Anticipative adaptive muscle control: Forward modeling with self-induced disturbances and recruitment

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1 Introduction

Both **maintaining posture** and making a goal directed **movement** have to be learned by animals and humans. The adaptation to perturbations ought to be fast and robust. Mechanisms that change neuronal responses through **synaptic plasticity** can be found in sensory systems, memory systems, but also in motor systems. For instance, two arm segments disturb each other while moving due to different movement speeds and loads attached to the segments. Compared to the cerebellum, which meets the demands of movement adaptation [2], artificial approaches nowadays have difficulties to **control movements in a dynamic way**. In this study we show that it is possible to learn anticipating self-induced disturbances by controlling the dynamics and not the kinematics [8]. This can be done with a forward model [1] that predicts the upcoming movement and is graded by recruitment. We will use an algorithm for **temporal sequence learning** introduced earlier [3, 5, 6]. We will apply it to a set of threshold sensitive units which, when combined at a summation neuron, will lead to accurate compensation in simulations as well as on a real mechanical arm with **two antagonistic muscles as actuators**.

2 Learning and Recruitment

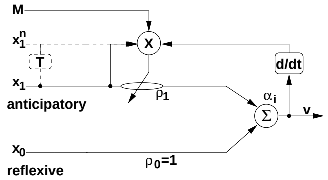
2.1 Learning a forward model

- Two inputs:
  - reflexive: signal x_0, weight ρ_0
  - anticipatory: signal x_1, weight ρ_1
- Output: $v = \rho_0 x_0 + \rho_1 x_1$
- Third factor differential Hebbian learning (ISO3 [7]):

$$\frac{d}{dt}\rho_j = \mu \cdot M \cdot x_j \frac{d}{dt} v \, , \; j > 0 \tag{1}$$

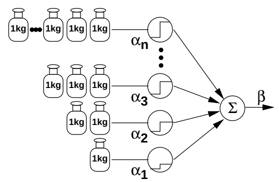
with learning rate μ and third factor M

- Convergence: $x_0 = 0 \Leftrightarrow$ no reflexive behavior



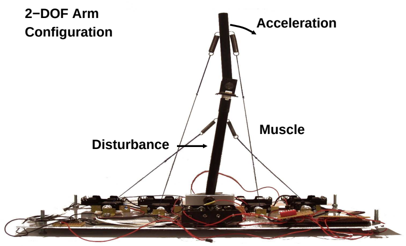
2.2 Recruitment mechanism for varying disturbances

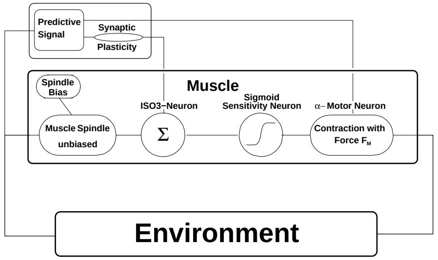
- Splitting the anticipatory pathway into
  - normalized learning circuit with operator $T : x_1^n = sign(x_1)$
  - operating circuit x_1
- Threshold mechanism: identical outputs α_i (threshold sensitive units) contribute to output $\beta = \sum_i \alpha_i$



3 Setup

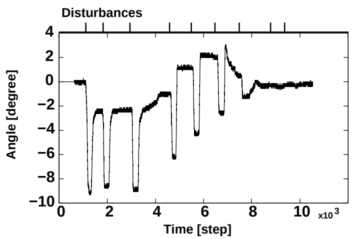
- Arm with one (1DOF - bottom part) or two degrees of freedom (2DOF)
- Antagonistic pair of muscles (simple actuators with springs)
- Mechanical setup - actuators are low geared motors
- Simulations - Open Dynamics Engine [4]
- Control of position: difference in force of paired muscle
- Control of stiffness: force of each muscle
- Reflexive muscle behavior → spinal monosynaptic reflex [2]:



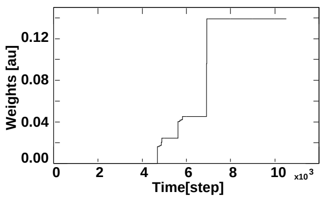


4 Result - Homeostasis

- Disturbances imposed on a reduced 1DOF arm
- Learning starts at $t > 3 \cdot 10^3$ time steps
  ⇒ immediate improvement

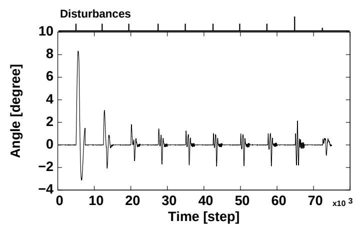


- Weight is stable at $t > 7 \cdot 10^3$ time steps
- Weight is stays stable with different force amplitudes

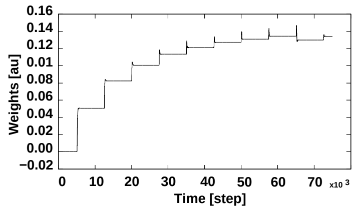


5 Result - Recruitment

- Disturbances imposed on 2DOF arm by accelerating the upper segment
- Learning reduces deviation trial by trial

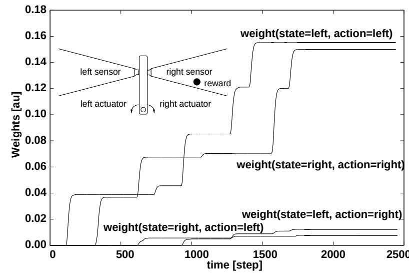


- Weight is approximately stable and deviations reduced to less then 2 degrees after about 7 trials
- Weight is also stable with different amplitudes of the disturbance (i.e. accelerations - last two trials)



6 Outlook - Goal-directed behavior

- Exchange reflex by reward
- Extend the anticipatory input
- Learn not to avoid but to attract towards the reward/reflex



7 Conclusion

Here we show that a **simple controller can quickly and robustly adapt to varying forces** both in simulations and in a mechanical setup. **Using compliant actuators** to keep homeostasis is a rather novel approach in contrast to standard methods in robotics which mainly rely on "stiff" joints and kinematic control [8]. The nervous system or more specific the cerebellum also has to cope with compliant actuators [2, 8] and this study offers a **complementary view on the learning mechanisms that are required for accurate movements and posture control**.

8 References

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