – guidance. Regarding skill learning in a dyad interaction, we demonstrated the advantages for the less skilled individual to train with a more proficient partner (Avila-Mireles et al. 2017; Avila-Mireles et al. 2016). This advantages were found only when the subject has the chance to explore the task individually before coupling with the skilled partner, otherwise the over – guiding of the expert ends up being detrimental.

Despite the fact of not identifying the exact amount and the kind of data exchanged during dyad interactions, we had managed to understand under which circumstances these kind of interactions can be beneficial or detrimental to the learning process of a novel task. With this understanding, we are able to continue with the development of a platform capable to promote learning and ultimately to create efficient rehabilitation protocols that include dyad training mediated by haptic devices and adapt to the needs of every patient.

Related Publications

1. **Avila-Mireles, E.J.** et al., 2015. Motor control strategies in the bimanual stabilization of an unstable virtual tool. In *Engineering in Medicine and Biology Conference*.
2. De Santis, D.; **Avila-Mireles, E.J.** et al., 2015. Dealing with instability in bimanual and collaborative tasks. In *Engineering in Medicine and Biology Conference*.
3. **Avila-Mireles, E.J.** et al., 2015. Are two people better than one? Comparing dyadic and bimanual training. In *Robotics and Interactive Technologies for Neuroscience and Neurorehabilitation Workshop.*
4. **Avila-Mireles, E.J.** et al., 2015. Motor control efficiency in bimanual and collaborative tasks. In *Society for Neuroscience Conference*.
5. **Avila-Mireles, E.J.** et al., 2016. Skill transfer and generalization after robot - mediated dyadic training. In *Human Friendly Robotics Workshop*. Genova, Italy.
6. **Avila-Mireles, E.J.** et al., 2016. Transferring knowledge during dyadic interaction : the role of the expert in the learning process. In *Engineering in Medicine and Biology Conference.*
7. **Avila-Mireles, E.J.** et al., 2017. Skill learning and skill transfer mediated by cooperative haptic interaction. In IEEE *Transactions on Neural Systems and Rehabilitation Engineering*.

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