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AMARSi Adaptive Modular Architectures for Rich Motor Skills
RobotDoC Robotics for Development of Cognition
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Computational implications of the muscle synergy hypothesis

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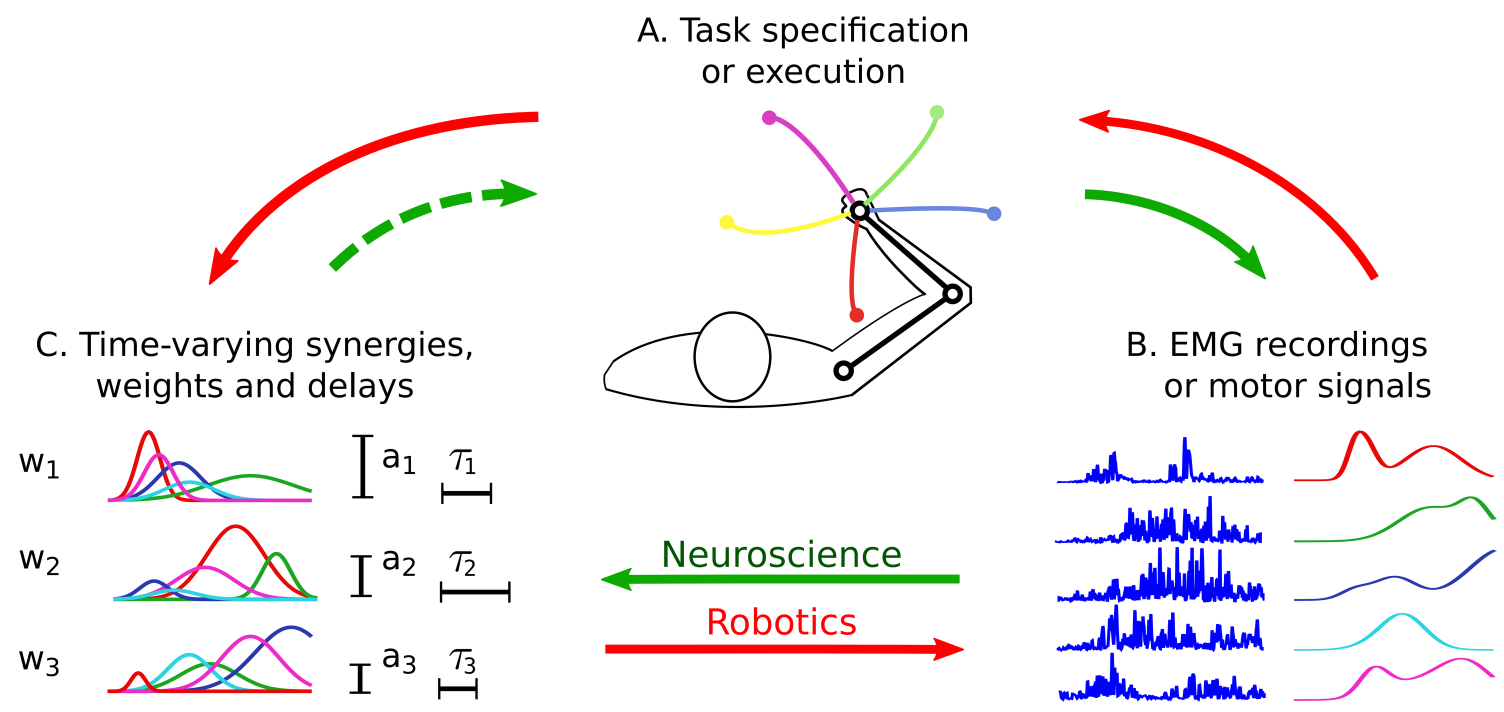
Introduction

A prominent hypothesis in motor neuroscience suggests that the central nervous system generates desired muscle activations by combining a parsimonious set of predefined primitives called synergies. Our work investigates the implications of this organization by considering the problem of controlling a simulated mechanical system in accordance with the model of time-varying synergies.

What can we learn from robotics?

In robotics synergies are synthesized (C) based on the requirements of the desired class of tasks (A). They are then used to generate appropriate control signals (B). The quality of the synthesized synergies is finally tested in terms of the obtained task performance (A).

In neuroscience the "muscle synergy hypothesis" is often evaluated by decomposing (C) a dataset of EMG signals (B) extracted during the execution of various tasks (A). Since the musculoskeletal system is non-linear, there is no guarantee that combinations of the extracted synergies lead to the observed task performance. A task-based assessment (dashed green line) is necessary.



Model of the physical system

$$\mathcal{D}\left(\boldsymbol{q}(t)\right) = \boldsymbol{u}(t)$$
$$\boldsymbol{y} = h(\boldsymbol{q})$$

Synergy-based controller

$$\boldsymbol{u}(t) = \sum_{i=1}^{N_\phi} b_i \boldsymbol{\phi}_i(t, \boldsymbol{p}) := \boldsymbol{\Phi}\boldsymbol{b}$$

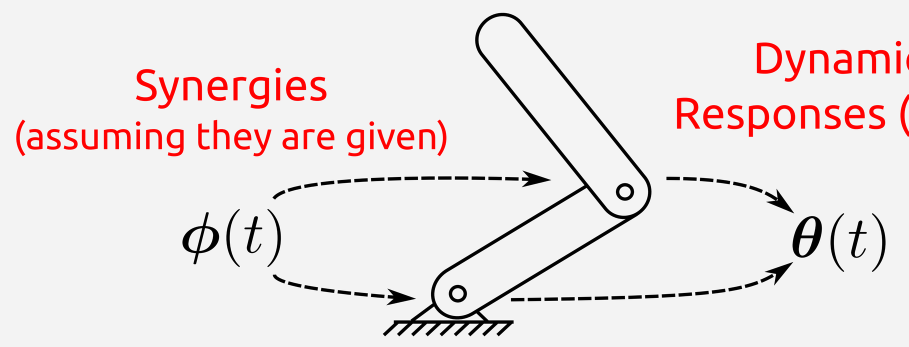
Task-based definition of synergies

$$d(\boldsymbol{y}_d, \hat{\boldsymbol{y}}) = \sum_{j=1}^{n} \left\| \hat{\boldsymbol{y}}\left(\boldsymbol{q}_0^j, \sum_i b_i^j \boldsymbol{\phi}_i(t)\right) - \boldsymbol{y}_{dj}(t) \right\| \qquad [\boldsymbol{\Phi}, \boldsymbol{b}] = \underset{\boldsymbol{\Phi}, \boldsymbol{b}}{\operatorname{argmin}}\ d(\boldsymbol{y}, \hat{\boldsymbol{y}})$$

$\hat{\boldsymbol{y}}(\boldsymbol{q}_0, \boldsymbol{u}(t))$: output of the system obtained with actuation $\boldsymbol{u}$ and initial condition $\boldsymbol{q}_0$

$\boldsymbol{y}_d(t)$: desired trajectory

Dynamic Response Decomposition (DRD)



0. Specification of the task as a set of point constraints

$$\begin{aligned} \boldsymbol{q}(0) &= \boldsymbol{q}_0, & \dot{\boldsymbol{q}}(0) &= \dot{\boldsymbol{q}}_0 \\ \boldsymbol{q}(t_v) &= \boldsymbol{q}_v, & \dot{\boldsymbol{q}}(t_v) &= \dot{\boldsymbol{q}}_v \\ \boldsymbol{q}(T) &= \boldsymbol{q}_T & \dot{\boldsymbol{q}}(T) &= \dot{\boldsymbol{q}}_T \end{aligned}$$

1. Interpolation of the task constraits with the DRs

$$\begin{pmatrix} \boldsymbol{\theta}_1(0) & \dots & \boldsymbol{\theta}_{N_\theta}(0) \\ \boldsymbol{\theta}_1(t_v) & \dots & \boldsymbol{\theta}_{N_\theta}(t_v) \\ \boldsymbol{\theta}_1(T) & \dots & \boldsymbol{\theta}_{N_\theta}(T) \\ \dot{\boldsymbol{\theta}}_1(0) & \dots & \dot{\boldsymbol{\theta}}_{N_\theta}(0) \\ \dot{\boldsymbol{\theta}}_1(t_v) & \dots & \dot{\boldsymbol{\theta}}_{N_\theta}(t_v) \\ \dot{\boldsymbol{\theta}}_1(T) & \dots & \dot{\boldsymbol{\theta}}_{N_\theta}(T) \end{pmatrix} \boldsymbol{a} = M\boldsymbol{a} = \begin{pmatrix} \boldsymbol{q}_0 \\ \boldsymbol{q}_v \\ \boldsymbol{q}_T \\ \dot{\boldsymbol{q}}_0 \\ \dot{\boldsymbol{q}}_v \\ \dot{\boldsymbol{q}}_T \end{pmatrix}$$

$$\boldsymbol{q}(t) = \sum_{i=1}^{N_\theta} a_i \boldsymbol{\theta}_i(t) := \boldsymbol{\Theta}\boldsymbol{a}$$

2. Inverse dynamics to compute the actuation

$$\mathcal{D}\left(\boldsymbol{\Theta}\boldsymbol{a}\right) = \tilde{\boldsymbol{u}}(t)$$

3. Projection of the actuation on the synergy span

$$\boldsymbol{\Phi}^+ \tilde{\boldsymbol{u}} = \boldsymbol{\Phi}^+ \mathcal{D}\left(\boldsymbol{\Theta}\boldsymbol{a}\right) = \boldsymbol{b}$$
$$\tilde{\boldsymbol{u}} = \boldsymbol{\Phi}\boldsymbol{b} + \epsilon_P$$

Task specification

e.g. start from $\boldsymbol{q}_0$, reach a via-point and come back (reversal via-pioint tasks); velocity is zero in each point.

$$[\boldsymbol{q}_0, \boldsymbol{q}(t_v), \boldsymbol{q}_0, 0, 0, 0]^T$$

Solving new tasks

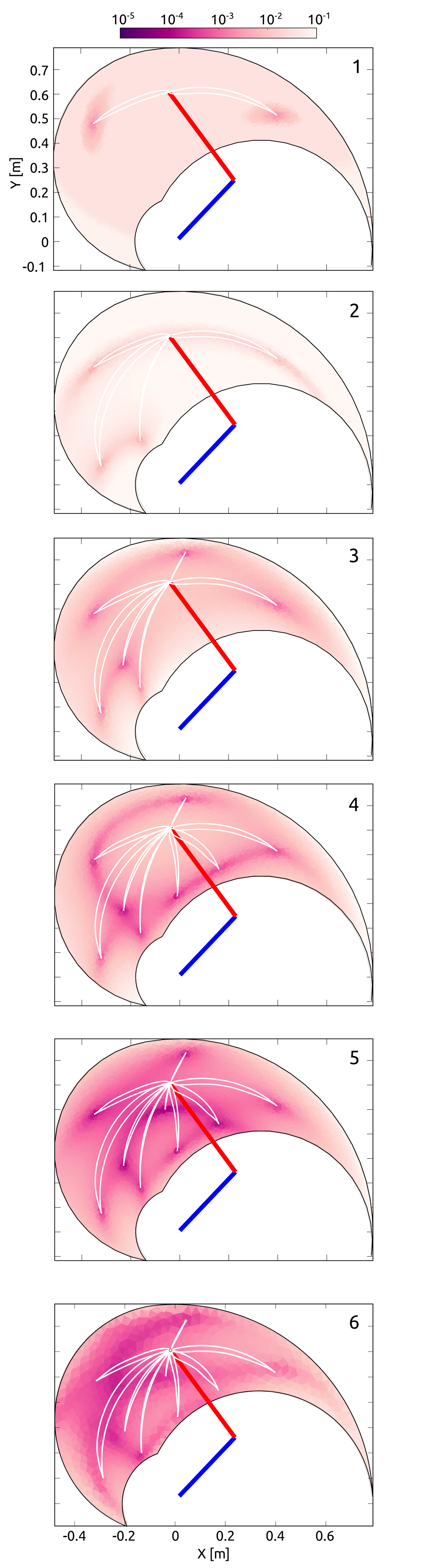
Use DRD with the new synergies and DRs.

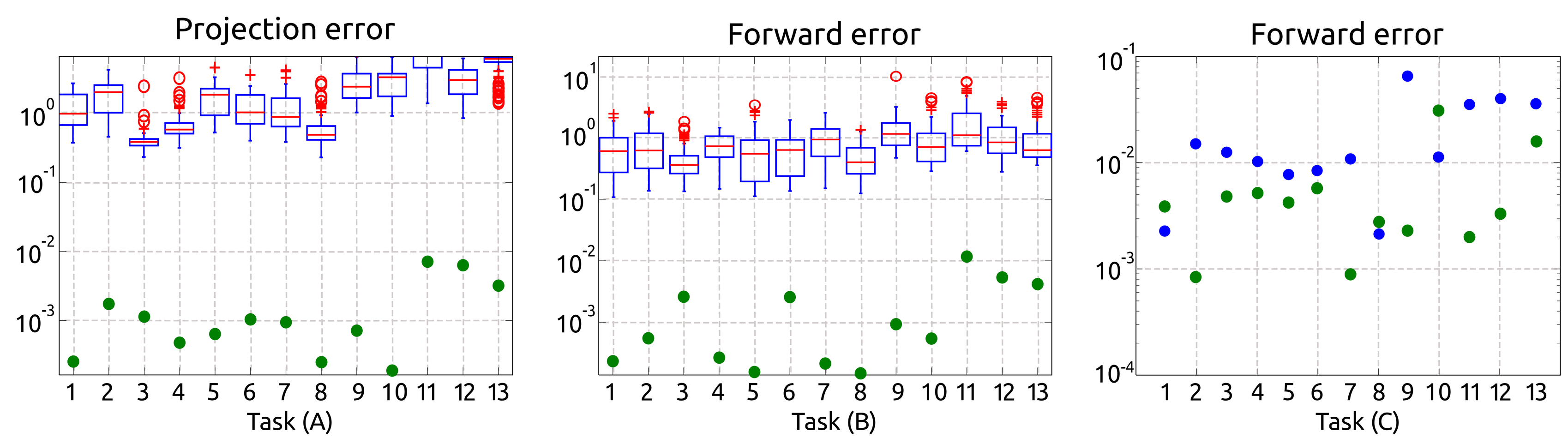
Synthesis of synergies

B1. *Exploration phase*: the agent is actuated with a large set of generic motor signals ϕ_e, and the corresponding DRs $\boldsymbol{\theta}_e$ are stored.

B2. *Reduction phase*: a handful of "proto-tasks" are interpolated by combining the DRs $\boldsymbol{\theta}_e$ (DRD, step 1). Inverse dynamics is used to compute the corresponding actuations (DRD, step 2). These actuations are then used as synergies for the next tasks.

The pictures on the right show the performance of DRD with an increasing number of synergies. The colour of each point indicates the error associated to the reversal task characterized by that via-point. In panels 1-5 the error estimates the ability of the synergies to approximate the desired actuation (projection error ϵ_P). Panel 6 indicates the error in performing the task when the approximated actuation is used (forward error). The white lines represent the end-effector solutions to the proto-tasks.





A,B. The synthesized synergies (green dots) perform better than many sets of primitives drawn from the exploration set (box plots). They seem to embed important dynamical properties that allow linear approximations of the actuations even if the dynamical system is non-linear. **C.** The DRD solutions for reversal via-point tasks (green dots) lead to better results than the concatenation of DRD point-to-point solutions (blue dots).

Conclusions

- We propose to define synergies as the input primitives that lead to satisfactory task performance.
- The solutions to proto-tasks are shown to be effective primitives. This suggests that synergies are strictly tailored to the dynamics of the system as well as to tasks to be solved.
- There exists a non-linear mapping between the mixing coefficients of the synergies and the ones of the DRs.
- The difference between projection and forward error shows the importance of evaluating synergies at the level of task.

References

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