

Composing and Coordinating body models of arbitrary connectivity and redundancy: A Biomimetic, field computing approach

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Abstract— The subjective ease with which we move gracefully in constraint filled uncertain environments often masks the enormously complex integrative apparatus needed to spell synergy among the thousands of sensors, joints, musculo-skeletal units and neuronal populations that contribute to any act's planning and execution. In this paper, we apply the computational framework of passive motion paradigm (PMP, Mussa Ivaldi et al, 1988) for task specific composition and coordination of the movements of a limb, network of limbs (e.g. left arm–waist–right arm) or networks of external objects coupled to the body of the 53 degrees of freedom humanoid robot ‘iCub’. The basic PMP model is further extended by formulation of a pair of branching nodes that allow compositionality and transfer of force fields from one relaxation network to another. The generality of the proposed approach is further illustrated using a simulation of a whole body reaching (WBR) tasks from a quiet standing posture that recruits virtually all the joints of the upper limbs, lower limbs, and trunk, binding together a large number of degrees of freedom into a functional unit that combines a focal task (reaching a target with the hand) and a postural task (keeping the projection of the center of mass within the bipedal support area). Preliminary comparisons of the solutions generated by the computational model with the movements of a human subject performing similar WBR task is presented.

I. INTRODUCTION

THE action of “reaching” is fundamental for any kind of goal directed interaction between the body and the world.

Considering the fact that motor commands needed to perform even seemingly simple actions like reaching a cup of coffee also requires spatiotemporal coordination of several variables both internal and external to the body like the current state of the arm, orientation of the body, range of motion for the joints, range of torques for the actuators, geometry of the task (shape of the cup) etc, robotitians have often wondered about the nature of the computational/neural

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substrate in the brain that makes “reaching” possible in humans and animals.

However, the explosive computational complexity of kinematic and dynamic equations of even deceptively simple devices like a robotic arm makes it difficult either to intuitively understand the neural control of movements or develop computational schemes for dexterous 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 spatiotemporal 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].

The Passive Motion Paradigm (or PMP: Mussa Ivaldi et al, 1988) extended and investigated in this paper is a force fields based computational model that addresses the problem of coordinating redundant degrees of freedom by means of a dynamical system approach, similar to the Vector Integration to To Endpoint (VITE model: Bullock and Grossberg, 1988). In both cases there is a “difference vector” associated with an attractor dynamics that has a point attractor in the designated target. The difference is that the VITE model focuses on the neural signals commanding a pair of agonist-antagonist muscles, whereas the PMP model focuses, at the same time, on the trajectories in the extrinsic and intrinsic spaces. The computational process of relaxation in the attractor landscape of the PMP is similar to coordinating the movements of a puppet by means of attached strings, the strings being 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 in this sense involves a process of passive simulation of movement as if it was imposed by an external agent, in such a way to distribute the desired motion to the global kinematic structure by recruiting joints, actuators, and tools while pulling the dynamical system to the equilibrium state. What makes it attractive from the computational point of view is its

simplicity and robustness. It is simple because the planner/controller does not have to be concerned with all the DoFs at the same time but only with a smaller number of “end-effectors”. It is robust because no model inversion is necessary and the relaxation to equilibrium in a conservative force field can never crash. It does not require any cost function to be specified in order to solve the indeterminacy determined by the excess DoFs but it allows to integrate internal and external constraints (in the intrinsic and extrinsic spaces, respectively). The basic PMP model was further extended in order to include terminal attractor properties (Tsuji et al, 1995) and applied to robot reasoning using virtual mental simulation of action [10]. In comparison with a recent computational model for reaching by Hersch and Billard (2008) that builds upon the VITE model, the proposed extension of the PMP model in this chapter is equally well a “multi-referential dynamical systems” for implementing reaching movements in complex, cognitive robots but *does not* require any explicit inversion and/or optimisation procedure.

The proposed extension of the basic PMP model, prior to for applying it to the complex structure of a humanoid robot, includes two main features:

- Terminal attractor dynamics, by means of a non-linear, dynamic timing mechanism, for allowing the synchronization of kinematic patterns in the extrinsic and intrinsic spaces;
- Branching nodes, for structuring the PMP network in agreement with the body model and the kinematic constraints of a specific task.

In this paper, a preliminary evaluation of the proposed approach has been carried out with the 53 degrees of freedom humanoid robot iCub, with particular reference to Reaching, orienting and whole upper body coordination (Right Arm-Waist-Left arm chain).

We further demonstrate the generality and flexibility of the proposed approach by formulating a PMP based computational model for whole body reaching (WBR) task that recruits virtually all the joints of the upper limbs, lower limbs, and trunk, binding together a large number of degrees of freedom into a functional unit that combines a focal task (reaching a target with the hand) and a postural task (keeping the projection of the center of mass within the bipedal support area). The fact that the two tasks are part of the same functional unit is proved by the anticipatory postural adjustments (Bouisset & Zattara 1987 [12]) that have been described at the kinematic and electromyographic levels. Different approaches have been attempted to quantify the coupling among the joints, in order to identify sub-components in the global reaching synergy: a typical example is the PCA analysis (Kaminski 2007 [13]). However, no generative computational model has been investigated so far. From the perspective of PMP, the focal and postural components of WBR can simply be associated to two different force fields and the complex, multi-joint coordinated patterns are a “side-effect” of the relaxation to equilibrium of the overall body model. Simulation results obtained using the model for whole body reaching tasks using a simplified body

model composed of 5 joints (Ankle-Knee-Hip-Shoulder-Elbow) are presented. We further compare the final solutions obtained (i.e posture, velocity profile and trajectories in the distal/proximal spaces) using the proposed nonlinear dynamical system with the movements of a human subject performing similar WBR tasks.

A simple learning mechanism for the optimal choice of the virtual impedance matrix to fit the solutions obtained by PMP to the human movements (measured through a motion capture device) is presented.

The article is organized as follows. The general formulation of the PMP is presented in the next section. Section 3 describes the iCub centric adaptation of the computational model, mainly focusing on the issues of ‘compositionality’. Implementation results of few bimanual coordination tasks using the humanoid is presented. In section 4 we extend the basic computational model to the scenario of whole body reaching and present a range of simulation results obtained using the model for whole body reaching tasks using a simplified body model composed of 5 joints (Ankle-Knee-Hip-Shoulder-Elbow). We further compare the final solutions obtained (i.e posture, velocity profile and trajectories in the distal/proximal spaces) using the proposed nonlinear dynamical system with the movements of a human subject performing similar WBR tasks. Concluding remarks are presented in the final section.

II. THE PASSIVE MOTION PARADIGM

The central theme behind the formulation of PMP is that motor commands for any kind of motor action, for any configuration of limbs and for any degree of redundancy can be obtained by an “internal simulation” of a “passive motion” induced by a “virtual force field” (Mussa Ivaldi et al, 1988) applied to a small number of task-relevant parts of the body. Here “internal simulation” identifies the relaxation to equilibrium of an internal model of limb (arm, leg etc, according to the specific task); “passive motion” means that the joint rotation patterns are not specifically computed in order to accomplish a goal but are the indirect consequence of the interaction between the internal model of the limb and the force field generated by the target, i.e. the intended/attended goal. It is important to note that, the force fields we are considering don’t really describe the biomechanical forces at play during the execution of movements, but are just computational metaphors that describe the dynamics of the internal computational engine.

Let x be the vector that identifies the pose of the end-effector of a robot in the extrinsic workspace and q the vector that identifies the configuration of the robot in the intrinsic joint space: $x = k(q)$ is the kinematic transformation that can be expressed, for each time instant, as follows: $\dot{x} = J(q) \cdot \dot{q}$ where $J(q)$ is the Jacobian matrix of the transformation. The motor planner/controller, which expresses in computational terms the PMP, is defined by the following steps that are also represented graphically by the PMP network of fig 1:

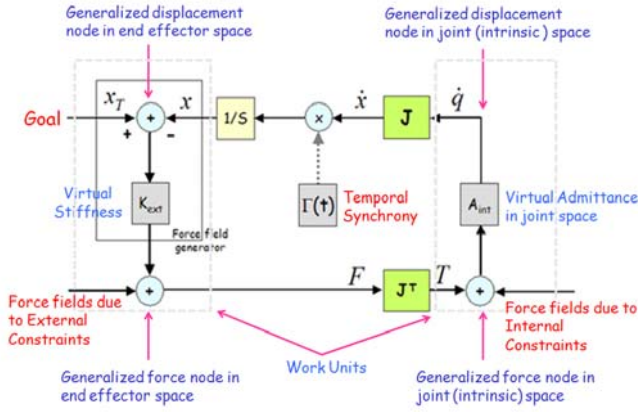


Fig 1. Basic computational scheme of the PMP for a simple kinematic chain. x is the position/orientation of the end-effector, expressed in the extrinsic space; x_T is the corresponding target; q is the vector of joint angles in the intrinsic space; J is the Jacobian matrix of the kinematic transformation $x = k(q)$; K_{ext} is a virtual stiffness that determines the shape of the attractive force field to the target; “external constraints” are expressed as force fields in the extrinsic space ($F = F(x, \dot{x}, \ddot{x})$); “internal constraints” are expressed as force fields in the intrinsic space ($T = T(q, \dot{q}, \ddot{q})$); A_{int} is a virtual admittance that distributes the relaxation motion to equilibrium to the different joints; $\Gamma(t)$ is a time-varying gain that implements the terminal attractor dynamics.

- 1) Associate to the designated target x_T an attractive force field in the extrinsic space

$$F = K_{ext}(x_T - x) \quad (1)$$

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:

$$T = J^T F \quad (2)$$

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

- 3) Relax the arm configuration in the applied field:

$$\dot{q} = A_{int} \cdot T \quad (3)$$

where A_{int} is the virtual admittance matrix in the intrinsic space: the implicit or explicit modulation of this matrix affects the relative contributions of the different joints to the reaching movement.

- 4) Map the arm movement into the extrinsic workspace:

$$\dot{x} = J \cdot \dot{q} \quad (4)$$

- 5) Integrate over time until equilibrium

$$x(t) = \int_{t_0}^t J \dot{q} d\tau \quad (5)$$

The timing of the relaxation process can be controlled by using a TBG (Time Base Generator (Tsuji et al 2002) and the concept of terminal attractor dynamics (Zak 1991): this can be simply implemented by substituting the relaxation equation (4) with the following one:

$$\dot{q} = \Gamma(t) \cdot B \cdot T \quad (6)$$

where a possible form of the TBG or time-varying gain that implements the terminal attractor dynamics is the following one (it uses a minimum-jerk generator with duration τ):

$$\Gamma(t) = \frac{\xi}{1 - \xi} \quad (7)$$

where

$$\xi(t) = 6(t/\tau)^5 - 15(t/\tau)^4 + 10(t/\tau)^3 \quad (8)$$

In general, a TBG can also be used as a computational tool for synchronizing two plans, coordinating two arms or even the movements of two robots. The algorithm always converges to an equilibrium state, in finite time (that is set using the TBG) under the following conditions:

- A. When the end-effector reaches the target, thus reducing to 0 the force field in the extrinsic space (1);
 - B. When the force field in the intrinsic space becomes zero (2), although the force field in the extrinsic space is not null and this can happen in the neighbourhood of kinematic singularities;
- Case (A) is the condition of success termination. But also in case (B), in which the target cannot be reached for example because it is outside the workspace, the final configuration has a functional meaning for the motion planner because it encodes geometric information valuable for re-planning (breaking an action into a sequence of sub-actions like using a tool [10]). Thus, the basic PMP is a robust non-linear dynamic approach to the solution of the inverse kinematic problem that does not require any explicit inversion or optimization task.

III. STRUCTURED PMP FOR UPPER BODY COORDINATION OF HUMANOID ICUB

As evident in figure 1, every motor space in a PMP network is represented using a generalized force and position node grouped together as a work unit (that is a scalar invariant across the different motor spaces). The vertical weights that link force and displacement nodes and vice versa (incrementally) are represented by the impedance matrices. The horizontal weights on the other hand link two different motor spaces and are represented by the jacobians. To coordinate the body of a complex humanoid we need to augment the basic formulation of the PMP with a set of additional nodes that allow proper connectivity and transfer of force fields from one part of the body to other. We present the new additions using two examples of composite PMP networks 1) Coordination of reaching and orienting 2) Coordination of Left arm-waist-Right arm network is shown in figure 2 and 3 respectively. Since there are many possible kinematic chains that can be coordinated simultaneously in the humanoid, it is necessary to identify the start and end points in the body model between which the force fields generated by the goal will propagate, and beyond which the force fields generated by the goal will not propagate.

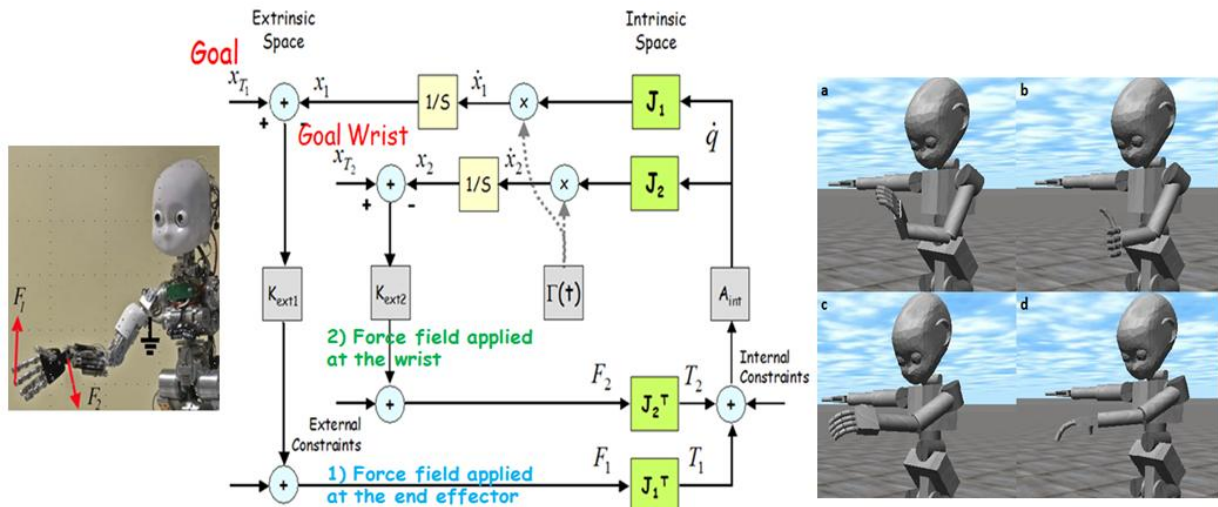


Fig 2. Composite PMP network with two attractive force fields applied to the arm of iCub: a field F_1 that identifies the desired position of the hand/fingertip and a field F_2 that helps achieving a desired pose of the hand via an attractor applied to the wrist. This network assumes that the shoulder of the arm is “grounded”: this means that the two force fields do not propagate beyond the shoulder joint. Four solutions generated by the computational model to reach the same target using the left arm, with different wrist orientations and starting from the same initial condition (left arm symmetric with respect to the right arm) is shown.

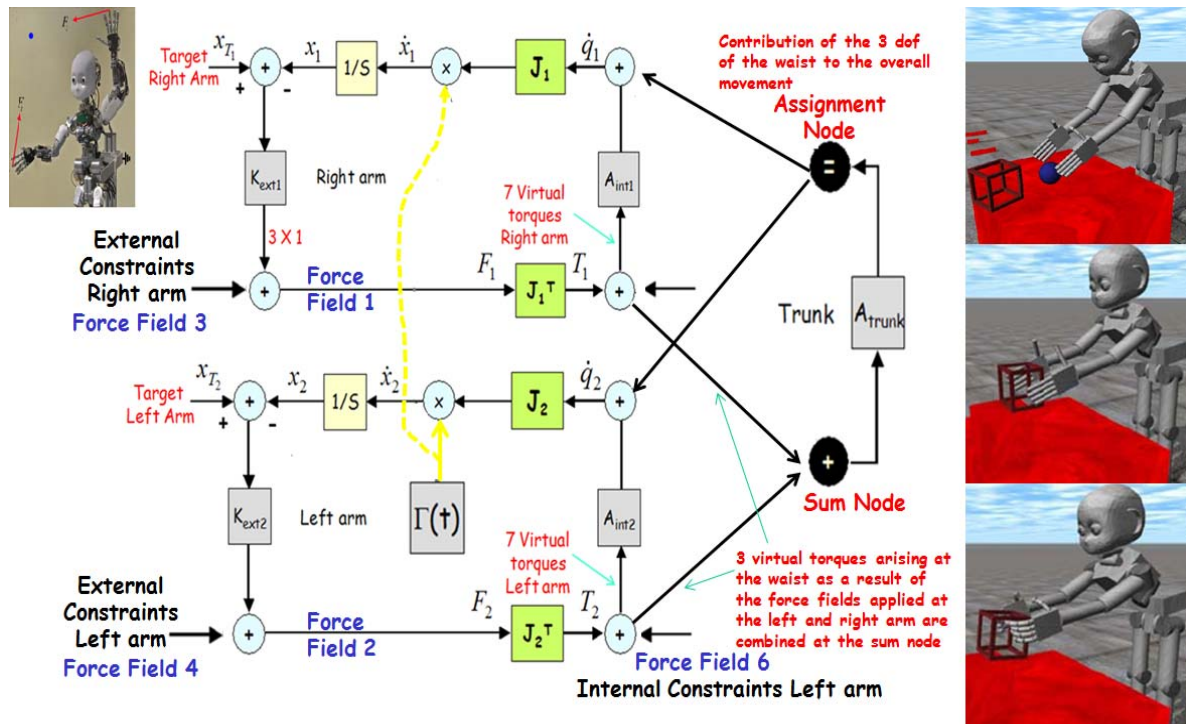


Fig 3. Composite PMP network for Left arm-Waist-Right Arm coordination. Force fields (FF) 1&2 are applied on the left and the right arm to reach the goal, FF 3 & 4 represent external constraints at the arm (like reaching with a specific wrist orientation like in figure 2), FF 5&6 represent internal constraints (for example joint limits etc). The net dynamically composed attractor landscape that determines the behaviour of the robot is a superposition of all these fields. The waist joint of the robot is “grounded” in this case. The “sum node” allows the two force fields to be combined in determining the motion of the waist. The “assignment node” propagates to the two arms the motion of the waist. In this way the motion of each arm is influenced by both force fields.

The shoulder and waist are grounded in fig 2 and 3 respectively, hence all DoF in between the end effector and

the designated ground node are involved in the relaxation process. Further, if the waist is very stiff (which can be controlled by modulating the A_{Trunk}), only the DoF of the arms contribute to the final solution reached by the dynamical system: this is equivalent to ‘‘grounding’’ both the shoulders.

Fig 3 shows the PMP computational chain to coordinate all degrees of freedom involved in the ‘‘right arm-waist-left arm chain’’ during the bimanual reaching task. Since the left and the right arm are act in parallel, it is easy to hint that for the case of bimanual reaching there will be two parallel computational chains (each similar to the one shown in figure 2) with respective end-effectors being pulled by the goal induced force field. The problem now is to couple these two dynamical systems into a single relaxation process. We also observe that the waist of the robot is linked serially to the two arms and we need a way to couple the overall relaxation of the two arms with the relaxation at the waist. In other words, the three degrees of freedom allowed at the waist must also contribute towards reaching the respective targets of the two arms (each having 7DoF). In order to achieve this, we introduce two new nodes (in addition to generalised displacement, force and ground nodes that already exist) in the computational framework : a sum node and an assignment node. The resulting computational chain for upper body coordination is shown in fig 3. In complex kinematic structures, characterized by several serial and parallel connections, the sum and assignment nodes can be used to add or assign displacements and forces to different connecting elements of the kinematic chain (in this case the left arm-waist-right arm network). A_{trunk} is the virtual admittance matrix of the waist. The transpose jacobians incrementally transform the force fields generated by the goal in each chain into ten virtual torques (7 for the respective arms and 3 for the waist). The virtual torques incrementally computed for the waist as a result of the force fields experienced by the two arms are summed at the sum node and transformed into 3 incremental joint rotations at the waist through the admittance matrix. The assignment node propagates the resultant incremental displacement computed at the waist back to the computational chain of the two arms. At the same time the incremental displacements at the joints of the each arm is also computed by using the 7 virtual joint torques and joint admittance matrices. The jacobians now compute the incremental update in the configuration of the body as a result of the incremental displacements at different joints. In this one cycle through the computational chain, the whole upper body has incrementally reconfigured to a new pose towards reaching the respective goals of the two end-effectors. Part of the solution contributed by the waist, part of it contributed by the degrees of freedom of the two arms, based on their relative admittances. This cycle of propagation of disturbances through the computational chain continues till the time the whole upper body attains equilibrium (i.e there are no disturbance forces circulating in the network). This is the final solution of the complete relaxation process. Three different bimanual reaching tasks coordinated using the computational model is shown in figure 3. The simulations were carried out

by linking various PMP networks to the kinematic/dynamic simulator of the iCub robot (Tikhanoﬀ et al 2008).

IV. COORDINATION OF FOCAL ARM MOVEMENTS AND POSTURAL STABILIZATION IN WHOLE BODY REACHING

After introducing the basic computational chain of the PMP in section II, in section III we presented two examples of composite PMP networks to coordinate the motion of the humanoid iCub. In this section we present a composite PMP chain that combines a focal task (reaching a target with the hand) and a postural task (keeping the projection of the center of mass within the bipedal support area) during a whole body reaching (WBR) task. Different approaches have been attempted to quantify the coupling among the joints during WBR, in order to identify sub-components in the global reaching synergy: a typical example is the PCA analysis [5]. However, no generative computational model has been investigated so far. In the context of the PMP, the focal and postural components of WBR can be associated to two force fields and the complex, multi-joint coordinated patterns are a ‘‘side-effect’’ of the relaxation to equilibrium of the overall body model. Fig 4 shows the simplified five link body model considered in this study and fig 5 shows the flow digram of the PMP based computational model for WBR.

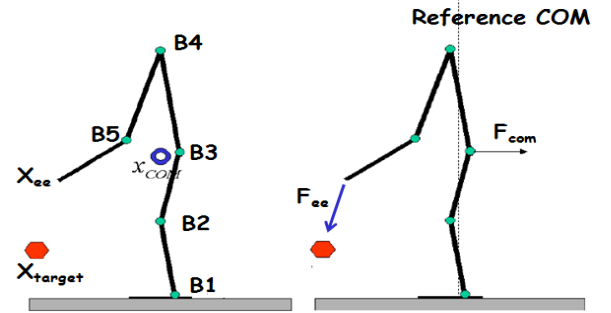


Fig 4. WBR kinematic model consisting of a ‘ankle-knee-hip-shoulder-elbow’ chain, with B characterizing the virtual admittance seen at the different joints.

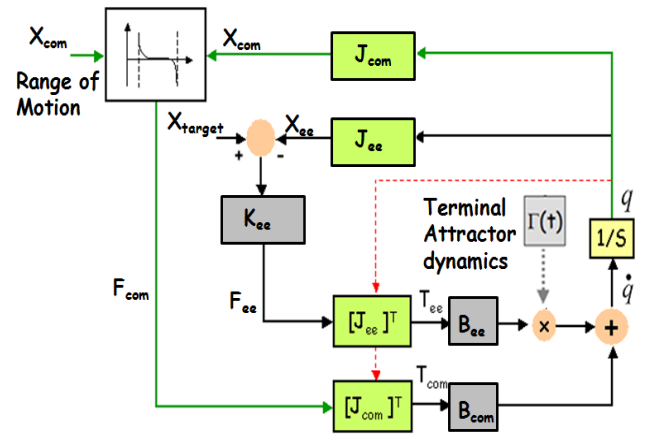


Fig 5. PMP based computational model for WBR.

As shown in fig 5, the PMP based computational model for WBR can be defined by the combination of two synergies: a focal and a postural synergy. Focal synergy: x_{ee} (the position

of the end-effector) must reach the target x_T at a given time t_f . Postural synergy: x_{com} (the position of the COM) must remain inside an admissible range of motion. Hence there are two force fields: a virtual attractive force field to a designated target (applied to the end-effector) and a repulsive force field (applied to the hip) to keep the COM in an admissible ROM

$$F_{ee} = K_{ee} (x_T - x_{ee}) \quad (9)$$

$$F_{com} = f(x_{com}, x_{min}, x_{max}) \quad (10)$$

The jacobians map the extrinsic force fields into intrinsic force fields and the body configuration is relaxed in the applied (superimposed) fields according to (11), B being the virtual admittance matrix.

$$\dot{q} = B_{ee} T_{ee} + B_{com} T_{com} \quad (11)$$

A way to explicitly control the time, without using a clock, is to insert in the non-linear dynamics of the PMP model a suitable time-varying gain $\Gamma(t)$ that grows monotonically as x approaches the equilibrium state and diverges to an infinite value in that state (like (6)). The technique was originally proposed by Zak [11] for speeding up the access to content addressable memories and then was applied to a number of problems in neural networks. Systems that have terminal attractor dynamics violate the Lipschitz criteria of ordinary differential equations, i.e., they have point attractors of infinite stability in the sense that the gradient of their Lyapunov function diverges at equilibrium point: a consequence is that they reach equilibrium in finite time (it is a terminal attractor). Our purpose, however, is not merely to speed up the operation time of the planner but to allow a control of the reaching time as well as the speed profile in order to fit the human reaching patterns. This can be implemented by substituting the relaxation (11) with the following one:

$$\dot{q} = \Gamma(t)(B_{ee} T_{ee} + B_{com} T_{com}) \quad (12)$$

We also point out that the admittance values in the computational chain are basically open parameters (positive definite) and there is no need to explicitly know or determine them. This is because the PMP essentially employs a relaxation paradigm in which displacements to a new planned position is obtained by a process that aims the disturbance force dF to a target point and keeps circulating in the chain till the time the target is reached [11]. This obviously implies that by pseudo randomly varying the admittance matrix a range of solutions can be generated of a given task, hence exploiting the inherent redundancy in the body model.

The PMP based computational model for WBR was implemented with respect to a simplified geometrical structure of the body with 5 joints (Ankle-Knee-Hip-Shoulder-Elbow). A range of reaching tasks mainly using the ‘‘Hip Strategy’’ or ‘‘knee freezing’’ and the ‘‘Ankle Strategy’’ or ‘‘normal

reaching’’ were simulated using the computational model. In an extended study, the solutions obtained using the computational model were compared with movements of human subjects performing similar tasks measured by a motion capture device (MOCAP).

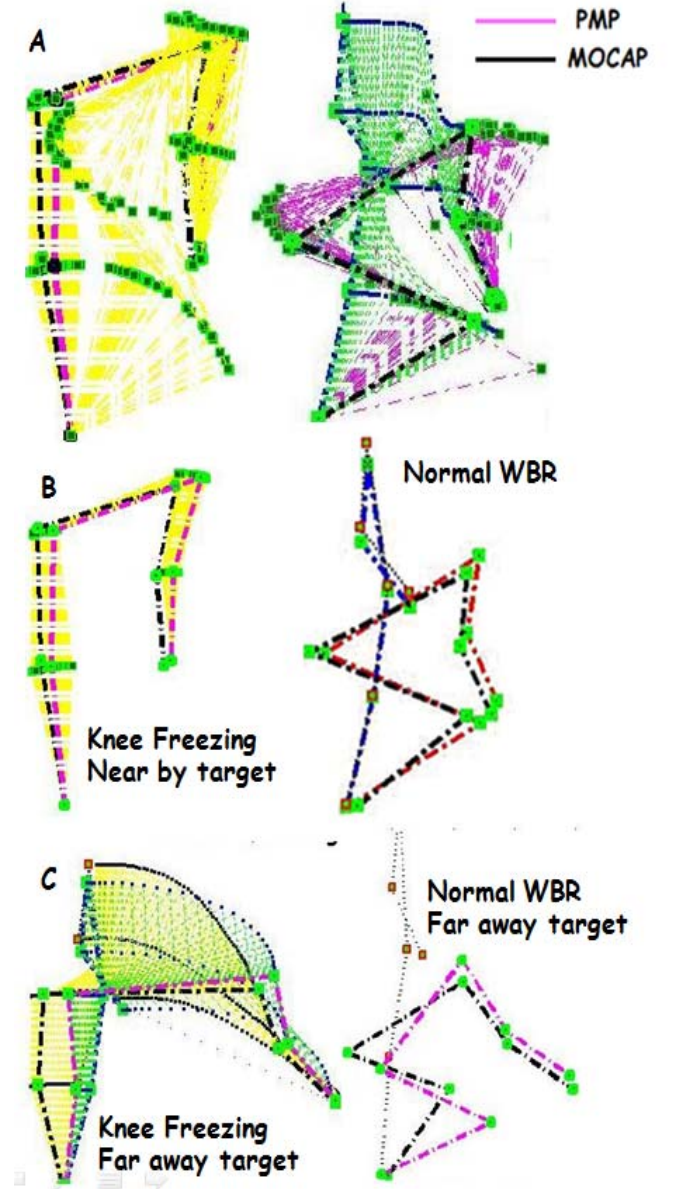


Fig 6: Comparison of solution obtained using the PMP based computational model for whole body reaching, with data of movements of human subjects obtained using a motion capture device. Panel A shows the range of solutions generated by the computational model through pseudorandom variations in the admittance matrix, for a knee frozen reaching task and a normal reaching task respectively. The solution (depicted in black) was the final posture of the human subject performing the WBR. Panel B shows the comparison between the solution generated by the computational model and that of the human subject. Panel C shows two additional examples, now of reaching far away targets using a knee frozen strategy and normal reaching strategy respectively. By pseudorandomly varying the admittance matrices in the

computational model, the solutions (final posture and velocity profiles) generated by the computational model were fitted to the movements of a human subject. As evident from fig 6, preliminary results suggest close correlation between the solutions obtained using the computational model and the movements of human subjects performing similar tasks (measured through motion capture device).

V. CONCLUDING REMARKS

The action of “reaching” is fundamental for any kind of goal directed interaction between the body and the world. In this paper, we presented a simple, distributed computational framework for representing and solving a range of ill-posed coordination problems arising in redundant humanoid platforms, by using a multi-referential non-linear dynamical approach that exploits the physics of passive virtual motion. The computational process of relaxation in the attractor landscape is similar to coordinating the movements of a puppet by means of attached strings, the strings in our case being 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. From this comes the nickname PMP (Passive Motion Paradigm) given to the model. The basic PMP scheme was further extended by formulation of a pair of branching nodes (sum, assignment and ground) that allow compositionality and transfer of force fields from one relaxation network to another in a complex body. We demonstrated the performance of the computational model with two examples of composite PMP networks used to coordinate motion in the 53 degrees of freedom humanoid iCub. We further adapted the computational model for a closely related problem of coordinating motion in reaching tasks that recruit almost all limbs in the body and combines the focal and postural components involved in reaching into a single functional unit. The power of the approach comes from the generality of potential field based methods: the focal and postural components of WBR can be associated to two force fields and the complex, multi-joint coordinated patterns are a “side-effect” of the relaxation to equilibrium of the overall internal model. Further, the timing of the relaxation can be controlled using a non-linear dynamical timing mechanism that provides terminal attractor properties to the computational model and endows the generated trajectories with human-like smoothness and precise control of the reaching time. Preliminary results suggest close correlation between the solutions obtained using the computational model and the movements of human subjects performing similar tasks (measured through motion capture device). The process of pseudorandom variations in the admittance matrix to generate a solution that fits the movement of the human can be also be thought (speculatively) as a mechanism of imitation (the computational model trying to imitate the motion of the human) by autonomously changing its internal variables (impedances in the musculoskeletal system). Future developments will include the integration of this synergy formation mechanism with

lower level, intermittent postural control [18] and formulation of a general learning mechanism for the optimal choice of the virtual admittance matrix that is at the heart of the coordination model.

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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. Bullock, S. Grossberg, “Neural dynamics of planned arm movements: emergent invariants and speed-accuracy properties”. *Psychol Rev*, 95, 49–90, 1988.
- [9] T. Tsuji, P. Morasso, K. Shigehashi and M. Kaneko, “Motion Planning for Manipulators using Artificial Potential Field Approach that can Adjust Convergence Time of Generated Arm Trajectory”, *Journal Robotics Society of Japan*, 13, 285-290, 1995.
- [10] V. Mohan and P. Morasso, “Towards reasoning and coordinating action in the mental space”, *International Journal of Neural Systems*, 17, 4, 1-13, 2007.
- [11] M. Hersch, A. G. Billard, “Reaching with multi-referential dynamical systems”, *Auton Robot* 25, 71–83, 2008.
- [12] S. Bouisset, M. Zattara, “Biomechanical study of the programming of anticipatory postural adjustments associated with voluntary movement”, *J Biomech*, 20:735–742, 1987.
- [13] T. R. Kaminski, “The coupling between upper and lower extremity synergies during whole body reaching”. *Gait & Posture*, 26, 2007.
- [14] V. Tikhonoff, A. Cangelosi, P. Fitzpatrick, G. Metta, L. Natale, F. Nori, “An Open-Source Simulator for Cognitive Robotics Research”. *Cogprints*, article 6238, 2008.
- [15] T. Pozzo, P. J. Stapley and C. Papaxanthis, “Coordination between equilibrium and hand trajectories during whole body pointing movements”, *Exp Brain Res*, 144:343-350, 2002.
- [16] J. Patron, P. Stapley and T. Pozzo, “Human whole-body reaching in normal gravity and microgravity reveals a strong temporal coordination between postural and focal task components”, *Exp Brain Res*, 165:84–96, 2005.
- [17] M. Zak, “Terminal attractors for addressable memory in neural networks”. *Phys. Lett. A*, 133, 218–222, 1988.
- [18] A. Bottaro, Y. Yasutake, T. Nomura, M. Casadio and P. Morasso, “Bounded stability of the quiet standing posture: an intermittent control model”, *Human Movement Science*, 27, 473-495, 2008.