Published in final edited form as:
Conf Proc IEEE Eng Med Biol Soc. 2012 ; 2012: 3052–3055. doi:10.1109/EMBC.2012.6346608.

Cortex Inspired Model for Inverse Kinematics Computation for a Humanoid Robotic Finger

Rodolphe J. Gentili,
Department of Kinesiology, School of Public Health, Maryland Robotics Center, Neuroscience and Cognitive Science Program, University of Maryland, College Park, MD 20742 USA

Hyuk Oh [IEEE Members],
Neuroscience and Cognitive Science Program, University of Maryland, College Park, MD 20742 USA (hyukoh@umd.edu)

Javier Molina,
Department of Systems Engineering and Automation, Technical University of Cartagena, 30202, Cartagena, Spain (javi.molina@upct.es)

James A. Reggia, and
Department of Computer Science, University of Maryland Institute for Advanced Computer Studies, University of Maryland, College Park, MD 20742 USA (reggia@cs.umd.edu)

José L. Contreras-Vidal [IEEE Senior Member]
Department of Electrical and Computer Engineering, University of Houston, Houston, TX 77004 USA (pepe.contreras@ee.uh.edu)

Abstract

In order to approach human hand performance levels, artificial anthropomorphic hands/fingers have increasingly incorporated human biomechanical features. However, the performance of finger reaching movements to visual targets involving the complex kinematics of multi-jointed, anthropomorphic actuators is a difficult problem. This is because the relationship between sensory and motor coordinates is highly nonlinear, and also often includes mechanical coupling of the two last joints. Recently, we developed a cortical model that learns the inverse kinematics of a simulated anthropomorphic finger. Here, we expand this previous work by assessing if this cortical model is able to learn the inverse kinematics for an actual anthropomorphic humanoid finger having its two last joints coupled and controlled by pneumatic muscles. The findings revealed that single 3D reaching movements, as well as more complex patterns of motion of the humanoid finger, were accurately and robustly performed by this cortical model while producing kinematics comparable to those of humans. This work contributes to the development of a bioinspired controller providing adaptive, robust and flexible control of dexterous robotic and prosthetic hands.

I. Introduction

The multiple joints, tendons and muscles of the human hand allow the fingers to reach diverse spatial positions via various trajectories, resulting thus in a high degree of versatility which is critical in daily activities [1]. Such finger flexibility involves a complex neural control system where a particular trajectory has to be selected, planned and executed to

Corresponding author, phone: 301-405-2490; fax: 301-405-2458; rodolphe@umd.edu.

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account for various task constraints (e.g., accuracy) or changing environments (e.g., external perturbation) [1].

Thus, it is not surprising that in recent years the field of humanoid robotics has devoted substantial efforts to design artificial anthropomorphic hands that are expected to achieve performance as close as possible to human hands. This work has tried to replicate hand/finger sensorimotor coordination, transformation and adaptability to the task demand as well as to the dynamics of unstructured environments [1],[2]. However, although multi-fingered humanoid hands are expected to have the versatility to perform fine and complex tasks that are impossible with a simple gripper, such multi-fingered humanoid hands are a complex kinematic system. In most recently developed humanoid robotic hands (e.g., Shadow Hand [3], Robonaut Hand [4]) each finger is an independent kinematic chain with multiple degrees of freedom. Since finger mechanical design is based on their human homologues, the last two joints of the fingers are mechanically coupled by employing linkage specialized mechanisms such as the tendon or timing belt (e.g. [4],[5]).

In order to command such complex kinematic mechanisms, a robotic controller has to learn the internal models of forward and inverse sensorimotor transformations (e.g., inverse kinematics) for reaching and grasping. However, this is a complex problem since the mapping between sensory and motor spaces is highly nonlinear and depends on the constraints imposed by the physical features of the robotic finger, such as the coupling of the two last joints, as well as by the changing environment [5],[6].

In order to solve this inverse kinematics problem, two neural modeling approaches can be contemplated. The first one includes models that do not account for any particular neurophysiological substrate, resulting in very limited biological plausibility (e.g., [7]). The second approach proposes neural models that are biologically conceivable by incorporating particular brain structures and/or functions such as the cerebellum [8],[9] or the population vector coding processes that were previously revealed in motor/premotor areas [10]–[14]. Consistent with the second approach, recently a cortical network model able to learn the internal inverse kinematics model of a simulated anthropomorphic robot finger was proposed [13],[14].

Here, we aimed to test if such a cortical model was robust enough to learn the internal inverse kinematics model for an actual anthropomorphic humanoid finger having its two last joints coupled and controlled by a bio-inspired actuator such as artificial antagonist pneumatic muscles.

II. Modeling Approach

A. Cortical Network Modeling

The cortical architecture developed here extends previous models of reaching [10],[11] that functionally (i.e., no explicit modeling of the cortical circuitry was included) replicate the population vector coding processes previously revealed in the motor and premotor cortices [15]. Specifically, our cortical model aims to learn the internal representations of the inverse kinematics of an anthropomorphic robotic finger by acquiring the mapping between spatial and joint displacements of the finger generated by the motor commands. Such an inverse kinematics mapping is learned by integrating i) visual information (fingertip motion, 3D targets localization); ii) proprioceptive information that encodes the current state of the humanoid finger (joint position); iii) the neural drive that conveys information about motor performance; iv) the goal-related information involved in motor planning; and v) the motor error (e.g., computed by the cerebellum; [8–9]).

The robotic platform employed here consisted of the ShadowHand™ finger [3] which is an anthropomorphic humanoid finger actuated by three pairs of pneumatic antagonist muscles (see Fig. 1). The first and second pair of muscles control the movement of adduction-abduction and flexion-extension of the metacarpophaleangeal (MCP), joint respectively. The third pair controls the movement of flexion-extension for both the proximal interphalangeal (PIP) and distal interphalangeal (DIP) joints. Thus, when considering such an actuation system, this (three degrees of freedom) humanoid finger includes a mechanical coupling between the PIP and the DIP making the computation of the inverse kinematics particularly challenging [5],[6].

Specifically, the relationship between spatial and joint velocities of the robotic finger can be described as follow:

$$\Delta \mathrm{x}=\mathrm{J}(\theta)\,\Delta\theta \quad (1)$$

where Δx, $\Delta\theta$ and J are the spatial and joint velocity and the Jacobian matrix of the humanoid finger, respectively. To obtain a joint rotation vector that moves the robotic finger at a desired spatial velocity, (1) can be rewritten as follow:

$$\Delta\theta=\mathrm{G}(\theta)\,\Delta \mathrm{x} \quad (2)$$

where $G(\theta) = J^{-1}(\theta)$ is an inverse of the Jacobian matrix. Here, the elements of the matrix $G(\theta)$ are denoted by $g_{ij}(\theta)$, where indices i and j refer to the joint space and the 3D workspace dimensions, respectively. Each entry of $G(\theta)$ was implemented by a radial basis function network that forms a 'context field' that changes its activity when recognizing a particular joint configuration (θ) as inputs [16]. The output of each network $g_{ij}(\theta)$ is given by:

$$\mathrm{g}_{\mathrm{ij}}(\theta)=\sum_{\mathrm{k}}\left(\frac{\mathrm{A}_{\mathrm{ijk}}}{\sum_{\mathrm{k}}\mathrm{A}_{\mathrm{ijk}}}\right)\left(\mathrm{w}_{\mathrm{ijk}}+\sum_{\mathrm{m}}\mathrm{c}_{\mathrm{ijkm}}\mathrm{z}_{\mathrm{ijkm}}\right) \quad (3)$$

$$\mathrm{c}_{\mathrm{ijkm}}(\theta)=\frac{\theta_{\mathrm{m}}-\mu_{\mathrm{ijkm}}}{\sigma_{\mathrm{ijkm}}} \quad (4)$$

where k is the index of the basis function, the vector c_{ijkm} represents the distance between the input value θ and the center of the k^{th} basis function, and A_{ijk} is the activation of the basis function with a Gaussian function where μ_{ijkm} and σ_{ijkm} are the centers and the standard deviations along the dimension m of the k^{th} Gaussian activation function, respectively. Each basis function is associated with a weight w_{ijk}, related to the level of the data 'under its receptive field'. The set of weights z_{ijkm} allow for locally and linearly approximating the slope of the data 'under its receptive field'. These weights were modified through a learning process described in the next section.

B. Sensorimotor Learning

The learning strategy consists of a sensorimotor exploration (or babbling) phase. Successive action-perception cycles were performed during which the motor commands were generated to execute various finger movements to reach random targets located in the 3D workspace (Fig. 1). Specifically, during each action–perception cycle, random joints angles ($\Delta\theta^R$; R denotes random movements) were endogenously generated from current joint configurations (denoted by θ) that were provided as inputs to the neural architecture as well as to the humanoid finger in order to reach the corresponding joint configuration. Simultaneously, the corresponding spatial displacements (Δx) of the fingertip in the 3D workspace was recorded by a motion capture system (Optotrak®) and then provided to the cortical model. Then, based on these spatial displacements, the cortical model estimated the joint angles ($\Delta\hat{\theta}$) that were compared to the corresponding random joint movements, providing therefore an error signal that guided the adaptation of the network parameters (e.g., w_{ijk}, z_{ijkm} in (3); for further details on the model implementation, see [11]–[14]).

C. Performance Assessment of the Cortical Model

After the learning period during which the internal model of the inverse kinematics of the humanoid finger was encoded, the performance of the cortical model was first assessed by performing 3D center-out reaching movements towards 12 targets placed in three different planes. The targets located in the back (n=3), middle (n=6), and front (n=3) plane involved: i) a combination of flexion/extension and adduction movements, ii) only flexion/extension movements and iii) a combination of flexion/extension and abduction movements, respectively (Fig. 2B). This assessment was also conducted throughout learning to examine the evolution of the formation of the internal model of the inverse kinematics of the humanoid finger. In addition, the robustness of this cortical network model was assessed by performing center-out reaching movements in the presence of perturbations. Namely, the humanoid finger was subjected to a sudden and brief perturbation representing a substantial increase of 10° of each estimated joint angle (i.e., computed by the cortical model) to the robotic finger during both the transient and steady-state phases of the motion. Finally, the capabilities of this cortical network model to control more complex motion with this humanoid finger were also investigated. Namely, the finger had to perform several reversal motions between the inside of two cylinders (~1 cm of diameter) without touching them, which required continuous and accurate control. The planning system for this task generated a set of four targets (2 outside and 2 inside each cylinder) that the finger had to successively reach continuously and accurately. Such a task combined flexion-extension motion of the MCP and, most importantly, of the PIP and DIP for which it was particularly critical that the cortical model learned efficiently their mechanical coupling in order to fulfill the task demand.

III. Results

The performance error and its variability (mean and standard deviation) were progressively reduced throughout the learning period for the targets located in the back, the middle and frontal planes. In particular, for all planes considered, the average reaching errors were equal to 25.98 ± 11.76 mm, 2.20 ± 0.81 mm and 0.51 ± 0.29 mm for the early, middle and late learning periods, respectively (Fig. 2A). Although the overall errors were small, the highest error values were obtained for the back and the front plane.

After learning, the cortical network was able to control the humanoid finger. The angular and linear displacements were sigmoid-shaped while the velocity profiles were generally single-peaked and bell-shaped. The trajectories were slightly curved and the targets were accurately reached (Fig. 2B and 3). The findings also revealed that the cortical model was robust to perturbations while performing reaching movements. Namely, when the perturbation was applied during both the transient and steady-state phases of the movement, the trajectory re-converged to the desired position and finally reached the target accurately. For instance, when the robotic finger had to reach a target placed in one of the most remote regions of the workspace by inducing a combined movement of flexion-extension and abduction-adduction, the cortical model was able to reach the target with a similar accuracy (~1°) for both unperturbed and the same perturbed reaching movement (Fig. 4A–B).

Finally, the results also revealed that the cortical model was able to control the humanoid finger in order to perform continuously and accurately multiple reversal movements between two cylinders without touching them (Fig. 4C–D).

IV. Discussion

A cortical network architecture functionally similar to the motor and premotor cortices was able to learn an internal model of the inverse kinematics of a humanoid robotic finger that included a mechanical coupling between the PIP and the DIP joints as in humans. Specifically, this cortical model was able to: i) produce similar linear and angular kinematics features as those observed in humans for finger motion and grip production [1],[17]; ii) maintain an accurate and robust control in the presence of perturbations and iii) perform relatively complex motions such as multiple reversals via continuous and accurate movements.

More specifically, once the inverse kinematics was learned, the cortical model was able to control the robotic finger in order to reach accurately the targets exhibiting sigmoid-shaped angular and linear displacements as well as single-peaked and bell-shaped angular and linear velocity profiles. For some targets a secondary (small) peak was observed in specific joints, which was in accordance with results from human studies [1]. Furthermore, consistent with previous experimental studies, the cortical model produced slightly curved trajectories [1],[17]. Overall, the present kinematics results obtained with a physical humanoid robotic finger confirm and extend those previously obtained in simulations [13],[14]. Although the kinematics obtained both in simulation and during this robotic experiment, appear to be comparable to those observed in humans, further testing is currently in progress to directly compare these kinematics with their human counterparts while performing the same task (e.g., center-out reaching, reversal movements).

In addition, this cortical network model was robust to sudden perturbations of substantial magnitude. This is an important and desirable feature since in daily tasks humanoid hands/fingers may be subjected to various types of perturbation during finger reaching and grasping, especially in unstructured environments [2]. Also, the changes observed in the joint angles computed by the cortical model under perturbed conditions indicate that the perturbations were not corrected through feedback but compensated by the cortical model that changed its on-line activity to re-converge to the targets. Further assessment of robustness is currently underway, including perturbations applied for a longer time period. Finally, the model was able to perform more complex tasks than single reaching motions, such as continuous multiple reversal movements under accuracy constraints. The good performance with such a task suggests that our cortical model is able to perform ecologically valid finger movements involving fine manipulations. In particular, these findings suggest that our cortical neural network learned accurately the coupling between the PIP and the DIP, and provides therefore a biologically-inspired solution for the inverse kinematics computation applied to humanoid hands/fingers that include a coupling of the two last joints. Such a cortical architecture provides a possible viable on-line alternative solution to the inverse kinematics problem, something that is particularly challenging for robotic fingers including coupled joins without using look-up tables combined with linear interpolation [5],[6].

Overall, the current findings suggest that our cortical model can reproduce accurate, flexible and robust ecologically valid finger reaching movements when controlling an actual anthropomorphic robotic finger. This is important since such a cortical model could provide a robust, accurate and flexible bio-mimetic controller for humanoid finger/hand motions

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providing thus a unique manual ability and versatility that is critical for many daily activities [1].

However, future work will need to further assess the capabilities of this cortical network to robustly perform other complex ecologically valid tasks such as typing, drawing and tracking tasks as well as its flexibility during on-line control for targets switching during on-going movements.

Although the focus of the present work was the kinematics, future work will also focus on the dynamics of the fingers since, for now, our cortical network model does not include any component accounting for biomechanical dynamics (e.g., gravity, inertia). This could be studied by incorporating a model of the cerebellar structures that have been considered to encode internal models of the inverse dynamics [8], [9]. The long term goal of this research is to design a bio-mimetic controller providing adaptive, robust and flexible control of dexterous robotic/prosthetic hands.

Acknowledgments

This author has been supported by La Fondation Motrice (Paris, France).

References

1. Kamper DG, Cruz EG, Siegel MP. Stereotypical fingertip trajectories during grasp. J Neurophysiol. 2003; vol. 90:3702–3710. [PubMed: 12954607]
2. Conforto S, Bernabucci I, Severini G, Schmid M, D'Alessio T. Biologically inspired modelling for the control of upper limb movements: from concept studies to future applications. Front Neurorobotics. 2009; vol. 3(3):1–5.
3. Shadow Robot Company: http://www.shadowrobot.com/.
4. Lovchik CS, Difler MA. The robonaut hand: A dextrous robotic hand for space. Proc. IEEE ICRA. 1999:907–912.
5. Jiang L, Sun D, Liu H. An Inverse-Kinematics Table-Based Solution of a Humanoid Robot Finger With Nonlinearly Coupled Joints. IEEE/ASME Trans. Mech. 2009; vol. 14(3):273–280.
6. Godler, I.; Hashigushi, K.; Sonoda, T. IEEE International Workshop on Advanced Motion Control. Nagaoka Japan: 2010. Robotic finger with coupled joints: a prototype and it sinverse kinematics; p. 337-342.
7. Oyama, E.; Chong, NY.; Agah, A. Inverse Kinematics Learning by Modular Architecture Neural Networks with Performance Prediction Networks; Proceedings of the 2001 IEEE International Conference on Robotics& Automation; Seoul, Korea. 2001.
8. Gentili RJ, Papaxanthis C, Ebadzadeh M, Eskiizmirliler S, Ouanezar S S, et al. Integration of gravitational torques in cerebellar pathways allows for the dynamic inverse computation of vertical pointing movements of a robot arm. PLoS 1. 2009; vol. 4(4):e5176. [PubMed: 19384420]
9. Schweighofer N, Arbib MA, Kawato M. Role of the cerebellum in reaching movements in humans. I. Distributed inverse dynamics control. Eur J Neurosci. 1998 Jan; 10(1):86–94. [PubMed: 9753116]
10. Bullock D, Grossberg S, Guenther FH. A self organizing neural model for motor equivalent reaching and tool use by a multijoint arm. J. Cog. Neuroscience. 1993; vol. 5(4):408–435.
11. Guenther, FH.; Micci-Barreca, D. Neural models for flexible control of redundant systems. In: Morasso, PG.; Sanguinett, V., editors. Self-Organization, Computational Mapsand Motor Control. Elsevier, Psychol. series; 1997. p. 383-421.
12. Molina-Vilaplana J, Feliu-Batlle J, Lopez-Coronado J. A modular neural network architecture for step-wise learning of grasping tasks. Neural Netw. 2007; vol. 20(5):631–645. [PubMed: 17442538]
13. Gentili, RJ.; Molina, J.; Oh, H.; Contreras-Vidal, JL. Neural Network Models for Reaching and Dexterous Manipulation in Humans and Anthropomorphic Robotic Systems. In: Custuridis, V.;

Hussain, A.; Taylor, JG., editors. Perception-action cycle: Models, architectures and Hardware. New York: Springer; 2011. p. 187-218.

14. Gentili RJ, Oh H, Molina J, Contreras-Vidal JL. Cortical Network Modeling for Inverse Kinematic Computation of an Anthropomorphic Finger. Proc. IEEE EMBS, Boston. 2011
15. Georgopoulos AP, Schwartz AN, Kettner RE. Neuronal population coding of movement direction. Science. 1986; vol. 233:1416–1419. [PubMed: 3749885]
16. Fiala, JC. Ph.D. dissertation, Cog. & Neural Syst. Boston, MA: Department, Boston University; 1995. Neural network models of motor timing and coordination.
17. Grinyagin IV, Biryukova EV, Maier MA. Kinematic and Dynamic Synergies of Human Precision-Grip Movements. J Neurophysiol. 2005; vol. 94(4):2284–2294. [PubMed: 15917316]

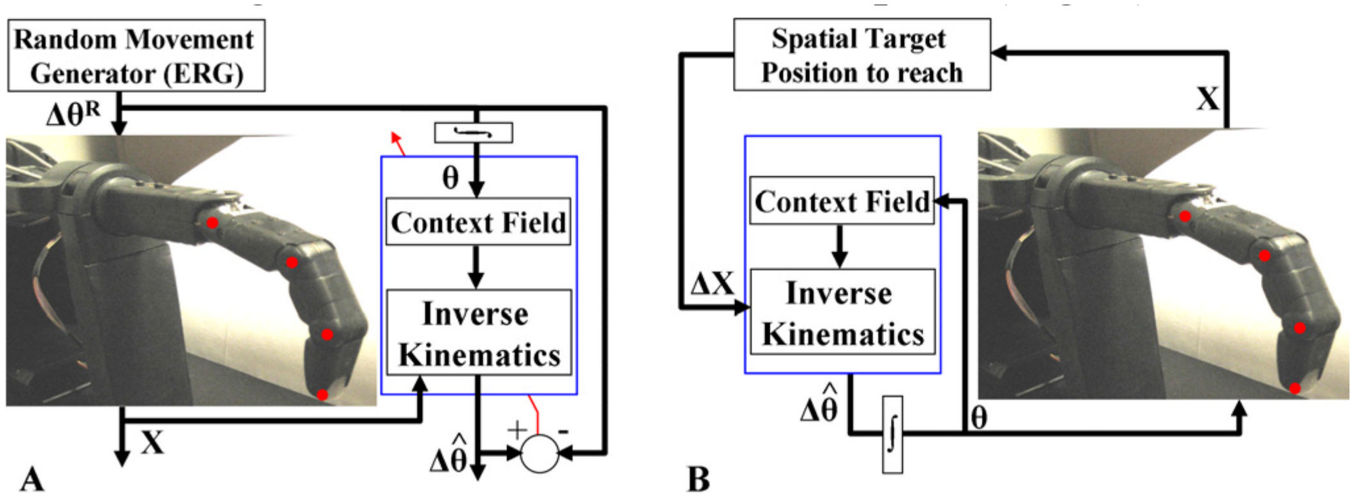

Fig 1.

Cortical model for inverse kinematics learning and control of the humanoid finger. (A) During learning, the Endogenous Random Generator (ERG) generates random angular displacements ($\Delta\theta^R$) resulting in spatial displacements (Δx) of the robotic finger. These displacements allow the cortical model to compute an estimation of angular displacements ($\Delta\hat{\theta}$) and compare them to those randomly generated. (B) During performance, the cortical model executed 3D reaching movements to various spatial targets. A PID controller received as input the angular joints computed by the cortical model and provided the corresponding pressure to the pneumatic muscles to move the finger accordingly. A movement-gating GO signal (not shown) triggered voluntary motion [8].

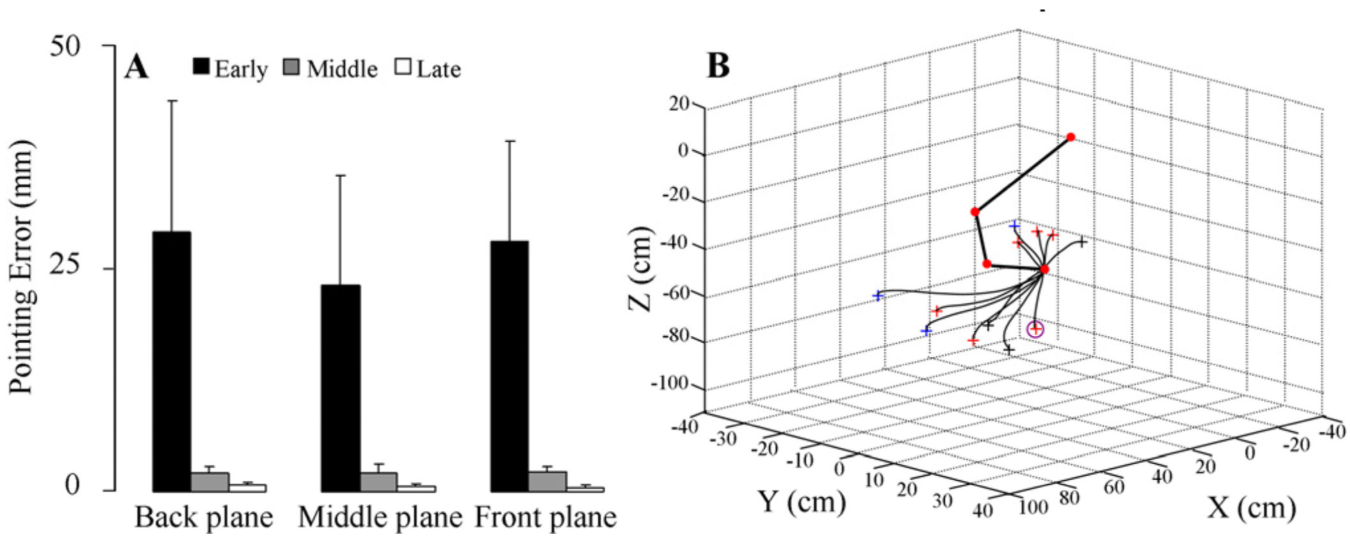

Fig 2.

(A) Performance (average reaching error and standard deviation) of the cortical model during early, middle and late learning. (B). Reaching trajectories of the humanoid fingertip (the stick diagram represents the initial position of the humanoid finger) toward the spatial targets (rear (blue), middle (red) and front (black) planes) placed in the workspace.

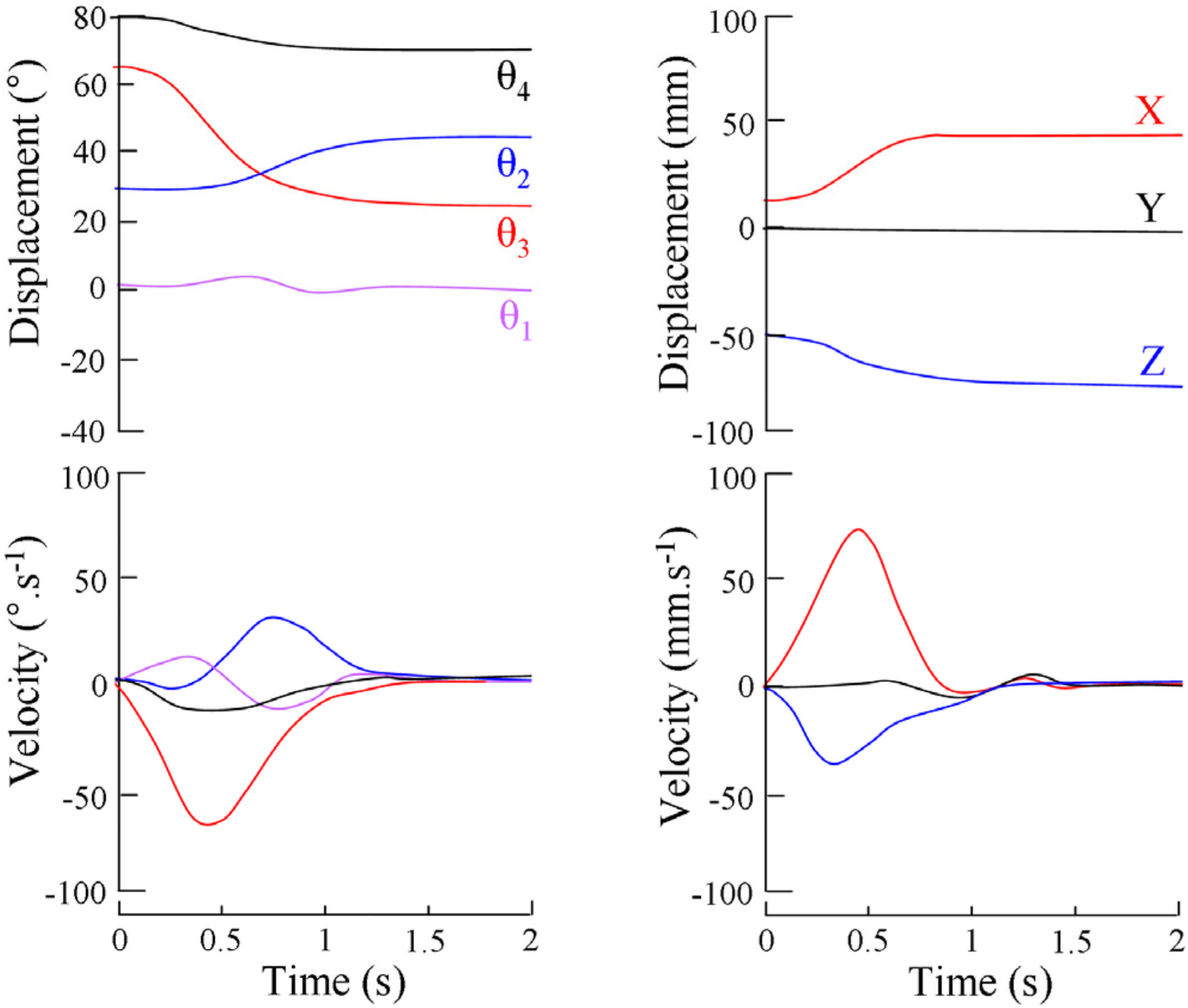

Fig 3.
Typical angular (left column) and linear (right column) kinematics generated by the cortical model after learning. Here the target reached is indicated in Fig. 2B by a purple circle. Displacement and velocity profiles are depicted in the first and second row, respectively.

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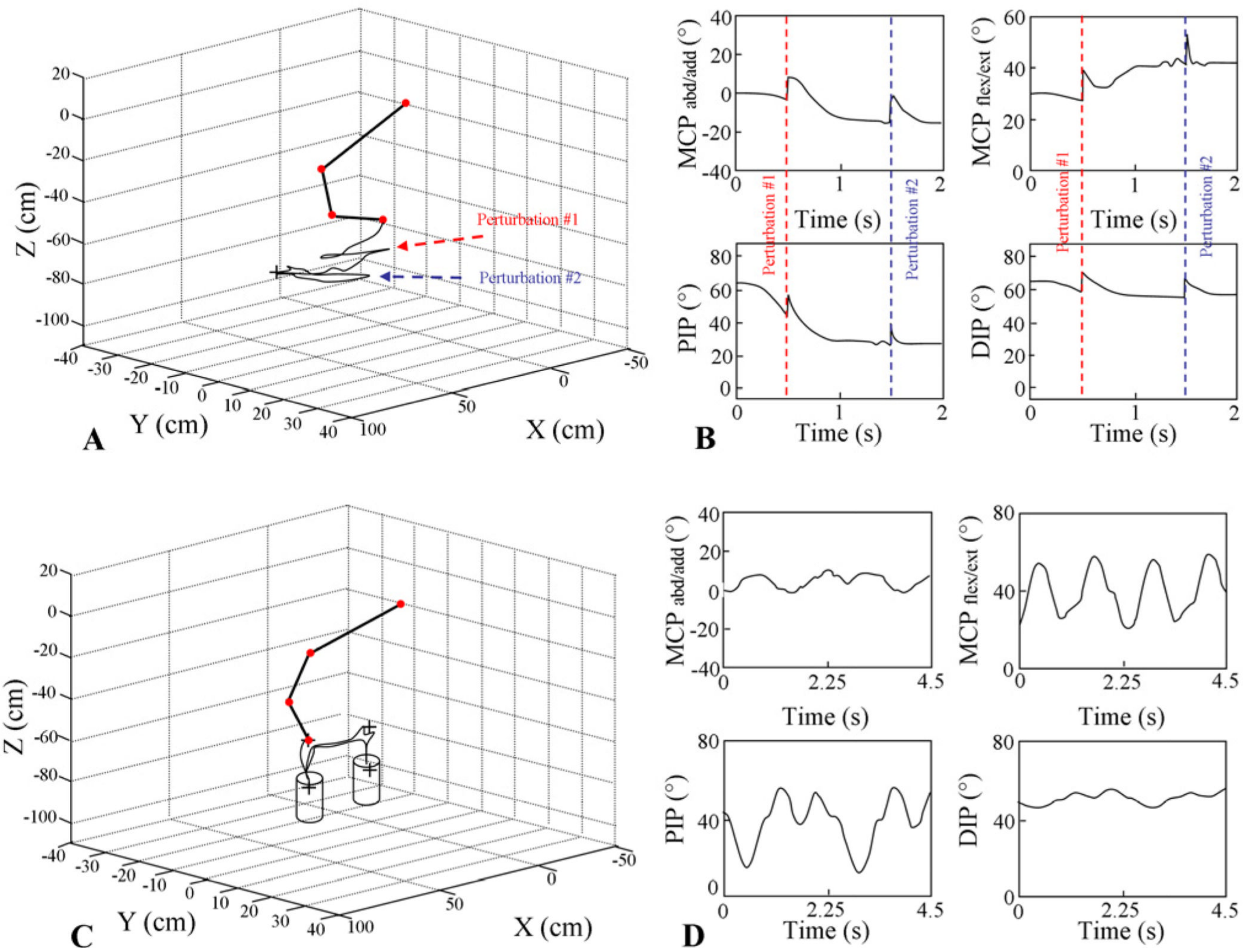

Fig 4.

(A–B) Response of the cortical model to two successive perturbations applied during the transient and steady-state phases of motion to a remote target by inducing flexion/extension and abduction/adduction motion. Effects of the perturbation on the trajectory (A) and the joints angles (B, computed by the model) of the humanoid finger. (C–D): Continuous and accurate performance (trajectories (C) and joint angles (D)) of the robotic finger during multiple reversal movements between two cylinders.