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

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1 Introduction

Both maintaining posture and movements has 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 themselves 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 [7]. 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

Fig. 1 A shows the basic components of the neural circuit. The normalised ICO-learner [3, 6] consists of two inputs x_0 and x_1 which are filtered with a function h: $u_j = x_j * h$. The filtered inputs u_j converge onto a single learning unit with weight ρ_j. Its output can be written as: $v = \rho_0 u_0 + \rho_1 u_1$. The resonator response h is given by: $h(t) = \frac{1}{b} e^{at} \sin(bt)$, where $a = -\pi f/Q$ and $b = \sqrt{(2\pi f)^2 - a^2}$ with frequency f and damping Q. Resonator parameters were $f = 0.01$ and $Q = 0.6$ unless otherwise noted.

The learning rule for the weight change ρ_j is $\dot{\rho_j} = \mu u_j \dot{u}_0$, $j > 0$, where only input signals are correlated with each other. Thus, this is a differential *heterosynaptic* learning rule. Note, in contrast to hebbian learning, the output determines only the *behaviour* of the system, but does not influence its learning. Furthermore, it is evident that these weights will stabilize if $x_0 = 0$. Hence x_0 can be interpreted as an error signal and the application of ICO-learning drives it towards zero, were weights will stop to change.

In order to create the recruitment mechanism for varying loads we split the anticipatory pathway into a normalized learning circuit where we use $x_1^n = sign(x_1)$ for learning and an operating circuit which still uses x_1. The modified architecture is displayed in Fig. 1 A. Recruitment is achieved by the threshold mechanism displayed in Fig. 1 B. Each neuron

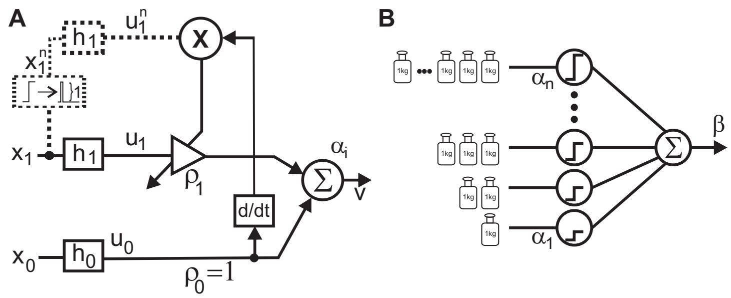

Figure 1: *Normalised learning rule (A) and recruitment mechanism (B). In panel A the resonators are denoted as h, x_0 represents the later and x_1 the earlier (anticipatory) input. The amplifier symbol denotes the changing synaptic weight. We split, different to our original approach [6], the x_1 pathway into an operating and a learning pathway. Panel B shows the recruitment mechanism. Threshold units α learn, the summation unit β, however, does not. Recruitment arises from summing the responses of the threshold units.*

α_i contains a threshold with equally distributed threshold values. Given a certain input force, the neurons will contribute with identical strength, one after another, to the output of neuron β, generating exactly the correct response strength. This mechanism is adapted from the peripheral nervous system used to recruit our muscles under different loads [2].

3 Setup

The arm consists of two degrees of freedom and therefore of two antagonistic pairs of muscles (Fig. 2 A). Here the muscles are modeled as simple springs and the force is is provided by the ODE-simulation [4] or by low geared motors in the mechanical setup. Each muscle of a pair is connected to one side of each arm segment. The difference in force of a paired muscle regulates dynamically the position. The force itself sets the stiffness of the joint.

The amplitude of this force is adjusted by a pulse width modulation (PWM). The firing rate, given by the output $v(t)$ of the adaptive controller, is the frequency of the modulation. In contrast, the recruitment strength is modeled by the width of the signal. To provide the controller with a reflex, we modeled a mono-synaptic reflex loop [2]. Therefore, the muscle comprises not only muscle fibers but also of a muscle spindle. It senses a relative change in the length of the muscle and transmits this signal directly to the alpha motor neurons which innervate the muscle fibers (see Fig. 2 B). To show the functionality, Fig. 2 C depicts the reflex (time before learning, i.e. step $<$ 4000) and the learning procedure with only one arm segment. After learning the joint stiffens and therefore the deflection of the angle is regulated to a minimum and learning stops. At this point, the weights are stable. In this experiment no recruitment was used.

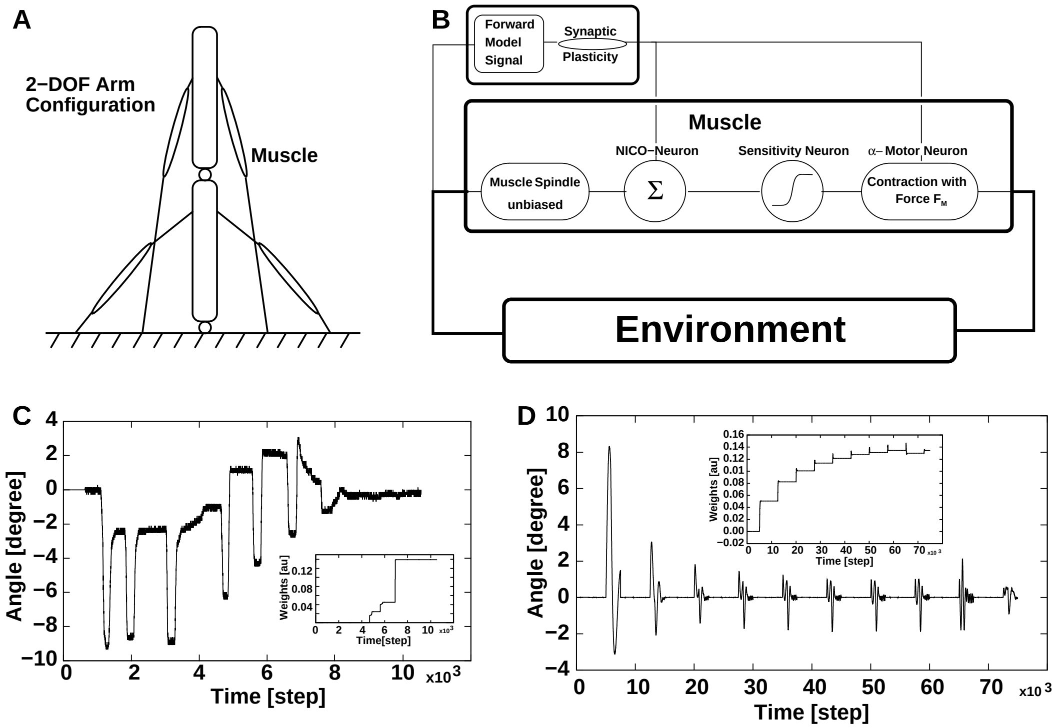

Figure 2: *Setup of the simulated and mechanical arm (A), scheme of the monosynaptic reflex with the additional recruitment input (B) and the learning results (C,D). The arm consists of two joints and two pairs of antagonistic muscles (A). The force is provided by the ODE-simulation [4] or by low geared motors in the mechanical setup. Panel B describes the coupling of each muscle with the environment. The forward model transmits the input to the normalised ICO-Neuron and therefore the muscle can contract sufficiently to avoid the self-induced disturbance. In Panel C the deviation from the wanted position (*14.8 *degree) of the mechanical arm is shown under external perturbations. At step* 4000 *learning starts and the arm stiffens within* 4 *trials. The weight is depicted in the inset. Panel D shows the change of the angle (*11.6 *degree) of the lower joint under self-induced disturbances. After* 6 *trials, the weight is stable and the deviations are reduced to less than* 2 *degrees. The last two trials are conducted with* 50% *more and* 50% *less acceleration. The difference in arm position stays within* 2 *degrees and the weights do change only marginally.*

4 Results

Now we disturb the lower segment by moving the upper segment with a specific acceleration. The knowledge of the movements initiation with a given strength is put into the anticipatory input x_1 to learn anticipating the upcoming deviation. Fig. 2 D shows the deviations during learning. The controller required six trials which are sufficient for the adaptation. Here sufficient means that the deviation is within a given threshold of 2 de-

grees. This is due to the springs mounted to the muscles. The weights become stable and the reflex is not triggered anymore.
With the last two movements we test the recruitment mechanism that accounts for different conditions. Firstly we reduced the acceleration by 50% and then increased it by 50% compared to the acceleration used during the learning phase. The deviation stays within 2 degrees without any additional learning. Thus the weights are stable and the controller works robustly.

5 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 [7]. The nervous system or more specific the cerebellum also has to cope with compliant actuators [2, 7] and this study offers an complementary view on the learning mechanisms that are required for accurate movements and posture control.

References

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