Towards a Multi-Level Neural Architecture that Unifies Self-Intended and Imitated Arm Reaching Performance*

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***Abstract*—Dexterous arm reaching movements are a critical feature that allow human interactions with tools, the environment, and socially with others. Thus the development of a neural architecture providing unified mechanisms for actual, mental, observed and imitated actions could enhance robot performance, enhance human-robot social interactions, and inform specific human brain processes. Here we present a model, including a fronto-parietal network that implements sensorimotor transformations (inverse kinematics, workspace visuo-spatial rotations), for self-intended and imitation performance. Our findings revealed that this neural model can perform accurate and robust 3D actual/mental arm reaching while reproducing human-like kinematics. Also, using visuo-spatial remapping, the neural model can imitate arm reaching independently of a demonstrator-imitator viewpoint. This work is a first step towards providing the basis of a future neural architecture for combining cognitive and sensorimotor processing levels that will allow for multi-level mental simulation when executing actual, mental, observed, and imitated actions for dexterous arm movements.**

I. INTRODUCTION

Human reaching skills are critical to flexibly interacting with our environment and others in social settings. Although redundant multi-jointed arms can produce various trajectories and postures, such kinematic redundancy is a complex problem since the mapping between sensory and motor spaces is highly nonlinear and depends on changing environmental constraints such as obstacles or perturbations [1]. Thus, the performance of 3D reaching movements with redundant, multi-jointed limbs depends on accurate, robust and flexible motor planning and learning capabilities.

Such superior performance is mainly due to the human ability to mentally plan, simulate and predict the consequences of one's own actions through covert cognitive-motor processes. Specifically, the mental simulation theory of action proposes that the human brain incorporates a simulation network that allows performing: i) self-intended actual movements (overtly executed), ii) self-intended mental or imagined movements (covert re-enactment of cognitive-/sensori-motor performance without motor output), iii) observation and imitation of others' actual movements (demonstrator) [2]. The human simulation network incorporates a fronto-parietal circuit that is important in performing actual/mental reaching movements and is also a critical element of the human mirror neuron system (MNS) enabling action observation [3-5]. Thus, this neuroscientific theory provides a unified framework to explain the human capability to: i) mentally simulate/predict the sensory consequences of our own actions, ii) mentally manipulate objects/environments such as mental rotation of a workspace, iii) observe/imitate others' actions [2,6-8].

Although interesting, most previous modeling efforts focusing on imitation of reaching generally used robotic techniques (e.g., Jacobian method, statistical methods) without biological relevance [9]. Conversely, with various degrees of biological plausibility, other work proposed biomimetic models of reaching mainly for self-intended performance and/or imitation learning [10-12]. As far as we know, while neural models have been proposed for reaching movements, none of them proposed a neural architecture that aimed to coherently articulates i) a high cognitive level (e.g., prefrontal cortex that plans abstract action sequences) and ii) a low sensorimotor level that integrates sensory and motor information (e.g., fronto-parietal network) for trajectory planning, sensorimotor predictions and execution of actual/mental, observed/imitated actions. Specifically, regarding the sensorimotor level, previous neural models for imitation learning do not include learning of visuo-spatial transformations of the frame of reference between a demonstrator and an imitator [10-12]. Such a visuo-spatial map is critical since it allows for imitating an action independently of the demonstrator-imitator viewpoint. Also, prior neural models integrated exclusively either the imitation component (without mental simulation) or mental simulation (without imitation) mainly for navigation [10-13]. Also, many previous models used explicit inversions or optimization for inverse kinematics computations (e.g., [9]).

Here our long-term goal is to develop a hierarchical neural architecture inspired by the human biological simulation network in order to coherently merge high (cognitive) and low (sensorimotor) levels for actual/mental, observed/imitated dexterous arm movements. In this contribution we present our initial effort towards this goal. Specifically, the proposed neural model includes a fronto-parietal network having three main circuits that capture critical sensorimotor features: learning inverse kinematics to perform self-intended actual/mental reaching; dealing with environmental perturbations; predicting sensory consequences of motion; and visuo-spatial remapping to imitate arm movements observed from various viewpoints.

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II. CORTICAL NETWORKS MODELING

A. Cortical Network for Sensorimotor Control of the Arm

The first circuit allows for actual execution and computes the sensorimotor map (inverse model) between the goal and the neural command sent to the arm that can be modified by peripheral feedback from actual motion. The second fronto-parietal circuit allows for mental simulation. By using a copy of efference of the neural drive, it predicts the sensorimotor consequences of arm motion (forward model) and may be located in the posterior parietal cortex (PPC) and intra-parietal lobule (IPL) [14]. The predictions are sent back to the motor/premotor regions (inverse model) to guide the computation of the neural drive, forming thus an internal simulation loop. Such mechanisms may be used during human "mental simulation" of motor action [6,7]. Here "mental simulation" refers to (first person) motor imagery, or movements executed covertly without overt muscle activation, to imagine action effects. Such fronto-parietal circuitry is employed to learn the internal model of the inverse kinematics transformation of a humanoid robot arm with seven degree of freedom (DOF; modeled using the Denavit–Hartenberg parameterization) in 3D by encoding the mapping between the spatial and joint displacement of the arm (Fig. 1). Based on previous computational models, the frontal region of this neural architecture functionally (i.e., no explicit modeling of the anatomical circuitry) reproduces the population vector coding processes evidenced in the motor/premotor regions which are implemented using hyperplane radial basis function network [15,16]. Specifically, our neural network learns the inverse kinematic mapping by integrating visual inputs (hand motion, target location explicitly coded in Cartesian coordinates); proprioception of the current joint positions; neural drives; predicted spatial position; the goal of the action; and motor error (computed by the cerebellum [1]).

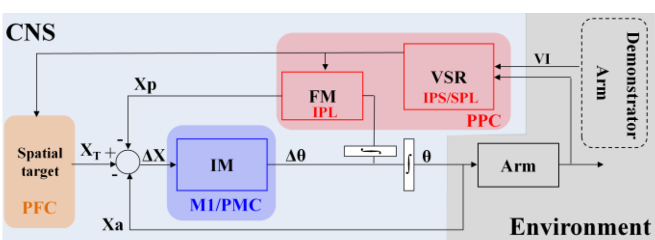

Figure 1: Overview of the structure of our neural architecture. The inverse model (IM) and the visuo-spatial remapping (VSR) are implemented using neural networks and the forward model (FM) using a closed-form. X and θ: spatial and joint position. X_T, Xa, Xp: the target, actual and predicted spatial arm position. ΔX: spatial displacements of the arm. The orange, dark blue and red areas represent the prefrontal (PFC), primary motor/premotor and parietal regions, respectively. VI: Visual Inputs.

Learning consists of generating random sensorimotor action-perception cycles where the neural commands are produced to execute various arm motions through the entire 3D workspace. During each action–perception cycle random joint displacements are endogenously generated from the current joint posture and are sent to the cortical network and the arm that moves, producing thus a corresponding spatial hand displacement. Using these spatial displacements, the model estimates corresponding joint displacements, comparing them to those randomly generated, resulting in an error signal used to adapt the network parameters. The detailed equations of this hyperplane radial basis network describing the computation of the inverse mapping to transform the Cartesian (ΔX) into joint (Δθ) displacements as well as the learning rules can be found in [15,16].

B. Cortical Network for Frame of Reference Remapping

The third fronto-parietal circuit transforms the observed movements from the demonstrator's (i.e., allo-centric coordinates) to the imitator's (i.e., ego-centric coordinates) frame of reference. The intra-parietal sulcus and superior parietal lobule (IPS/SPL) would implement such networks since those cortical areas are critical for humans to perform such frame of reference transformations [8,17,18] (Fig. 1). Then, those remapped visual inputs are conveyed to the two other fronto-parietal circuits allowing thus for movement observation and imitation [8,18]. Based on human neurophysiology, a radial basis function network was used to model this IPS/SPL region [8,17,18]. This neural network does not explicitly model the anatomical circuitry but the hypothesized functionalities. As such, this network's model implements viewpoint transformations by remapping the frame of reference using mental rotation, placing thus the demonstrator in the same perspective/orientation as the imitator to mentally simulate and imitate observed actions. By using an orthogonal least squares learning algorithm, this neural network learned a mapping that can be mathematically expressed as:

$$f_T = T_R(\theta_I, \theta_D) \quad T_R(u, v) = \begin{pmatrix} \cos(u-v) & -\sin(u-v) & 0 & 0 \\ \sin(u-v) & \cos(u-v) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (4)$$

where θ_I, θ_D, T_R represent the viewpoint angles (rotation around the z-axis) and the rotation, respectively. The angular displacement for mental rotation between the demonstrator and the imitator's viewpoints was defined as the rotation θ_I-θ_D. This network was trained using 25 uniformly distributed spatial reference points that covered the demonstrator's workspace. After training, mental rotation could be performed by the network that was trained separately from those implementing the inverse computation. Thus, as a first step, this fronto-parietal network is, to some extent, relatively consistent with the simulation network (mental simulation theory) that performs self-intended actual/mental actions [2,3], observed/imitated actions (fronto-parietal MNS) and mental rotation [4,5,8,17,18].

After learning, the neural model's performance was assessed on its self-intended actual and mental center-out reaching movements from an initial position (elbow flexed at 90°) towards 14 targets located in the 3D workspace at various distances from the initial wrist position. For each center-out reaching movement, the robustness of this neural model was assessed by examining online re-planning capabilities in the presence of unexpected perturbations during actual self-intended and imitated movements. The perturbations were impulses resulting in a change of 20% of the joint angle during both transient and steady-state motion. For both unperturbed/perturbed motion the reaching accuracy was assessed by computing reaching errors for each target. Finally, movement imitation capabilities were also examined during imitation of simple mirror actions using manipulation of small boxes (sequence of three movements). Three different viewpoints/orientations (i.e., demonstrator located in front as well as at 45° and 225° on the right and left side of the imitator) between the demonstrator and imitator with and without perturbing the imitator's movements were used. For each viewpoint, the remapping and reaching errors were computed with and without perturbation. Also, while the neural model did not aim to imitate point-to-point the entire observed trajectory, similarities between imitated and observed trajectories were assessed by computing their correlation coefficients (only in the absence of perturbation since movements from the demonstrator were unperturbed).

III. Results

After learning, the kinematic trajectories produced by our neural architecture were consistent overall with those observed during previous human experimental studies and the targets were accurately reached (average reaching error < 1 cm; for all targets). The joint and hand displacements were smooth and sigmoid-shaped, the joint and hand velocity profiles were generally single-peaked and bell-shaped while both joint and hand acceleration overall had biphasic profiles (e.g., [19]; Fig. 2). Also, the fronto-parietal internal loops allowed the neural model to mentally simulate/predict the consequences of neural commands (i.e., displacement of the hand in the Cartesian space) during self-intended reaching movements without overt output (Fig. 2, second row).

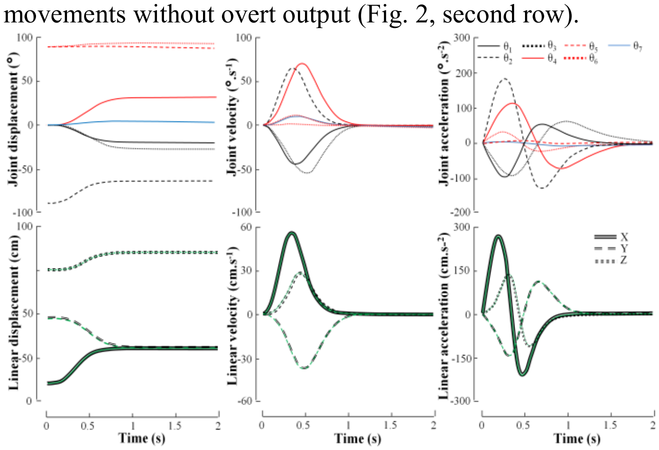

Figure 2: Kinematic performance of reaching movements. Typical displacement, velocity and acceleration profiles are represented in the left, center and right column, respectively. The first and second rows represent the joints and hand kinematics, respectively. The black and green lines are the actually and mentally executed hand movements, respectively.

Also, our cortical model was fairly robust to perturbations having significant amplitudes and applied during the steady-state and transient movement period during actual self-intended reaching movements. Specifically, in the presence of an impulse-type perturbation during both the transient and steady-state phases of movements, the joint and end-effectors trajectories re-converged towards the target and reached it with an accuracy comparable (<0.5%) to unperturbed conditions (Fig. 3). This confirms and extends previous results showing that this class of model provides flexibility even with a highly redundant non-linear kinematics chain such as an upper extremity [15,16,20]. Finally, our model accurately imitated observed movements executed by a demonstrator independently of demonstrator-imitator viewpoint (Fig. 4).

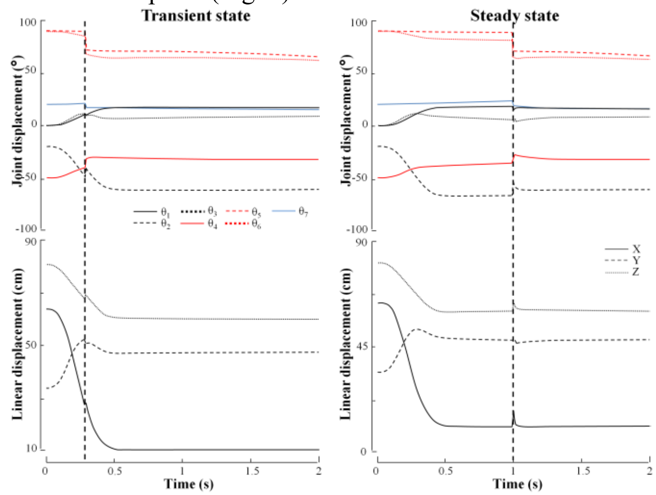

Figure 3: Kinematic assessment of the robustness of the neural model to unexpected perturbations. Responses of the cortical model to a brief perturbation applied during the transient (left column) and the steady (right column) states of the movement. Effects of the perturbation on the joint and hand displacements are shown in the first and second rows, respectively. The vertical dashed lines represent when the perturbation was applied.

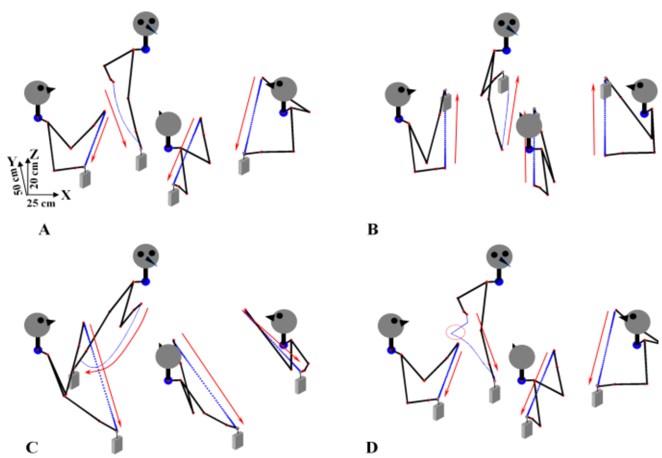

Figure 4: Imitation of mirror movements (reach (A), lift (B) and move (C) the box). The demonstrator is placed in front as well as at 45° and 225° on the right and left side of the imitator. (D) Imitated trajectories with perturbation (see within the dotted red circle). The blue lines and red arrows represent the hand trajectory and the movement direction, respectively.

The correlation coefficient between the imitated and observed trajectories ranged from 0.90 to 0.98, while the remapping and reaching errors were smaller than 3% of the limb length and 1.20 cm, respectively. Our neural model could also imitate the same action sequence executed by the demonstrator even when perturbed. While the imitated paths were fairly different due to the perturbation, reaching errors were similar (<0.5%) to unperturbed conditions (Fig. 4D).

IV. Discussion

We presented a neural architecture based on human mental simulation theory that coherently combines self-intended actual/mental observed/imitated movements by modeling three fronto-parietal circuits for sensorimotor processing (visuo-spatial coordinate mapping, sensorimotor predictions). The main finding is that our model was able to perform accurate, flexible and robust 3D reaching movements with a seven DOFs anthropomorphic arm under various execution modalities (self-intended actual/mental and imitated movements) while reproducing joint and end-effector movements with human-like kinematics [6,19] even when challenged by unexpected perturbations. This confirms and extends previous work suggesting that this class of neural model can reproduce neurophysiological and psychophysical data and emphasizes its capabilities when applied to upper limb reaching movements [15,16,20].

Although simplified (e.g., single reaching, closed-form forward model), our neural architecture could mentally simulate the consequences of neural drives (hand displacements) without overt execution. This is promising since it could serve as a future basis for higher-level cognitive structures (prefrontal cortex) enabling thus more complex mental simulations such as covert processing of the workspace constraints (reachable parts, obstacles, etc.). Our work complements some previous studies that examined mental simulation in robots by focusing on arm reaching rather than maze navigation and by proposing a neurally inspired architecture that allows for self-intended mental and actual performance as well as imitated movement [13,21].

Also, our model can imitate movements from various demonstrator-imitator viewpoints. This is consistent with past studies showing the existence of viewpoint dependent and independent neurons in the MNS, and more generally with the recruitment of a simulation network to execute mental/actual self-intended and observed/imitated actions [2, 22]. Although the kinematic correspondence between imitated and demonstrated movements was generally good, here the aim was not to imitate the demonstrator's trajectory point-to-point per-se but rather to re-map the relevant contact points (e.g., box handle) that can be considered as sub-goals of an action or task. This philosophy is in line with the idea that observation/imitation is further linked to the goals of action than kinematics [9-12]. Also, when considering previous learning by demonstration or MNS modeling studies (e.g., [9-12]), generally our work complements those efforts by proposing neural circuitry integrating visuospatial processing for frame of reference remapping as a system that subserves the MNS. However, here arm movements are not learned by imitation but by using a combination of self-intended actual motion via a babbling stage and performing visuo-spatial transformations such as mental rotation.

Thus, future work will focus on integrating into our model imitation learning, and will explore its combination with learning using self-intended actual and mental movements since these may accelerate motor learning in humans and robots [12]. Also, a higher cognitive level including a model of prefrontal cortex will be developed in order to enable a bi-directional flow of information between higher and lower levels as in the human prefrontal-parietal network. As a first step, the current neural model focused on kinematics without including the dynamics of effectors and object properties. These will be addressed by including neural elements to account for biomechanical and object dynamics (e.g., cerebellum [1]). Future work will also expand our model to control two arms, thus enabling bimanual performance with physical robotic arms in a real world environment involving object manipulations.

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