Bimanual interactions in humans and humanoid robots

P. Morasso, M. Casadio, L. Masia, G. Metta, V. Mohan, G. Sandini, V. Sanguineti, V. Squeri

***Abstract* – A fundamental aspect of mobiligence, intended as the intelligence for generating adaptive motor function, is the ability to coordinate/synchronize the two arms in the same task or to allow the two arms to carry out independent tasks at the same time. The presentation surveys activities going on at the Italian Institute of Technology (dept. of robotics, brain and cognitive sciences) on such topics, based on the 53 degrees of freedom iCub platform, for humanoid robotics, and on the 12 degrees of freedom bimanual haptic manipulandum BdF, for the study of neuromotor control in humans. The two lines of research share, among other things, a focus on coupled forward/inverse internal models for control.**

I. Introduction

Unlike the range of direct problems common in conventional physics, which require to compute the effects of forces on objects, brains have to deal with the inverse problems of determining the motor commands that would permit the intended, goal-directed mechanical interaction with the world. Strikingly, many of the inverse problems faced by the brain to control movements are indeed similar to the ones roboticists must solve to make their robots move intelligently and act flexibly in the world. Hence, while the field of neuroscience benefits from the theories of construction and control of man-made bodies, roboticists have the profound parallel opportunity to learn about the structural and functional organization of the central nervous system. However, the explosive computational complexity of kinematic and dynamic equations of even deceptively simple devices and tasks make it difficult either to intuitively understand the neural control of movements or develop computational schemes for dextrous control of artificial manipulators and humanoids.

How do humans decide what to do with their extra joints, and how should humanoid robots control all their joints in order to generate coordinated movement patterns? Moreover, is the selection/coordination of redundant DoFs independent of the spatio-temporal organization of the reaching movements? Early studies of human arm trajectory formation [1,2] showed invariant spatio-temporal features, such as a symmetric bell-shaped speed profile, which can be explained in terms of minimization of some measure of *smoothness*, such as jerk [3] or torque-change [4]. Later studies emphasized the importance of physical or computational force fields in the neural control of movement or motor learning [5-7].

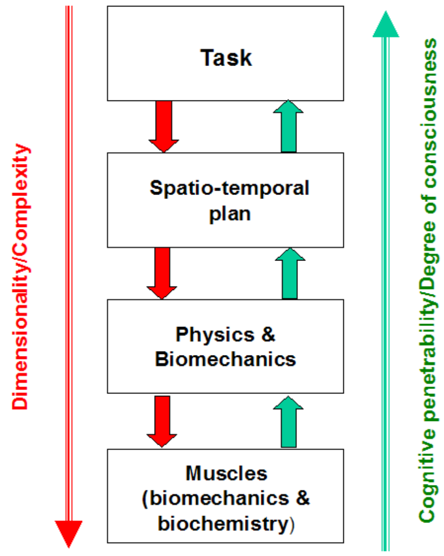

Figure 1. Hierarchical organization of motor control.

Most approaches to motion planning in robotics were derived from the development of RMRC (Resolved Motion Rate Control) [8], which is based on the real-time inversion of the Jacobian matrix of the kinematic transformation, i.e. the function that links the variation of the joint angle vector dq to the pose dx of the end-effector. Clearly, for redundant kinematic chains RMRC must be modified by using one form or another of pseudo-inversion, as the Moore-Penrose matrix that provides a minimum norm solution for dq or other more general pseudo-inversion methods [9] that can be associated with an arbitrary cost function for the inversion calculation. Another method (Extended Jacobian Method: [10,11]) extends the usual Jacobian matrix with additional rows that take into account virtual movements in the null space of the kinematic transformation. In any case, the classical approaches to robot planning/control work well only inside

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the workspace and far away from kinematic singularities. If this is acceptable for an industrial robot, which has no or a limited number of excess DoFs and operates in a well defined and predictable environment, it is not feasible for a humanoid robot supposed to carry out, as humans, activities of daily life in a generally unknown environment.

A method of motion planning that can be applied both to humanoid robots and the neural control of movements is based on an artificial potential field approach (Passive Motion Paradigm: [5]) combined with terminal-attractor dynamics [12] that has also been applied to robot reasoning using virtual mental simulations of action [13]. This method, which is further analysed in the following sections in relation with bimanual coordination, takes into account the computational scheme of fig. 1 and focuses on the two higher modules.

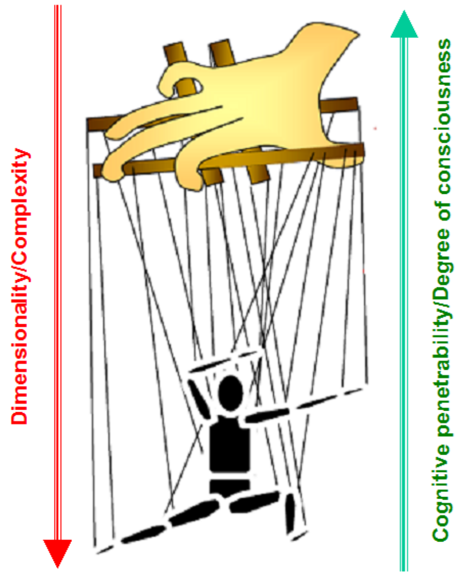

Figure 2. Computational metaphor of the PMP.

II. The Passive Motion Paradigm

In this paper, we explore a force-field based computational scheme that organizes the massive computational load of task planning into a simple network of loosely coupled work units, operating in a local distributed fashion and simultaneously capable of dealing with heterogeneous optimality criteria. The computational process of relaxation is similar to coordinating the movements of a marionette by means of attached strings (fig. 2): the strings in the computational model are the virtual force fields generated by the intended/attended goal and the other task dependent combinations of constraints involved in the execution of the task. The computational mechanism involves a process of passive simulation of movement as if it was imposed by an external agent and distribution of this imposed motion on the remaining proximal elements (joints, muscles etc) so as to pull the dynamical system to a new equilibrium. All elements in the computational chain (tool space, end effector space, joint space, muscular space) locally compute their own reaction to the imposed external motion based on their local virtual impedance, the overall configuration attained by the relaxation globally minimizing the elastic potential energy of the system.

No matrix inversion is necessary and the computational mechanism does not crash near kinematic singularities or when the robot is asked to achieve a final pose that is outside its intrinsic workspace: what happens, in this case, is the *gentle degradation* of performance that characterizes humans in the same situations. Moreover, the remaining error at equilibrium is a valuable information for triggering a higher level of reasoning, such as searching for an alternative plan like making/using an environmental object as tool. The control of the timing of the relaxation process using the notion of terminal attractor dynamics further endows the generated trajectory with human-like smoothness and includes the capability to deal complex tasks like bimanual coordination, interference avoidance and precise control of the reaching time.

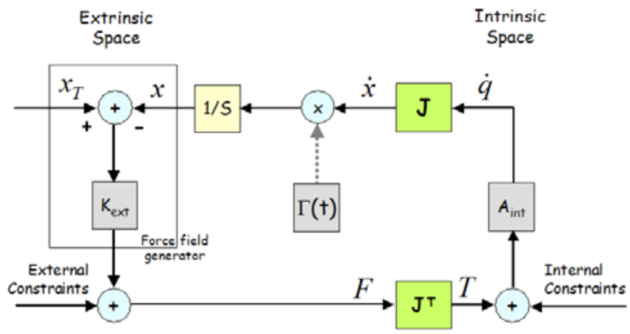

Figure 3. Basic computational scheme of the PMP for a simple kinematic chain.

Let x be the vector that identifies the pose of the end-effector of a kinematic chain (e.g. a human or robotic arm) in the extrinsic workspace and q the vector that identifies the configuration of the robot in the intrinsic joint space: $x = f(q)$ is the kinematic transformation that can be expressed, for each time instant, as follows:

$$\dot{x} = J(q) \cdot \dot{q} \qquad (1)$$

where $J(q)$ is the Jacobian matrix of the transformation. The motor planner/controller, which expresses in computational terns the PMP, is defined by the following steps, which are graphically summarized in fig. 3:

1) Associate to the designated target x_T a conservative, attractive force field in the extrinsic space

$$F = K_{ext}(x_T - x) \qquad (2)$$

where K_{ext} is the virtual impedance matrix in the extrinsic space. The intensity of this force decreases monotonically as the end-effector approaches the target.

2) Map the force field into an equivalent torque field in the intrinsic space, according to the principle of virtual works:

$$T = J^T F \qquad (3)$$

Also the intensity of this torque vector decreases as the end-effector approaches the target.

3) Relax the arm configuration in the applied field:

$$\dot{q} = A_{\mathrm{int}} \cdot T \tag{4}$$

where A_{int} is the virtual admittance matrix in the intrinsic space: its modulation does not affect the trajectory of the end-effector but modifies the relative contributions of the different joints to the reaching movement.

4) Map the arm movement into the extrinsic workspace, by using eq. 1. By integrating this equation over time we obtain a trajectory in the extrinsic space, whose final position corresponds to an equilibrium configuration x_F.

By definition, the trajectory of the end-effector is the unique flowline in the force field passing through $x(t_0)$ and converging to x_F. The algorithm always converges to a "reasonable" equilibrium state, whatever the degree of redundancy of the robot: if the target is within the workspace of the robot, it is reached; if it is not reachable, the robot settles on the point of the boundary of the workspace that is at a minimum distance from the target. The force field described by equation 2 can be isotropic or anisotropic as a function of the matrix stiffness K_{ext} and, accordingly, the flowlines can e either straight or curved. On the other hand, the joint admittance matrix A_{int} determines the degree of involvement of each DoF in a given reaching movement.

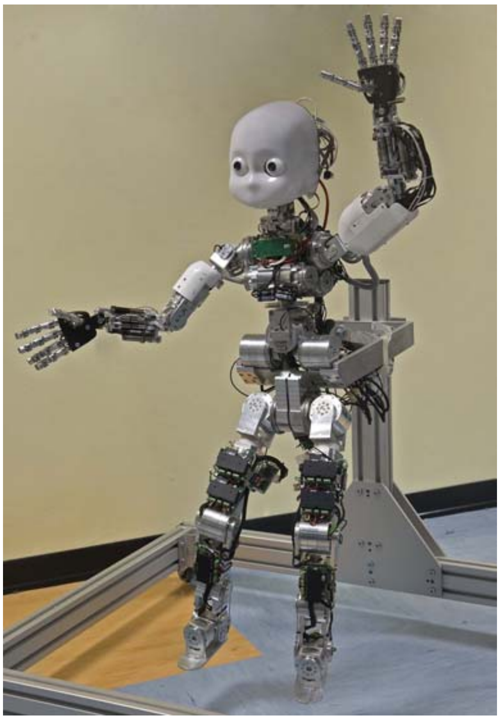

Figure 4. The iCub humanoid robot (53 DoFs).

For example, a joint rotation can be "frozen" by setting to zero the corresponding admittance value. Both matrices can be modulated, thus allowing to exploit redundancy in a goal-oriented way. The scheme of fig. 3 also includes three additional elements: 1) a force field in the intrinsic space for implementing internal constraints (e.g. obstacle avoidance), 2) a force field in the extrinsic space for implementing external constraints (e.g. range-of-motion limits of the joints), 3) a time varying gain $-\Gamma(t)-$ or time base generator for implementing terminal attractor dynamics, i.e. a relaxation mechanism for reaching an equilibrium state in a controllable time [12].

In contrast with monolithic optimal control based approaches [14], the relaxation process associated with the PMP computational model does not look for optimal activation patterns based on a particular control law but rather focuses on a divide and rule strategy: it addresses the dynamic formation of motor synergies so as to simultaneously incorporate multiple task-dependent constraints, on one hand, and destroys as many degrees of freedom (DoF) as possible (in the Bernsteinian sense), on the other hand. The same process can coordinate the movements of a limb, network of limbs and/or networks of external objects kinematically and dynamically coupled to the body/internal body model.

III. BIMANUAL COORDINATION IN HUMANOID ROBOTS

Humanoid robots have a large number of "extra" joints, organized in a humanlike fashion with several kinematic chains. Consider, for example, Cog [15] with 21 DoFs, DB [16] with 30 DoFs, Asimo [17] with 34 DoFs, H7 [18] with 35 DoFs, and iCub [19] with 53 DoFs. How to coordinate so many DoFs in a principled manner is still an open question. The PMP is a general approach to shape such complexity according to a uniform computational structure that can be applied to the actual execution of coordinated movements or mental simulations that can support sensorimotor reasoning. Here we focus our attention on iCub (fig. 4). The iCub is a small humanoid robot of the dimensions of a three and half year old child and designed by the RobotCub consortium, a joint collaborative effort of 11 teams from Europe, 3 teams from Japan and 2 teams from USA.

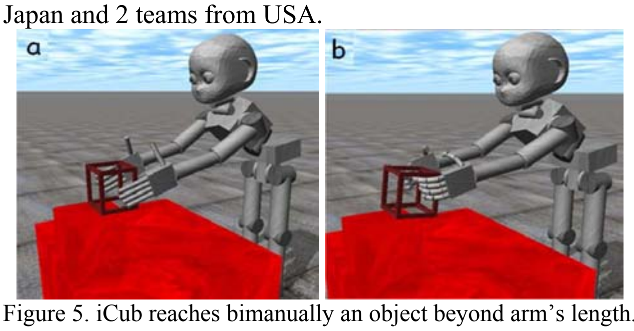

Figure 5. iCub reaches bimanually an object beyond arm's length.

The PMP described in the previous section was integrated with the middle ware of iCub software architecture, which is based on YARP [20], an open-source framework that supports distributed computation with a specific impetus given to robot control and efficiency.

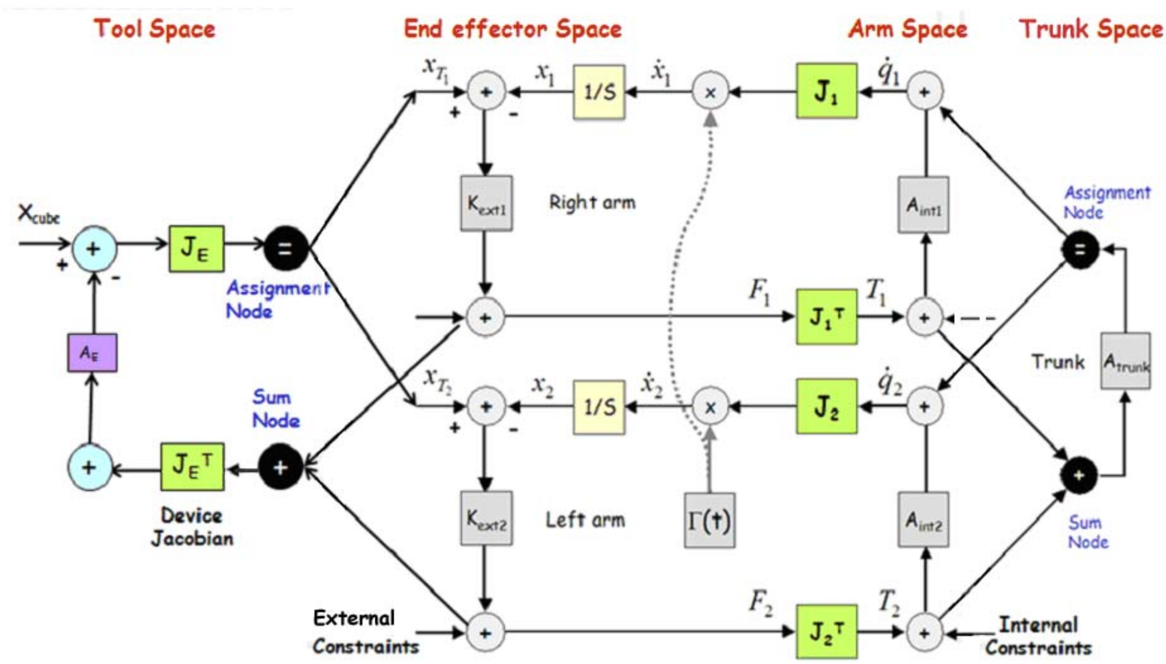

Figure 6. PMP network for bimanual coordination

Fig. 5 shows an exmple of bimnual reaching and grasping an object that is beyond arm's reach. The PMP network is composed of two copies of the model of fig. 3, connected to the PMP net of the trunk. Two force fields are used, one is applied to the right hand and the other to the left hand. These force fields are propagated to the overall network thus recruiting the appropriate motion of the trunk. Two additional elements are used in the composite network: a summing and an assignment node that allow the dynamic interaction among the different sub-networks.

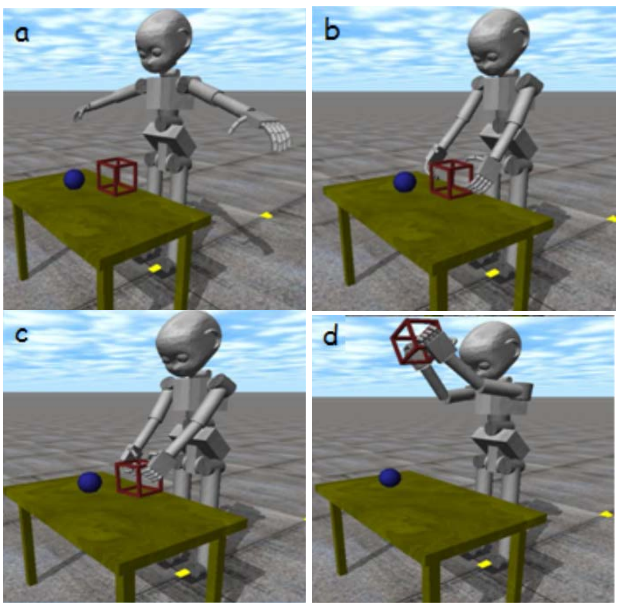

Figure 7. a: initial position; b: end of the reaching phase; c: end of the grasping phase; d: end of the lifting phase.

In order to carry out bimanual coordinated movements, such as the apparently simple task of reaching, grasping, and lifting an object, we need to consider a dynamically reconfigured PMP network that includes different sub-networks: one for the right arm, one for the left arm, one for the trunk, and one for the cube. This network is shown in fig. 6 as regards the final lifting phase: a single force field, applied to the grasped object, propagates throughout the global network, recruiting the joints with appropriate timing.

Figure7 shows four snapshots of the composite bimanual task that includes a reaching phase, a grasping phase, and a lifting phase. The smooth coordination of the different kinematic variables is shown in figure 8.

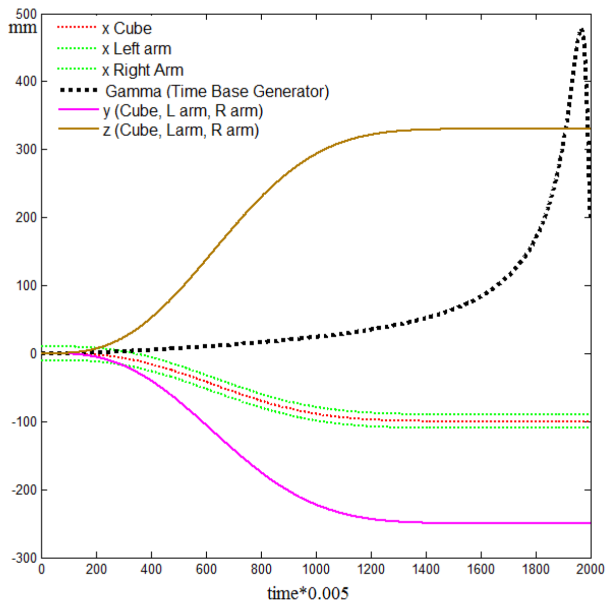

Figure 8. Time course of kinematic variables in the final lifting phase of the task, determined by the PMP network of fig. 6.

It is necessary to emphasize that the force fields operating on the PMP networks don't really describe the biomechanical forces at play during the execution of movements, but are computational metaphors that describe the complex dynamics of the internal computational engine. The internal model associated with the force-fields stores a whole family of geometrically possible solutions as a sort of holographic memory, from which one solution is implicitly selected on the basis of the specific context in which a given task is executed.

Further, the proposed architecture is also endowed with nice computational properties like robustness, run-time optimization, fast task-adaptation, interference avoidance and local to global computation that makes it both biologically plausible and extremely useful in the control of complex robotic bodies.

IV. Bimanual Coordination In Humans and Force Field Adaptation

Complex bimanual coordination patterns escape our conscious perception, although can adapt easily to a changing environment, as in opening a jar or steering a car while changing gear. As a matter of fact, such skills exemplify two general classes of bimanual coordination: 1) direct or unitary bimanual coordination, which is driven by a single motor task and occurs in the same workspace, with a common timing; 2) indirect bimanual coordination, which is characterised by two independent motor tasks, one for each hand, occurring in different parts of the space and with different timing. In the latter case, we can still speak of coordination but it occurs at a more abstract level, remote with respect to dynamic and muscular patterns. In both cases, however, it is of great importance to investigate the interaction between coordination and learning.

Experiments of indirect bimanual coordination were performed by Tcheang et al. [21]. They used a pair of haptic robots that generated viscous curl fields, a de facto standard benchmark for the study of motor adaptation in the uni-manual case, after the seminal paper by Shadmehr and Mussa-Ivaldi [7]. For both arms the task was out-and-back reaching movements from a home position to one of eight targets, uniformly positioned on a circle with a 10 cm diameter, without stopping at the peripheral targets. The two circular workspaces were well separated sideways and the peripheral targets were selected randomly and independently for each hand. Thus the experimental design challenged the ability of the subjects to learn two independent tasks. The main result of that study was that indeed simultaneous dynamics are learned without interference.

In a recent study [22] Casadio et al. addressed a paradigm of direct bimanual coordination. The experimental set-up is similar but the task is different: 1) the two circular workspaces coincide, 2) only one target is activated at any time, 3) both hands are required to reach it at the same time and stop there for a suitable time. So, the experimental design stresses the ability to carry out the same unitary task (same space, same time) while adapting to viscous curl force fields that can be characterised by equal or opposite rotation. In contrast with the bimanual indirect coordination paradigm described above, the direct coordination paradigm aims at achieving a unitary spatio-temporal synergy between the two arms, which is indeed complex if we look beyond the apparent simplicity: the workspace is globally the same both in extrinsic and intrinsic coordinates but the combined reaching movements are characterized by strongly different joint rotation and muscle activation patterns, except for the forward/backward movements. Therefore, it is of interest to evaluate the robustness of the synergy on face of the adaptation task.

The experimental setup consisted of two haptic BdF robots [23], mounted as shown in fig. 9. The positions of the two robots were calibrated with respect to a common reference frame that was also used for the targets of the reaching movements. Subjects were seated on a chair, with their trunk and wrist restrained by means of suitable holders while grasping the handles of the two manipulanda, in such a way to limit the arm movements to shoulder and elbow rotations. The screen was positioned right in front of the patients, about 1m away in order to display the current positions of the two hands and the target, with a 1:1 visual scale factor: targets were displayed as round green circles (2 cm diameter) and the position of right and left hand were displayed as a yellow and a red circle (0.4 cm diameter) respectively. In the experiments 8 targets were used, positioned on a circle with a 10 cm diameter, plus a home target in the center of the circle.

Figure 9. Bimanual haptic BdF robot.

The sequence of target presentations alternated the central target and one of 8 peripheral targets, selected in random order. A target set included 48 center-out movements (6 reaching movements for each peripheral target) and 48 homing movements. Only the center-out movements were analysed. The task was to reach the targets at the same time with both hands, while adapting to two force fields simultaneously applied to the two hands; the subjects were encouraged to keep approximately constant the reaching time (600 ±100 ms), by means of acoustic and visual feedbacks that were coded in such a way to inform the subject whether the reaching time was too short, correct, or too long. The two force fields were both viscous curl and could have equal or opposite rotation directions (CW-CW or CCW-CW) with a viscous coefficient of 20 N/m/s. The well-known force field adaptation paradigm proposed by Shadmehr and Mussa-Ivaldi [7] was used and, in particular, the experimental protocol was organized into the following phases:

(i) **Familiarization** (4 target sets), in which the robot generated no force. The purpose of this phase was to evaluate the background level of performance;

(ii) **Adaptation** (6 target sets), in which the force field was turned on (it included random catch trials);

(iii) **Wash-out** (2 target sets), in which forces were turned off to evaluate the persistence of the induced adaptation (if any).

The experimental subjects (young, healthy, right-handed) were divided into two age-matched and gender-balanced groups:

– Group 1: 3 males and 4 females (age: 25.7±1.8y);
– Group 2: 4 males and 3 females (age: 25.3±2.6y).

The two groups differed for the combination of force fields used in the adaptation phase:

Subjects	L-hand	R-hand
Group1	CW	CW
Group2	CCW	CW

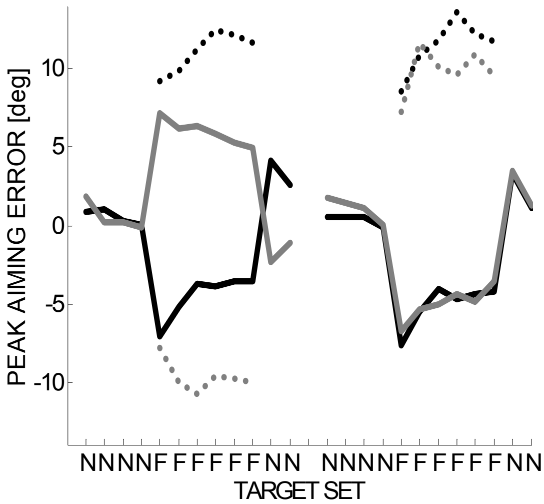

Figure 10. Force field adaptation profile for the left hand (left panel) and the right hand (right panel). N: null field trials; F: field trials. Positive aiming direction denotes counter-clockwise deviation. Dotted lines indicate catch trials, solid lines indicate force field trials. The values are averages over the 8 directions. CW-CW group (black lines); CCW-CW group (grey line).

Force field adaptation

In order to evaluate the force field adaptation, we evaluated for both hands the *aiming error*, defined as the angle between the ideal reaching trajectory and the line joining the starting point to the point of the real trajectory at which speed is maximum. This error, which is an overall measure of lateral deviation of the trajectory, was evaluated for the field and the catch trials, respectively. Fig. 10 shows the evolution of this error in the two groups and the two hands.

Adaptation to the force field is evident for both groups of subjects and both hands, as demonstrated by the opposite patterns of lateral deviation displayed by the catch (black lines) and the force field trials (grey lines). Moreover, the catch trial trajectories are curved in the opposite direction with respect to the field trials. The statistical analysis shows that during the adaptation phase the aiming error decreases (significant TIME effect, $F(1,12)=37.18$, $p=0.00054$) and there is no significant TIME×GROUP interaction. Thus it is possible to conclude that the two hands can independently adapt to two curl force fields (either different or the same).

Bimanual Coordination

The second relevant aspect that was worth investigating in the bimanual adaptation task is the evolution of the coordination patterns. The task assigned to the subjects was to keep the two hands aligned in time and space during the adaptation process. The two force fields have an effect as regards the spatial alignment but not the time alignment. For this reason we analysed the time course of the absolute values of the orthogonal (top) and tangential (bottom) components of inter-hand displacement (fig. 11).

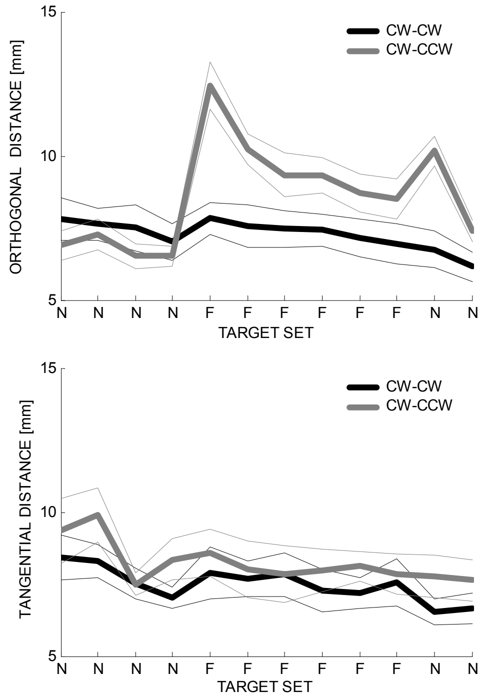

Figure 11. Absolute values of the orthogonal (top panel) and tangential (bottom panel) components of the distance between the hands, averaged over all movement directions. CW-CW group (black lines); CCW-CW group (grey line). Thin lines: standard error around the mean.

During the null field phase, the tangential and orthogonal components have similar magnitudes. In observing the force field and the wash-out phases, we need to distinguish the CW-CW and CCW-CW groups. As could be expected from the nature of the paradigm, the force-field perturbation had little effect on both components of the inter-hand distance for the CW-CW group; on the contrary the effect was sizable for the orthogonal component in the CCW-CW groups and then decreased as adaptation proceeded. In general, these results suggest that the force field is perceived as a novel condition, which challenges bi-manual coordination. We then focused our attention on the tangential component of the distance. Fig. 5 suggests that the force field has little or no influence; however, the influence could be masked by the fact that the figure displays the averages over the different directions of the tangential component. For this reason, we also analysed the signed tangential component and the dependence upon movement direction. Fig. 12 displays the direction-dependent polar plot of this parameter. The circle corresponds to zero value of the parameter (i.e., right and left hands move synchronously); values inside/outside the circle indicate that the left hand is leading/lagging the right hand.

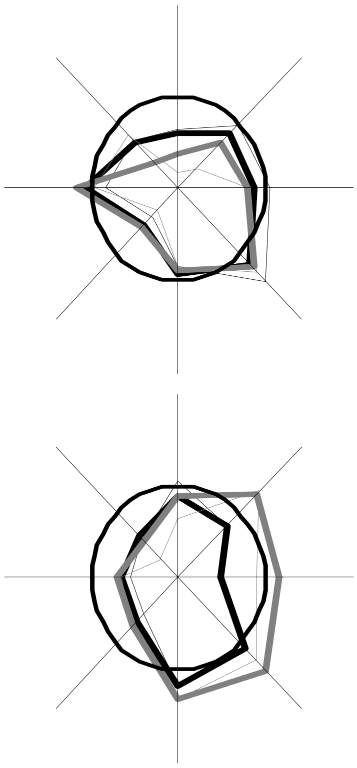

Figure 12. Direction dependence of the tangential displacement between the two hands during the familiarization phase (top panel) and adaptation phase (bottom panel). Thin and thick lines denote early and late phases. Black and grey traces indicate, respectively, the CW-CW and the CCW-CW groups. The circle (radius = 1.5cm) indicates zero displacement. Points outside the circle denote positive displacement (i.e. the right hand leads).

During the null field phase, the figure shows that the left hand tends to lead the bi-manual movement: the effect is slightly direction-dependent and is the same for both groups.

On the contrary, during the force field adaptation phase the two groups differ in a significant way: 1) the two hand are approximately synchronous in the 90° and 270° directions for both groups of subjects; 2) the left hand leads the right hand for movement in all other directions (CW-CW group); 3) the left hand leads the right hand for movements in the leftward directions while the right hand leads in the rightward directions (CCW-CW group). The statistical analysis for the final target-set of the adaptation phase confirms a significant difference between the two groups ($F(1,10)=5.48$; $p=0.041$). In conclusion, these preliminary results suggest that when considering bimanual tasks, the adaptation to novel dynamical environments is only part of the story and subtle coordination effects must be taken into account, with regards to the specific features of the task, hand dominance and workspace position.

In the near future this study, that involved only 4 DoFs (shoulder+elbow for both arms) will be extended by integrating the movements of both wrists and hands, for a total of 12 compliant DoFs.

V. Conclusions

In spite of many open question, we believe that the interaction between the study of bimanual coordination in humans and humanoid robots is a fruitful one.

At a higher, more cognitive level, we may consider the possible role of handedness for a humanoid robot. For a composite, bimanual PMP network, like the one of fig. 6, the issue is related to the representation of space. The assumption for the current computational model is to have a uniform representation (and a uniform level of resolution) for all the relevant variables (e.g. x_1, x_2, x_{cube} in fig. 6). However, this is not necessarily the case: resolution and representation may be function of practice and thus handedness might emerge from actual "experience" and "training" of the robot in the real world.

At a lower computational level, we should consider (as suggested in fig. 1) the interaction between the levels related to spatio-temporal planning and the levels related to dynamics and muscles: internal model control (feedforward and/or feedback) vs. muscle impedance control. As a matter of fact, PMP networks provide different interaction points with the lower (and higher) control levels, where modulation can occur in a bi-directional way. For example, spatial stiffness matrices can be modulated as a function of the task "commitment" to a specific reaching trajectory; joint admittance matrices can be chosen in such a way to influence the pattern of "recruitment" of the different joints; the time base generator can be tuned in relation with the performance of the previous trial, and so on.

References

[1] P. Morasso, "Spatial control of arm movements." *Experimental Brain Research*, vol. 42, pp. 223-227, 1981.

[2] W. Abend , E. Bizzi, P. Morasso, "Human arm trajectory formation." *Brain*, vol. 105, pp. 331-348, 1982.

[3] T. Flash, N. Hogan “The coordination of arm movements: an experimentally confirmed mathematical model.” *J. Neurosci.* , vol. 5, pp. 1688-1703, 1985.

[4] Y. Uno, M. Kawato, R. Suzuki “Formation and control of optimal trajectory in human multijoint arm movement. Minimum torque-change model.“ *Biol. Cybern.*, vol. 61, pp. 89-101, 1989.

[5] F.A. Mussa Ivaldi, P. Morasso, R. Zaccaria “Kinematic Networks. A Distributed Model for Representing and Regularizing Motor Redundancy.” *Biol. Cybern.*, vol. 60, pp. 1-16, 1988.

[6] E. Bizzi, F.A. Mussa Ivaldi, S. Giszter “Computations underlying the execution of movement: a biological perspective.” *Science,* vol. 253, pp. 287-291, 1991.

[7] R. Shadmehr, F. A. Mussa-Ivaldi, "Adaptive representation of dynamics during learning of a motor task." *J. Neurosci.*, vol. 14, pp. 3208-24, 1994

[8] D.E. Whitney “Resolved Motion Rate Control of manipulators and human Prosthesis.” *IEEE Transactions on Man-Machine Systems*, vol. MMS-10, pp. 47–53, 1969.

[9] A. Liegeosis “Automatic Supervisory Control of the Configuration and Behavior ofMultibodyMechanisms.” *IEEE Trans. on Systems, Man, and Cybern.*, vol. **7** , pp. 868–871, 1977.

[10] J. Baillieul “Kinematic Programming Alternatives for Redundant Manipulators.” In *IEEE International Conference on Robotics and Automation*, pp. 722–728, 1985.

[11] M. Šoch, R. Lórencz “Solving Inverse Kinematics – A new approach to the extended Jacobian technique.” *Acta Polytechnica*, vol. 45, pp. 21-26, 2005.

[12] T. Tsuji, P. Morasso, K. Shigehashi, M. Kaneko “Motion Planning for Manipulators using Artificial Potential Field Approach that can Adjust Convergence Time of Generated Arm Trajectory.” *J. of the Robotics Soc. of Japan*, vol.13, pp. 285-290, 1995.

[13] V. Mohan, P. Morasso “Towards reasoning and coordinating action in the mental space.” *Intl. J. of Neural Systems*, vol. 17, pp. 1-13, 2007.

[14] E. Todorov “Optimality principles in sensorimotor control.” *Nature Neurosci*., vol. 7, pp. 907–915, 2004.

[15] R.A.. Brooks “The Cog Project.” *J. of the Robotics Soc. of Japan*, vol. 7, pp. 968-970, 1979.

[16] C.G. Atkeson, J.G. Hale, et al. “Using Humanoid Robots to Study Human Behavior.” *IEEE Intelligent Systems,* vol. 15, pp. 46-56, 2000.

[17] M. Hirose, K. Ogawa “Honda humanoid robots development.” *Philos. Transact. A Math. Phys. Eng. Sci.*, vol. 365, pp. 11-9, 2007.

[18] K. Nishiwaki, J. Kuffner, et a. “The experimental humanoid robot H7: a research platform for autonomous behaviour.” *Philos. Transact. A Math. Phys. Eng. Sci.*, vol. 365, pp. 79-107, 2007.

[19] L. Natale, F. Orabona, G. Metta, G. Sandini “Sensorimotor coordination in a "baby" robot: learning about objects through grasping.” *Progr. in Brain Res*., vol. 164, pp. 403-24, 2007.

[20] G. Metta, P. Fitzpatrick, L. Natale (2006) “YARP: Yet Another Robot Platform.” *Intl. J. of Advanced Robotics Syst*., vol. 3, pp. 43-48, 2006.

[21] L. Tcheang, P. M. Bays, J. N. Ingram, and D. M. Wolpert, "Simultaneous bimanual dynamics are learned without interference." *Exp. Brain Res.*, vol. 183, pp. 17-25, 2007.

[22] M. Casadio , V. Squeri, L. et al., “ Characterizing ‘direct’ bi-manual coordination while adapting to a dynamic environmnt,” IEEE BioRob 2008, Scottsdale, AZ.

[23] M. Casadio, P. Morasso, V. Sanguineti, V. Arrichiello “Braccio di Ferro: a new haptic workstation for neuromotor rehabilitation.” *Technol. Health Care*, vol. 14, pp. 123–142, 2006.