Speed Optimization of a 2D Walking Robot through STDP

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Introduction. To achieve adaptive and fast walking in artificial bipeds is still a very difficult problem, the solution of which should contribute to our understanding of human locomotion [5]. We approach this problem by combining a novel biomechanical design of a small robot with a neural controller that is based only on sensor-inputs and does not use CPGs [2] or specific trajectory planning. This way the robot achieves a very high walking speed and is rather robust against fast parameter changes [1]. This allows us to implement on-line adaptation using spike timing-dependent plasticity (STDP) [3] to gradually change the robot's walking speed.

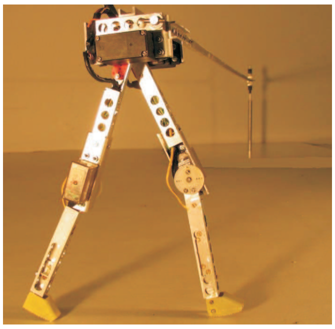

Figure 1: A picture of the planar robot.

Design of the robot. Our robot is 23 cm high, foot to hip joint axis (see Fig. 1). It has four joints: left hip, right hip, left knee, and right knee. Each joint is driven by a modified RC servo motor. We constrain the robot sagitally by a boom (planar robot). All three axes (pitch, roll and yaw) of the boom can rotate freely and have no influence on the dynamics of the robot in the sagittal plane. A detailed description of the robot is given in [1].

Neural network. We use a hybrid neural network for control consisting of two components: 1) The motor control circuit (inside dashed box in Fig. 2) which operates with linear, Hopfield-type neurons and 2) the learning control circuit (outside box) which uses spiking neurons to more realistically emulate plasticity. The motor control circuit contains motor neurons (EM, FM), which, being linear, can send their signals unaltered to the motors. Ground contact sensors (GL, GR) influence all motor neurons of both legs. Stretch receptors, sensitive to the anterior extreme position of the hip (AL, AR), influence each joint individually (joint level) and extensor as well as flexor sensor neurons (ES, FS), sensitive to joint angles, only operate on their respective motor neuron (intra-joint level). The output of the motor-neurons directly drives the motors of the joints, not employing any kind of position or trajectory tracking control algorithms. Details of the controller and its basic parameters are described in [1].

Learning scheme. The learner has inputs x_1 from the left and x_0 from the right hip which converge onto the learning unit L (Fig. 2) where signals from the left leg (x_1) preceed signals from the right (x_0) as shown in Fig. 3 A. We use a copy of input signal x_1 delayed by a time delay τ to be able to employ STDP. A time delay T between x_0 and delayed signal x_1 depends on a walking speed of the robot. When walking slowly, time difference T between x_0 and x_1 is relatively large. When walking speed is increasing, T is getting smaller and when the robot reaches a desired speed specified by the time delay τ of the input signal x_1, the time difference T equals 0 and according to STDP synaptic weights stop changing [3]. Inputs x_0 and x_1 feed into a summation unit v. The output is calculated by $v = \sum_j \rho_j u_j$, where $u = h * x$ is a convolution of input x with resonator h. We define $h(t) = \frac{1}{b} e^{at} \sin(bt)$, where $a = -\pi f/Q$ and $b = \sqrt{(2\pi f)^2 - a^2}$, with $f =$

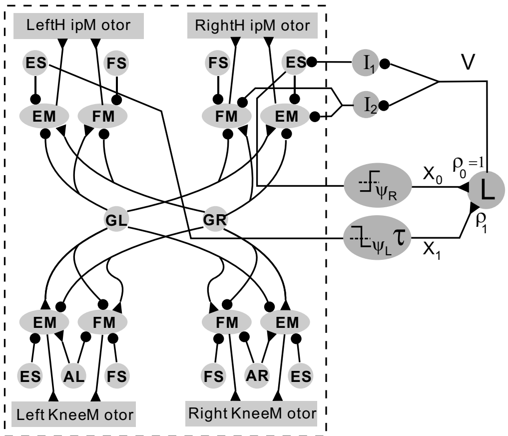

Figure 2: A hybrid neural network: control circuit (inside dashed box) and learning circuit (outside box). Triangles and circles denote excitatory and inhibitory synapses, respectively

5 Hz the frequency and $Q = 0.6$ the damping.

Only weight ρ_1 changes according an STDP-like, input-input correlation rule: $\dot{\rho}_1 = \mu u_1 \dot{u}_0$, $j > 0$, $\mu = 4 \times 10^{-6}$. The behaviour of this rule and its convergence properties are discussed in [4].

Walking speed of the robot depends mostly on two parameters of the hip: the threshold of the extensor sensor-neuron θ_{ES} and the gain of the motor-neuron G_M (see Fig. 2). Initial values are $\Theta_{ES} = 120\, deg$ and $G_M = 1.8$. The learner unit L essentially excerts disinhibition at neurons EM, FM and ES and this disinhibition increases as soon as weight ρ_1 grows leading to the desired changes in Θ_{ES} and G_M and, hence, to a speed increase.

Results. Learning results are shown in Fig. 3 B-E. Synaptic weight ρ_1 is presented in panel B and stabilizes as soon as the desired speed is reached (in around 40 s) because at that point the order of the spikes becomes reversed (see Fig. 3 A). The robot reaches maximum speed (more than 90 cm/s) after 40 s and afterwards oscillates around the speed of 80 cm/s (see panel C). Changes of the controller parameters are presented in panel D and E, which stabilize with a remaining small oscillation as soon as $T \approx 0$ is obtained. Due to the symmetry of the circuitry, equivalently, the robot would slow down if it is started with a high speed.

Conclusion. In this short paper we have shown that it is possible to combine neural control with learning in a fast walking robot and that the targeted control parameters will converge when implementing an STDP rule to increase the robot's speed. Hence, similar self-stabilization should also be possible with other parameters, which will allow investigating more general adaptive properties, like adaptation to changing terrain.

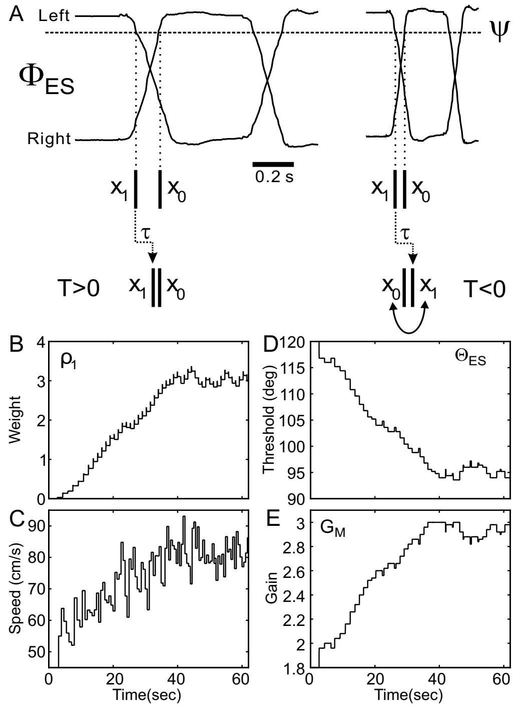

Figure 3: Results of the learning experiment. **A)** Inputs of the learning unit. Φ - joint angle of left and right hip, Ψ - threshold, inputs x_0 and x_1, τ - time delay of x_1, T - time difference between x_1 and x_0. **B)** Synaptic weight ρ, **C)** change of the walking speed, **D)** threshold θ_{EM} and **E)** gain G_M.

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