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Expert Strategy Switching in the Control of a Bimanual Manipulandum with an Unstable Task

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Abstract—**The goal of this study is to better understand how the central nervous system switches between alternative stabilization strategies when presented with an unstable task. A haptic, bimanual manipulandum has been used to emulate an unstable task, which requires subjects to stabilize a virtual mass under the action of a saddle force field with two non-linear springs, whose stiffness increases with the amount of stretch. Subjects learn to position the mass at various target points by adjusting the rest length, and thus the stiffness of the two springs. From a previous study we know that subjects can stabilize the mass by either 1) applying large forces to stretch the springs and increase the mechanical stiffness of the system beyond a critical level or by 2) applying small force impulses that intermittently adjust the position of the mass. In this study we report the performance of a subject who was trained extensively to use one strategy or the other in order to characterize the mechanism of target switching, from the high-stiffness to the low-stiffness regime and back.**

I. Introduction

MANY common tasks in everyday life involve some kind of unstable dynamics, which can be compensated by means of two basic stabilization mechanisms: 1) a high-stiffness strategy (SSS) where the elastic muscle properties are exploited by learning optimal co-activation patterns that achieve asymptotic stability; 2) a low-stiffness positional strategy (PSS) where bounded stability is achieved by intermittent, event-driven stabilization bursts [1]. The former strategy is high-bandwidth, because the implicit positional feedback coming from muscle stiffness is instantaneous, but high-effort, because it requires co-activation of agonist and antagonist muscles. In contrast, the latter strategy is low-bandwidth, because it employs delay-affected explicit positional feedback, and low-effort, because it does not require muscles co-activation. The experiments reported by Burdet et al [2] can be explained in the SSS framework whereas the experiments by Loram et al [3] are consistent with the PSS model, thus suggesting that the brain is capable of employing both strategies. However, the experimental setups of the studies quoted above forced subjects to use one strategy or the other, without an alternative choice. For this reason a new setup was implemented [4] which allows the subjects to choose one strategy or the other. The setup is based on a bimanual haptic interface that emulates a virtual underactuated bimanual manipulandum (VUBM), whose end-effector is under the action of an unstable saddle-like force field. VUBM includes two elastic elements with quadratic length-tension curves, thus allowing the subjects to modulate the stiffness ellipse of the manipulandum in amplitude, by stretching the two springs, and orientation, by changing the relative positions of the two hands with respect to the end-effector of the VUBM. In the preliminary experiments reported in [4] we found that subjects could learn rather quickly, in a single experimental session, to solve the stabilization tasks but did not choose the stabilization strategy in a uniform way. Rather, nearly half the population adopted the SSS model, in spite of the higher effort, and the remaining chose the more complex PSS mechanism. The unconscious choice was made in the early part of the training. In this paper we present the results of a study in which a single subject was trained for a long time (11 sessions) with the aim of becoming an "expert". As an expert, the subject was fully conscious of the existence of two stabilization strategies and capable to operating with both of them. The purpose of this study was to characterize the mechanism of target switching, from the high-stiffness to the low-stiffness regime and back.

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II. METHODS

A. Experimental Apparatus

The experiments use a virtual underactuated bimanual manipulandum (VUBM), which is simulated by means of a bimanual haptic interface (BdF2, Celin srl, La Spezia, Italy, a direct evolution of the uni-manual robot manipulandum Braccio di Ferro[5]) (Fig. 1, top panel).

VUBM consists of a virtual mass M of 15kg and a pair of non-linear springs attached, on one side, to the mass and, on the other, to the two hands, respectively. In addition to the two spring forces ($\vec{F}_1, \vec{F}_2$), M is also under the action of an unstable, saddle-like force field:

$$\vec{F}_u = \begin{bmatrix} -K_u & 0 \\ 0 & +K_u \end{bmatrix} \begin{bmatrix} x - x_0 \\ y - y_0 \end{bmatrix} \tag{1}$$

where (x,y) identifies the position of M and (x_0,y_0) the origin of the force field (Fig. 1, middle panel).

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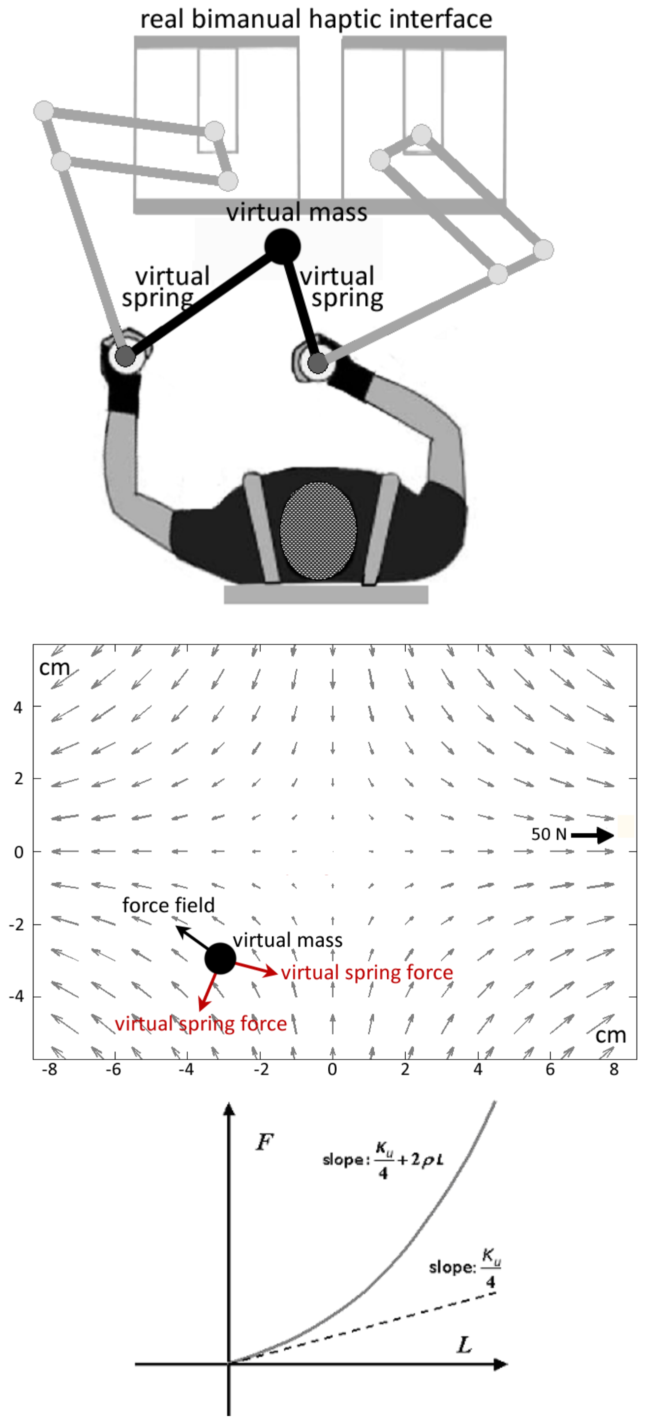

Fig. 1. Top panel: experimental setup, which emulates a virtual underactuated bimanual manipulandum (VUBM) by means of a bimanual haptic interface. Middle panel: force-field acting on the virtual mass together with the two virtual spring forces. Bottom panel: length-tension curve of the two virtual springs.

The bimanual robot system consists of two identical planar manipulanda, each with two degrees of freedom, mounted in a mirrored configuration on the same frame. The two robots are positioned horizontally with a distance between the axes of the motors of 38.5cm. The vertical position of the two robots is adjusted to avoid interference between the two hands.

The virtual manipulandum is underactuated because the subject has no direct control on the position of the virtual mass, whose movements are characterized by the following unstable dynamics:

$$M\begin{bmatrix}\ddot{x}\\ \ddot{y}\end{bmatrix}+B\begin{bmatrix}\dot{x}\\ \dot{y}\end{bmatrix}+\vec{F}_u=\vec{F}_1+\vec{F}_2 \qquad (2)$$

where B is a viscous coefficient that damps oscillations of the load.

Each spring has a linear and a quadratic component (Fig. 1, bottom panel): $F = K_s L + \rho_s L^2$, where L stands for the length of one spring or the other (L_1,L_2). Therefore, the stiffness Z of each spring is not constant but depends on L: $Z = K_s + 2\rho_s L$. The overall stiffness of VUBM is a non-linear function of Z_1,Z_2 and the positions of the two hands with respect to the virtual mass:

$$K_{VUBM}=\frac{\partial \vec{F}_M}{\partial \vec{p}_M}=\begin{bmatrix}K_{xx} & K_{xy}\\ K_{yx} & K_{yy}\end{bmatrix} \qquad (3)$$

where $\vec{F}_M$ is the force applied to the virtual mass and $\vec{p}_M=[x,y]$ is the corresponding position in the field. In particular, we are interested with the stiffness element K_{xx}, which is the VUBM virtual stiffness in the direction of the unstable manifold,:

$$K_{xx}=[Z_1+Z_2]-\rho_s\left[\frac{\Delta y_1^{\,2}}{L_1}+\frac{\Delta y_2^{\,2}}{L_2}\right] \qquad (4)$$

where $\Delta y_1 = y - y_1$ and $\Delta y_2 = y - y_2$. What is relevant, from the point of view of stability, is the ratio between K_{xx} and the instability coefficient K_u

The following values of the system's parameters were used: M = 15kg; B = 132N/m/s; K_u = 592N/m; $K_s = K_u/4$ = 148N/m; ρ_s = 1480N/m^2. With such parameter values and for small values of L, the total stiffness of the controller, even in the best condition, is only half the negative stiffness of the force field, along the unstable manifold. Moreover, these parameters ensure "well-behaved" dynamics along the stable manifold (natural frequency of 1Hz and damping factor of 0.7) and a falling time constant along the unstable manifold of 306ms, compatible with an intermittent, low-stiffness PSS.

B. *Task & protocol*

The task is to stabilize M (1cm diameter) in one of 9 circular areas (2cm diameter), uniformly distributed on the periphery of a circle (8cm diameter) and in the center. The stabilization requirement is to constrain the mass oscillations inside the current target for a continuous time interval of 4s. The unstable force field is continuously active throughout a whole experimental session, which included 4 target-sets (12 center-out movements and 12 return movements, each target set). The expert user (male, 26 years old) practiced for 11 sessions, alternating target-sets in which he aimed at adopting either the PSS (2 target-sets per session) or SSS strategy (2 target-sets per session).

The following indicators were computed for each stabilization interval:

- Stiffness Size Index: $SSI = mean\left(\frac{K_{xx}}{K_u}\right)$;
- Stiffness Orientation Index: $SOI = mean(cos\alpha)$, where α is the angle of the main axis of the stiffness ellipse with the medio-lateral axis x;
- Effort Index: $E = mean\left(\left|\vec{F}_1\right| + \left|\vec{F}_2\right|\right)$.

III. Results

The typical trajectories for the two different strategies at the beginning and at the end of the learning phase are shown in Fig. 2: A (initial performance, SSS strategy); B (initial performance, PSS strategy); C (final performance, SSS strategy); and D (final performance, PSS strategy).

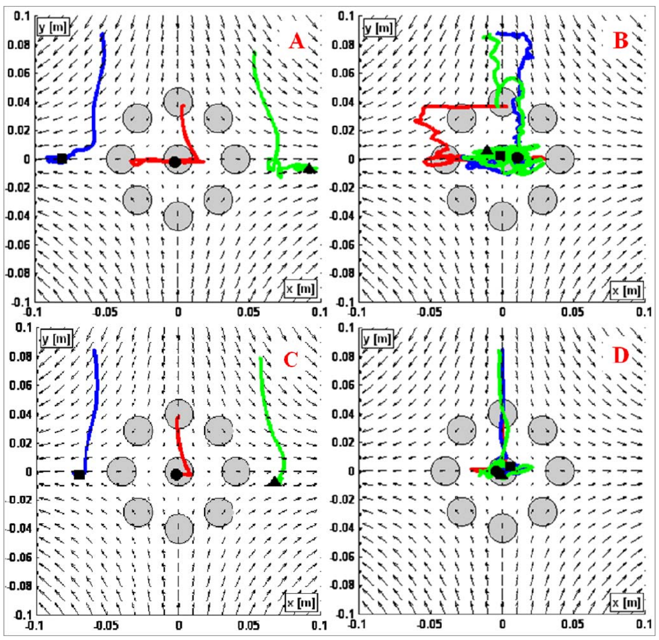

Fig. 2. Shift of stabilization from the forward/middle target to the central target. Trajectories of the virtual mass (red), left hand (blue), and right hand (green) are shown, together with the corresponding final positions (black dots/squares/triangles, respectively). A (initial performance, SSS strategy); B (initial performance, PSS strategy); C (final performance, SSS strategy); D (final performance, PSS strategy).

The figure shows several interesting features: 1) in the SSS strategy the two hands are well separated sideways whereas in the PSS strategy they tend to overlap; 2) the excursion of the two hands is much larger than the excursion of the virtual mass in both strategies; 3) in the initial phase of learning the subject is unable to shift the equilibrium position of the mass in a direct way, but requires a couple of corrections (in the SSS case) and many more in the PSS case; 4) in the final phase of learning the equilibrium shift is direct in both strategies, following a rather straight path, but several control bursts are necessary for the stabilization in the new target area with the PSS strategy.

Since the subject switched from one strategy to the other during each session, we can say that strategy switching does not appear to interfere with the learning of each single strategy.

Fig. 3 plots the *SOI* vs. *SSI* values during all the sessions: red markers correspond to session in which the subject consciously attempted to implement the PSS strategy and the blue markers corresponds to the SSS sessions. The two clusters are well separated and this means that there is correspondence between intention and actual performance. In other words, there is a strongly significant difference in terms of magnitude and orientation of the VUBM stiffness matrix for the two strategies. With regard to the orientation of the stiffness matrix, in the SSS strategy it remains fixed to the optimal value (*SSI*=1), i.e. the major axis of the stiffness matrix is well aligned with unstable manifold of the field, whereas in the PSS strategy it is more variable. In both strategies, however, as learning proceeds *SSI* decreases, thus reducing the effort employed for implementing the strategies. Table I stores the corresponding numerical values.

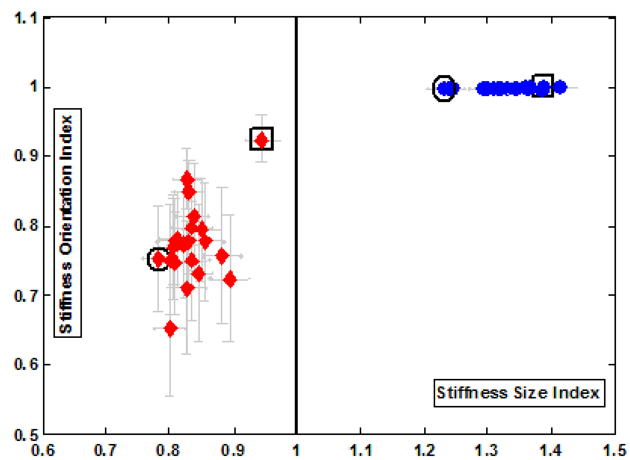

Fig. 3. *SSI* versus *SOI*: average values with standard errors for each session. The red markers represent the values related to PSS whereas the blue markers those related to SSS. The black square refers to the first session and the black circle to the last session in each strategy.

TABLE I
PERFORMANCE DURING THE EXPERIMENT

Strategy	SSS_i	SSS_f	PSS_i	PSS_f
SSI	1.387± 0.028	1.231± 0.025	0.946± 0.027	0.782± 0.025
SOI	0.999± 0.001	0.997± 0.001	0.924± 0.003	0.753± 0.008
E	51.23± 2.35	38.98± 2.33	22.68± 1.88	14.52± 1.48
TT	3.6± 0.3	1.1± 0.1	16.5± 2.2	3.4± 0.5
MVP	0.013± 0.002	0.004± 0.001	0.020± 0.002	0.011± 0.001
D_{lr}	0.177± 0.006	0.143± 0.005	0.018± 0.003	0.008± 0.001

All are average values for each target set. *SSI* = Stiffness Size Index; *SOI* = Stiffness Orientation Index; *E* = Effort Index[N]; *TT* = time to target[s]; *MVP* = magnitude of the velocity peaks in the stabilization interval for the virtual mass[m/s]; D_{lr} = distance between the two hands[m]; SSS_i (first set), SSS_f (last set) = Stiffness Stabilization Strategy; PSS_i (first set), PSS_f (last set) = Positional Stabilization Strategy.

With regard to the Effort index, the table shows that from the initial to the final session there is a significant decrement in both strategies. Moreover, the effort in the PSS strategy is always smaller than in the SSS strategy and this fact is further emphasized by the histogram in Fig. 4: the two distributions of the effort index, respectively for the two strategies, have no overlap.

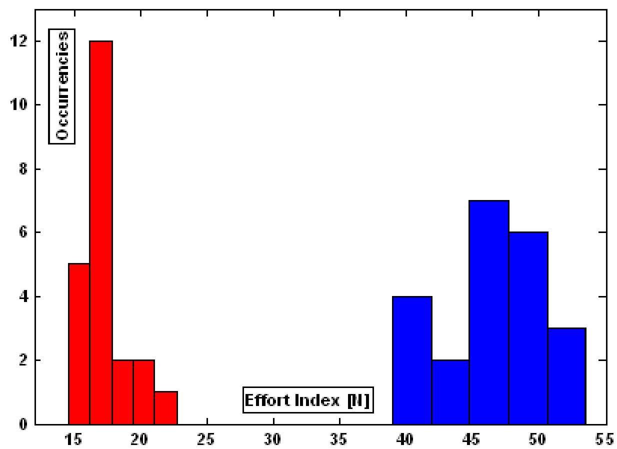

Fig. 4. Histogram of the Effort Index: the red color refers to PSS and the blue to SSS.

The learning process can be monitored by looking at the variation, over time, of performance indicators. For example, Fig. 5 plots the evolution of the *TT* indicator, but a similar behavior is exhibited by *E*. For both strategies there is an improvement trend, from higher to lower values of the required time. However, in the PSS strategy the decrement (about four times) is greater than in the SSS strategy (about two times). Moreover, the variability for any session is much greater in the PSS than in the SSS strategy. This suggests that the SSS strategy is "simpler" than the PSS strategy because training has a larger effect on performance.

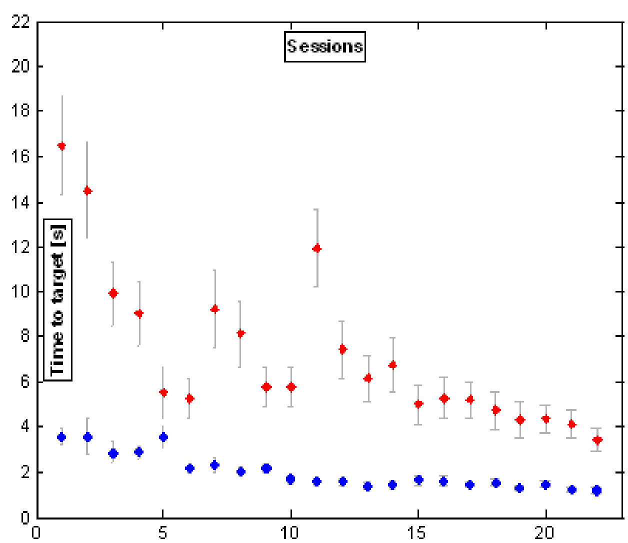

Fig. 5. Average time to target in each session with standard error (red for PSS and blue for SSS).

Regarding the virtual mass, during the stabilization interval, we have also identified the velocity peaks as the local maxima in a temporal window of 100ms, and calculated the relative magnitude *MVP* (as shown in Table I). For each strategy the *MVP* decreases significantly during the learning period and at the end of the PSS we can always see a higher value with respect to the SSS. This is in accordance with the general hypothesis underlying the PSS in which the control is mainly based on a sequence of little displacements around the target position.

Finally, let us consider the mean distances between the two hands D_{lr} during the first and the last training sessions (Table I). In the SSS this parameter decreases for the improved ability to control the unstable environment with less co-activation, as also suggested by the Effort Index. In the PSS instead, what is suggested is the improvement of the bimanual coordination, i.e. the tendency of the subject to treat the two hands as a single unit.

IV. Discussion

The experiments have demonstrated that if a subject is required to stabilize an unstable load and the dynamics of the load allows two different control strategies, namely a high-stiffness/high-effort strategy and a low-stiffness/low-effort strategy, suitable training is sufficient to master both strategies. In general, this is a preliminary but relevant piece of information for the understanding of how the brain can switch from one strategy to another during complex motor tasks, as car drivers switch from one gear to another in different driving conditions.

This study was limited to a single subject but in the near future we plan to extend it to a larger population in order to evaluate the robustness of the employed indicators.

Another issue that requires specific experiments is generalization: to what extent the expert knowledge acquired during training can be generalized to novel, un-experienced conditions?

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