# Biologically-Based Functional Mechanisms of Coarticulation


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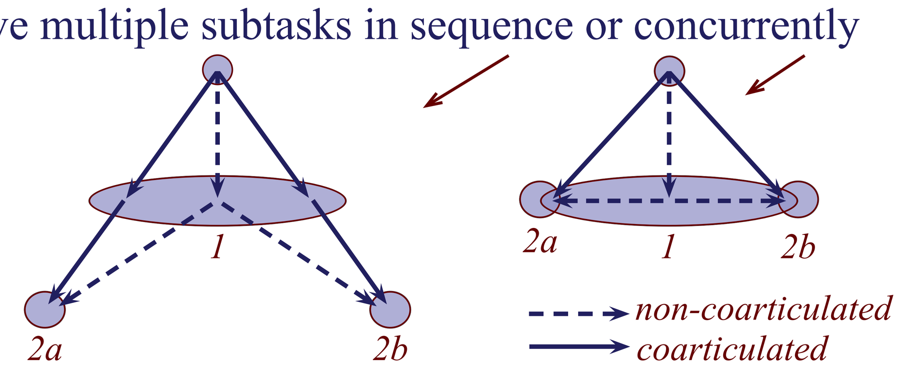
## Introduction

Often, a complex motor task can be decomposed into a set sequence of subtasks. When there is *redundancy* in how each subtask is performed, we choose a way that tends to be best for the overall task. This behavior, termed *coarticulation*, is characteristic of a learned motor skill. Previous theories of motor control suggest that coarticulation may be elicited by explicitly combining motor commands of contiguous movements[17,18] or by introducing tertiary objectives, such as smoothness[14], in solving a task. While these theories provide valuable clues as to what strategies are useful in learning a task, they were not based on biologically-plausible mechanisms. In this poster, we present a model in which functional mechanisms attributable to brain areas control a redundant system in order to solve a set sequence of subtasks. Resulting behavior displays characteristics of coarticulation.

## Coarticulation

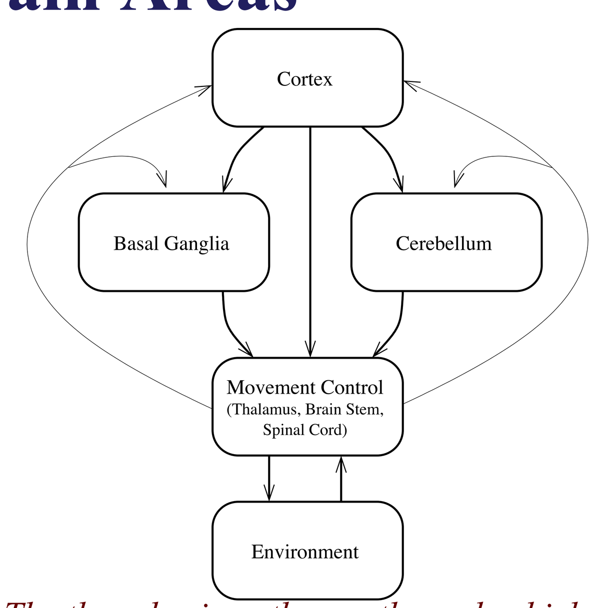
- ❑ Exploit excess DOFs to best solve multiple subtasks in sequence or concurrently
- ❑ For a given subtask, the coarticulated strategy may
  - differ depending on overall task
  - be suboptimal in isolation
- ❑ Seen at many levels:
  - how fingers are recruited[2]
  - how a chosen arm[3] or hand[13] is used
  - preshaping[12] ,bimanual coordination[22]
  - transfer of sensory representation[11]




*Schematic illustrating coarticulation effects. The task is to move from the top region to region 1, and then to either region 2a or to 2b, with the shortest possible path. Redundancy in the target regions allow for coarticulation.*

## Mechanisms Attributable to Brain Areas

- ❑ Different areas perform different functions
  - cortical areas: represent task[6,19], devise reasonable solutions[6], working memory[8]
  - cerebellum: error correction[15]
  - basal ganglia: exploration[10] and reward-mediated learning[4,21], critical for coarticulation[20]
- ❑ Exploration occurs on several levels
  - coarse action (*e.g.*, which arm or finger to use)
    - possibly due to coarse segregation of pathways[1,16]
  - fine action (*e.g.*, how to use an arm or hand)
    - possibly due to fine integration of pathways[9]
  - sensory[5,7,9] (*e.g.*, which sensory modality to use)
- ❑ Different functions cooperate to solve task
  - BG explores and uses rewards to find better solutions
  - cortex and cerebellum restrict exploration to the *null space* of the subtask
    - space of action and sensory choices such that the subtask is always solved




*The three basic pathways through which voluntary movement is controlled.*

## Hypotheses

- ❑ In a redundant system, coarticulation and, hence, better movement, is elicited by
  1. evaluating movements based on *overall task*, not subtask, performance
  2. exploring over several levels simultaneously

## References and Acknowledgements


1. Alexander GE, Delong MR, and Strick PL (1986). Parallel Organization of Functionally Segregated Circuits Linking Basal Ganglia and Cortex. *Annual Review of Neuroscience.* 9:357-381.
2. Baader A, Kasennikov O, and Wiesendanger M (2005). Coordination of Bowing and Fingering in Violin Playing. *Cognitive Brain Research*. 23:436-443.
3. Breteler MK, Hondzinski J, and Flanders M (2003). Drawing Sequences of Segmens in 3D: Kinetic Influences on Arm Configuration. *Journal of Neurophysiology*. 89:3253-3263.
4. Centonze D, Picconi B, Gubellini P, Bernari G, and Calabresi P (2001). Dopaminergic Control of Synaptic Plasticity in the Dorsal Striatum. *European Journal of Neuroscience.*13:1071-1077.
5. Debaere F, Wenderoth N, Sunaert S, Hecke PV, and Swinner S (2003). Internal vs External Generation of Movements: Differential Neural Pathways Involved in Bimanual Coordination Performed in the Presence or Absence of Augmented Visual Feedback. *Neuroimage.* 19:764-776.
6. Duncan J (2001). An Adaptive Coding Model of Neural Function in the Prefrontal Cortex. *Nature Reviews Neuroscience.* 2:820-829.
7. Flaherty AW and Graybiel AM (1991). Corticostriatal Transformations in the Primate Somatosensory System. Projections From Physiologically Mapped Body-Part Representations. *Journal of Neurophysiology.* 66:1249-1263.
8. Goldman-Rakic PS (1995). Celluar Basis of Working Memory. *Neuron.* 14:477-485.
9. Graybiel AM, Aosaki T, Flaherty AW, and Kimura M (1994). The Basal Ganglia and Adaptive Motor Control. *Science.* 265:1826-1831.
10. Gurney K, Prescott T, and Redgrave R (2001). A Computational Model of Action Selection in the Basal Ganglia. I. A New Functional Anatomy. *Biological Cybernetics.*84:401-410.
11. Hikosaka O, Nakahara H, Rand MK, Sakai K, Lu X, Nakamura K, Miyachi S, and Doya K (1999). Parallel Neural Networks for Learning Sequential Procedures. *Trends in Neuroscience*. 22:464-471.
12. Jeannerod M (1981). Intersegmental Coordination During Reaching at Natural Visual Objects. *Attention and Performance IX*. Long J and Baddeley A (eds). pages 153-169, Hillsdale, NJ: Lawrence Erlbaum Associates.
13. Jerde T, Soechting J, and Flanders M (2003). Coarticulation in Fluent Finger Spelling. *The Journal of Neuroscience*. 23:2383-2393.
14. Jordan MI (1992). Constrained Supervised Learning. *Journal of Mathematical Psychology*. 36:396-425.
15. Kitazawa S, Kimura T, and Yin P (1998). Cerebellar Complex Spikes Encode Both Destinations and Errors in Arm Movements. *Nature.* 392:494-497.
16. Middleton FA and Strick PL (2000). Basal Ganglia and Cerebellar Loops: Motor and Cognitive Circuits. *Brain Research Reviews.* 31:236-250.
17. Platt R, Fagg A, and Grupen R (2002). Nullspace Composition of Control Laws for Grasping. *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems.*
18. Rohanimanesh K, Platt R, Mahadevan S, and Grupen R (2004). Coarticulation in Markov Decision Processes. *18th Annual Conference on Neural Information Processing Systems*, Vancouver, BC, Canada.
19. Tanj J. (2001). Sequential Organization of Multiple Movements: Involvement of Cortical Motor Areas. *Annual Review of Neuroscience.* 24:631-651.
20. Tyrone M, Kegl J, and Poizner H (1999). Interarticulator Coordination in Deaf Signers with Parkinson's Disease. *Neuropsychologia.* 37:1271-1283.
21. Wickens J, Reynolds J, and Hyland B (2003). Neural Mechanisms of Reward-Related Motor Learning. *Current Opinion in Neurobiology.* 13:685-690.
22. Wiesendanger M and Serrien D (2001). Toward a Physiological Understanding of Human Dexterity. *News in Physiological Science*. 15:228-233.



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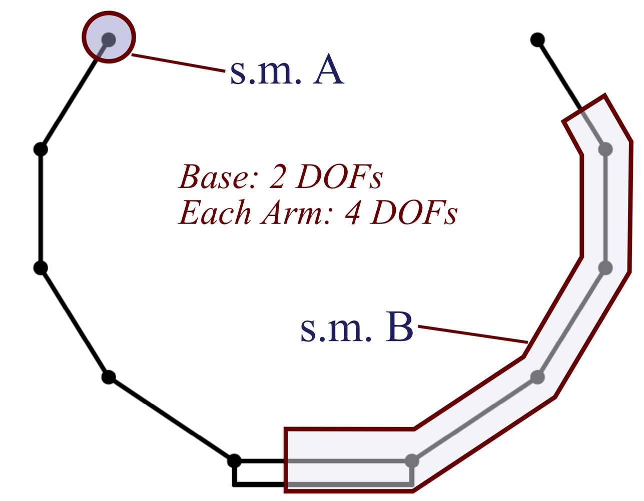
## Model Description

- ❑ System: 10 DOF planar kinematic "robot[14]"
- ❑ Task: hit a set sequence of extrinsic targets ($\mathbf{x}_i^{targ}$) with its "hands" in minimum time
- ❑ Must specify a $\mathbf{q}_i$ to hit $\mathbf{x}_i^{targ}$
- ❑ Movement: constant velocity from $\mathbf{q}$ to $\mathbf{q}_i$

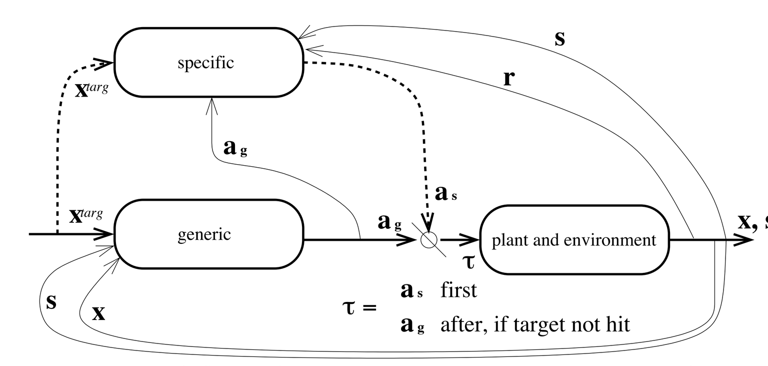
$$\mathbf{q} \leftarrow \mathbf{q} + \alpha \frac{\mathbf{q}_i - \mathbf{q}}{||\mathbf{q}_i - \mathbf{q}||}$$




- ❑ Termination of movement depends on sensory modality (s.m.):
  - s.m. A, analogous to vision
    - based on extrinsic information
    - terminates movement when hand hits target or expected end-point
    - only directed towards one hand at a time
  - s.m. B, analogous to proprioceptive
    - based on intrinsic information
    - terminates movement when $\mathbf{q} = \mathbf{q}_i$ for chosen arm and base
    - includes a penalty of 10 time steps
  - if one arm uses s.m. B, the other can move with s.m. A concurrently

## General Control Scheme

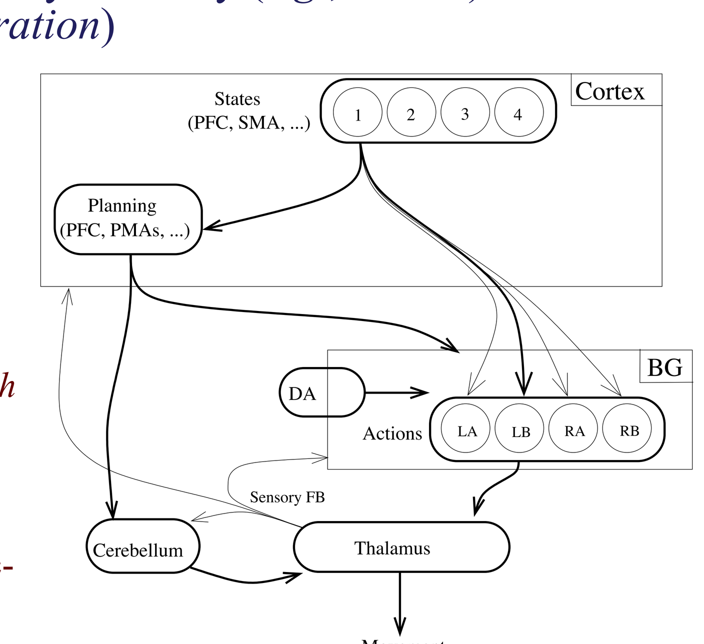
- ❑ Generic controller, **G**
  - can find a reasonable $\mathbf{q}_i$ (most direct solution) to hit any target
  - provides initial solutions and corrections
  - uses Jacobian matrix
  - requires s.m. A
- ❑ Specific controller, **S**
  - uses exploration and reward information to find better solutions




*Control flow diagram.* **S** *suggests a control signal, such as a candidate configuration. After the system moves, if the target isn't hit,* **G** *calculates a configuration from the current one that does hit the target.* **S** *uses reward information to update its solutions.*

## Neural Representation

- ❑ ***State***: current target + limited history (none or previous action)
  ***Action***: choose arm (*e.g.*, L or R) and sensory modality (*e.g.*, A or B) (*coarse action* and *sensory exploration*)
- ❑ $\mathbf{q}_i$ stored in action and can be modified (*fine action exploration*)
- ❑ Reward information (*e.g.*, DA) modulates weights of corticostriatal mapping
  - represented in model as best reward received for taking that action in that state




*Neural representation of control scheme, illustrated for a task consisting of four targets and a system which represents the current target with no history and has four* Actions *(LA, LB, RA, RB). The* Planning *area and* Cerebellum *provide the functions of the generic controller, while the* BG *provide the functions of the specific controller. The thin arrows from* State 1 *to* Actions *LA, RA, and RB indicate that the associated rewards are less than the current best choice,* LB.

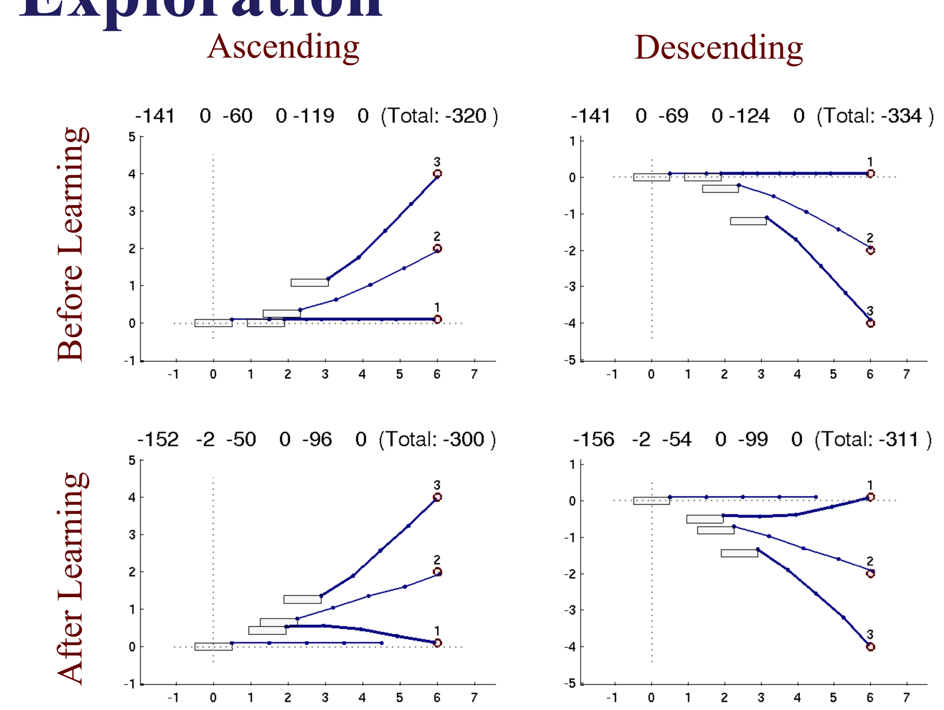
## Learning

- ❑ For each state, make a movement:
  1. select an action based on reward information (ε-greedy, coarse action & sensory exploration)
  2. add noise, $N(0,\sigma)$, to selected $\mathbf{q}_i$ (fine action exploration)
  3. move towards noisy target configuration until termination
  4. if necessary, use **G** to make a corrective movement
  5. record reward and new configuration as $\mathbf{q}_i^*$
  6. transition to next state
- ❑ After entire task is completed, for each selected action, if total reward > current best reward, replace stored $\mathbf{q}_i$ with $\mathbf{q}_i^*$ and update current best reward
  - analogous to modifying weights of corticostriatal mapping

*The following figures illustrate the kinematic robot's behavior for several tasks. Shown are the robot's configurations when it hits the targets. On the top of each graph are the rewards received for each movement, including a corrective movement if necessary, and the total reward. For each figure, the top graph shows the robot's configurations before learning (using just the generic controller to find configurations), and the bottom graph shows the robot's configurations after learning for about 15,000 trials. For clarity, the left arm is plotted in red and the right arm is plotted in blue. In addition, the configuration of the robot is plotted with an alternating pattern of thick and thin lines.*

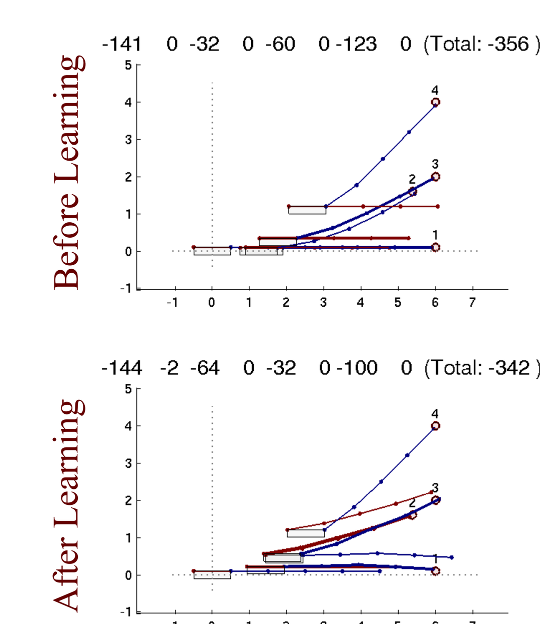
## Task 1: Fine Action Exploration

- ❑ Inspired by behavioral[3] and theoretical[14] studies
- ❑ Task: hit three targets with right arm
  - ***States***: current target
  - ***Actions***: RA
- ❑ Train on two sets of targs.: ascending and descending (first targ. same for both)
- ❑ Hypothesis #1 supported
  - arm configuration for 1st target depends on context
  - solution suboptimal for 1st target in isolation



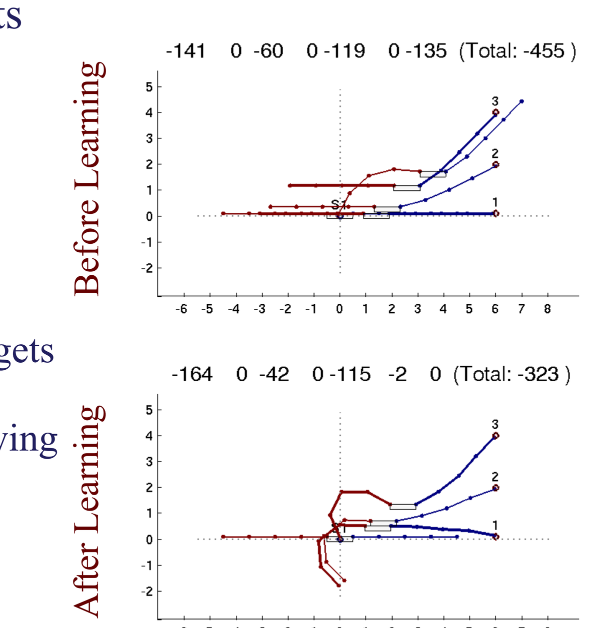

## Task 2: Coarse and Fine Action Exploration

- ❑ Inspired by behavioral studies[2]
- ❑ Task: Hit sequence of four targets with either arm
  - ***States***: current target + previous action
  - ***Actions***: LA, RA
- ❑ Hypotheses #1 and #2 supported
  - initial solution uses right arm for all 4 targets
  - after actions modified, best solution uses left arm for 2nd target (not found in every run)
- ❑ Notes
  - *fine action exploration*: search in continuous space
    *coarse action exploration*: allows for discrete learning mechanisms and more effective search
  - for additional leverage of excess DOFs, can allow other arm to move while one arm moves towards target




## Task 3: Action and Sensory Exploration

- ❑ Task: use either arm to hit sequence of three targets (primary task) and a secondary target at any time
  - ***States***: current primary target
  - ***Actions*** (*for primary targets*): LA, LB, RA, RB
  - restricted to always use **G** for secondary target
  - initial solution restricted to use only s.m. A
- ❑ Hypotheses #1 and #2 supported:
  - initial solution uses RA for each of the three primary targets and then LA for the secondary target.
  - learned solution uses RB for some primary targets, allowing LA to move left arm to secondary target concurrently
- ❑ Note
  - without secondary target, best to use RA for all primary targets




## Conclusion and Remarks

Coarticulation is a measurable behavioral characteristic of a learned motor skill. We used a learning scheme, based on functional mechanisms attributable to brain areas, to show that a search in the null space of subtasks and an evaluation based on the overall task produces improved movements and coarticulated behavior in a redundant system. We also showed that a multi-level search strategy, including sensory exploration, produces improved movements and coarticulated behavior. Finally, the strategies used do not rely on any assumptions as to what constitutes better movements; they rely on a reward signal as defined by the task. Such a strategy allows for flexibility in what objectives are optimized. For example, when signing two letters that are easily distinguishable, sign language users may choose configurations that are as similar as possible to expedite transition[13]. When signing two letters that look similar, signers may choose configurations that are as distinct as possible to expedite discrimination[13]. The learning process presented in this poster can be used for both objectives.