Exploiting Sensorimotor Stochasticity for Learning Control of Variable Impedance Actuators

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1 - Introduction

Novel anthropomorphic robotic systems increasingly employ **variable impedance actuation** in order to achieve robustness to uncertainty, superior agility and efficiency that are hallmarks of biological systems. Controlling and modulating impedance profiles such that it is **optimally tuned to the controlled plant** is crucial to realise these benefits.

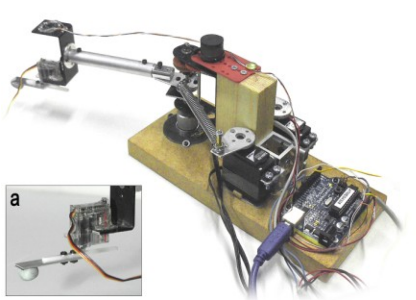
We propose a methodology to generate **optimal control commands for variable impedance actuators** under a prescribed **trade-off** of **task accuracy** and **energy cost**.

2 - A novel antagonistic actuator design

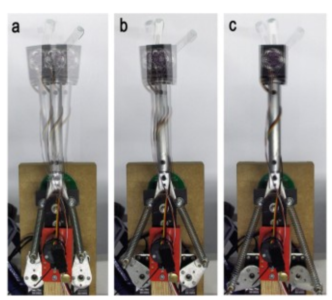
To study impedance control, we developed an **antagonistic Series Elastic Actuator (SEA).**

This SEA is:

- mechanically simple
- Cheap and easy to build
- Well suited for biologically inspired control architectures (antagonistic)

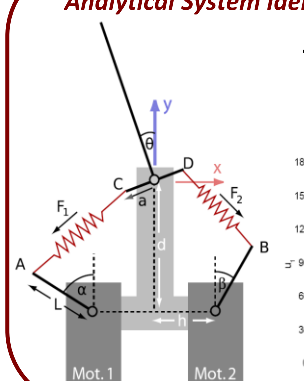


a) Perturbation motor



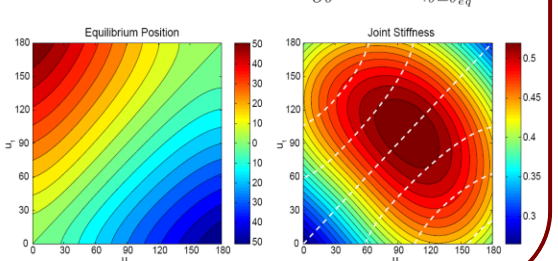
a) No co-contractiojn
b) Medium co-contraction
c) Maximum co-contraction

Analytical System Identification



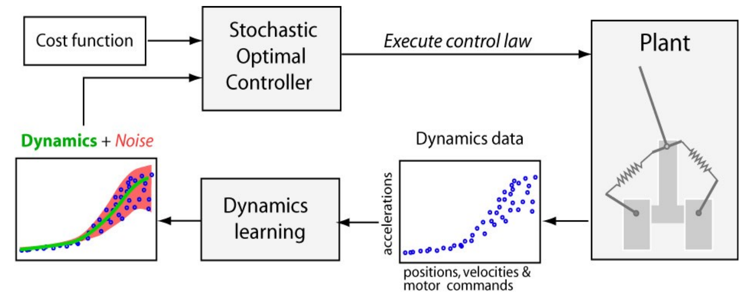
Joint torque: $\tau(\alpha,\beta,\theta) = \hat{\mathbf{z}}^T(\mathbf{F}_1 \times \mathbf{a}_1 + \mathbf{F}_2 \times \mathbf{a}_2)$

Joint stiffness: $K(\alpha,\beta) = \frac{\partial}{\partial\theta}\tau(\alpha,\beta,\theta)\Big|_{\theta=\theta_{eq}}$



3 - Stochastic Optimal Control with Learned Dynamics

Classical optimal control methods typically require an accurate analytical plant dynamics model. However we employ a **supervised learning** paradigm to acquire both the **process dynamics as well as the stochastic properties**. This enables us to prescribe an optimal impedance and command profile **(i)** tuned to the hard to-model stochastic characteristics of a plant and **(ii)** adapt to the systematic changes such as a change in load.



Schematic diagram of our proposed combination of stochastic optimal control (SOC) and learning. The dynamics model used in SOC is acquired and constantly updated with data from the plant. The learning algorithm extracts the dynamics as well as stochastic information contained (noise model from confidence intervals). SOC takes into account both measures in the optimisation.

4 - Energy optimal (equilibrium) position control

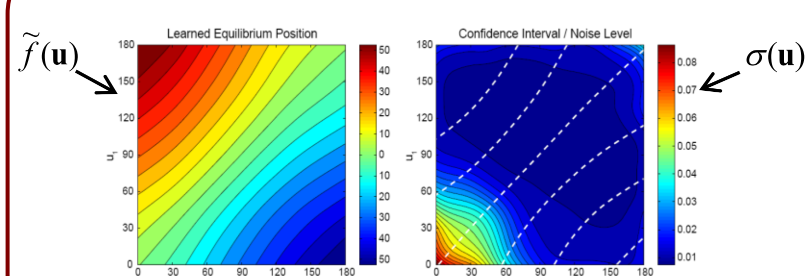
For position holding or slow movements we can reduce the stochastic dynamics to an equilibrium position controller.

Stoch. Equilibrium positions: $dx = f(\mathbf{u})dt + F(\mathbf{u})d\xi \quad , \quad \xi \sim \mathcal{N}(0,1)$

Objective: $J = \langle w_p(f(\mathbf{u}) - \hat{\theta})^2 + |\mathbf{u}|^2 \rangle$

$$J = w_p(\langle f(\mathbf{u})\rangle - \hat{\theta})^2 + w_p\left\langle \left(f(\mathbf{u}) - \langle f(\mathbf{u})\rangle\right)^2 \right\rangle + |\mathbf{u}|^2$$

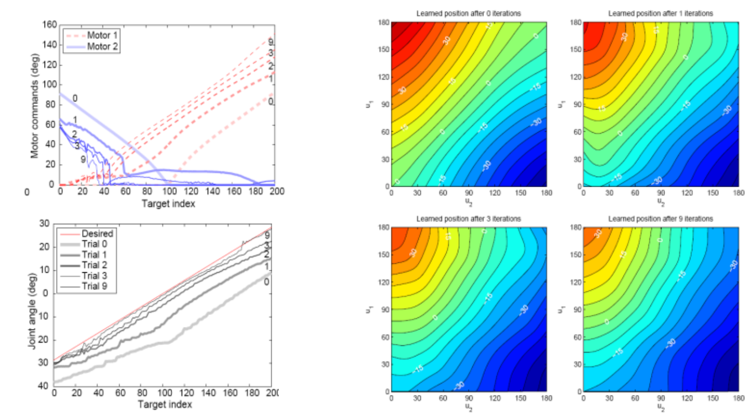
Learned Equilibrium positions using LWPR



$$J = w_p(\tilde{f}(\mathbf{u}) - \hat{\theta})^2 + w_p\sigma^2(\mathbf{u}) + |\mathbf{u}|^2$$

Result 1: Adaptation towards change in dynamics

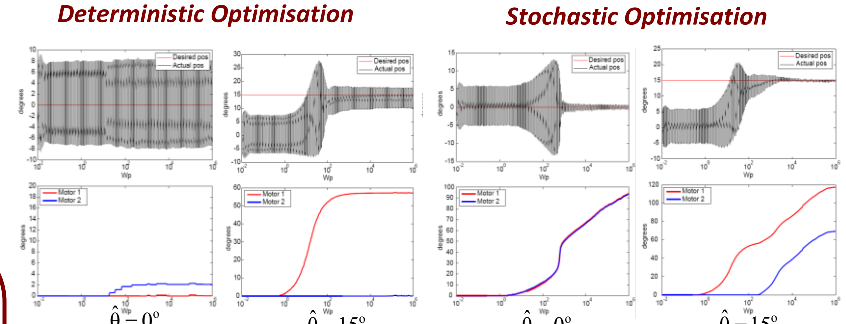
The advantage of a learned dynamics is that it can adapt online towards changes. We replace spring 1 (between points A and C) with one of unknown lower spring constant. **Over trials** we can update the internal model and **learn the new equilibrium positions**.



Result 2: The role of stochastic information for impedance control

We can **increase the accuracy demands** in our cost function and the SOC **increases co-contraction** to reduce the negative effects of the learned perturbation.

Deterministic Optimisation | *Stochastic Optimisation*



5 – Conclusion

We proposed a stochastic optimal control model for antagonistically actuated systems.

- **Learned dynamics** and **stochasticity** from sensorimotor plant feedback
- Motor co-activation (impedance) **not specified explicitly → emerges** from the actual learned stochasticity within the system
- Exploitation of sensorimotor stochasticity through learning applicable to govern to **any kind of control or state dependent uncertainties**.

e.g. resonances, oscillations, friction in the system.