Neural Self-organization for Muscle-Driven Robots

Elias Fischer[1(✉)], Bulcsú Sándor[2], and Claudius Gros[1]

[1] Institute for Theoretical Physics, Goethe University Frankfurt a.M., Frankfurt am Main, Germany
fischer@itp.uni-frankfurt.de

[2] Department of Physics, Babes-Bolyai University, Cluj-Napoca, Romania

Abstract. We present self-organizing control principles for simulated robots actuated by synthetic muscles. Muscles correspond to linear motors exerting force only when contracting, but not when expanding, with joints being actuated by pairs of antagonistic muscles. Individually, muscles are connected to a controller composed of a single neuron with a dynamical threshold that generates target positions for the respective muscle. A stable limit cycle is generated when the embodied feedback loop is closed, giving rise to regular locomotive patterns. In the absence of direct couplings between neurons, we show that force-mediated intra- and inter-leg couplings between muscles suffice to generate stable gaits.

Keywords: self-organization · robots · muscles

1 Muscle-Driven Robots

A substantial effort is devoted to the development of robotic artificial muscles [9], with possible applications ranging from interactive soft robotics [7] to the recreation of human walking via compliant legs [2]. In comparison, only a somewhat limited number of studies have been devoted to the study of robotic control principles for synthetic muscles [1,4]. Here we examine control principles based on embodied self-organization that have been developed previously for robots driven by rotating actuators (motors) [3,6]. For pairs of antagonistic muscles that are controlled independently, viz without cross-control, we find spontaneous anti-synchronization due to the indirect coupling via the moving limb. Our studies are carried out using Webots, an open-source mobile robot simulation software developed by Cyberbotics Ltd [8].

The core processing unit of our controller is a single neuron with membrane potential $x(t)$ and a variable threshold $b(t)$. The neuron receives two types of inputs via constant synaptic weights, w_s and w_y, as illustrated in Fig. 1. The first, w_s transmits information about the current status $s = s(t)$ of the actuator,

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with the second, w_y, corresponding to an excitatory self-coupling:

$$\tau_x \dot{x} = -x + w_s s_{\text{rel}} + w_y y, \qquad s_{\text{rel}} = \frac{s - s_{\min}}{s_{\max} - s_{\min}}, \tag{1}$$

$$\tau_b \dot{b} = y - y_b, \qquad y = \frac{1}{1 + \mathrm{e}^{a(b-x)}} \tag{2}$$

where the neuronal activity $y \in [0, 1]$ is determined by a sigmoidal with gain a and threshold b. The time constants for the evolutions of membrane potential and threshold are respectively τ_x and τ_b. The position s of the actuator is bounded by physical constraints, such that $s \in [s_{\min}, s_{\max}]$. Using the relative position $s_{\text{rel}} \in [0, 1]$ as an input to the membrane potential, as done in (1), allows to directly compare the sizes of w_s and w_y. Entering (2) is the desired steady-state value y_b for the neural activity y. It is reached however only if activities would cease altogether.

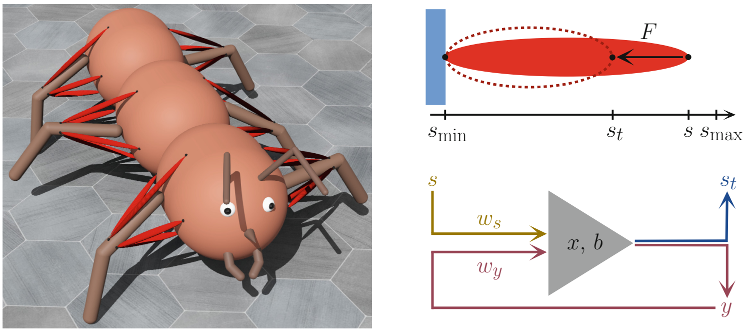

Fig. 1. Left: Six-legged robot driven by 24 muscles. Each leg is controlled by two pairs of antagonistic muscles, enabling movement both in up-down and forwards-backwards direction. Simulations were performed using the Webots open-source robot simulation software by Cyberbotics Ltd [8]. **Right:** Schematics of the single neuron controller. The neuron takes the current actuator position s and its own activation y as inputs, weighted respectively with synaptic weights w_s and w_y. The target position s_t determines via (3) the actuating force F [Link to the video]

The one-neuron controller acts by generating a target position $s_t \in [s_{\min}, s_{\max}]$ for the actuator, which in turn is translated to a force F via

$$F = -\gamma \dot{s} + K_s \frac{s_t - s}{s_{\max} - s_{\min}}, \qquad s_t = s_{\min} + (s_{\max} - s_{\min}) y \tag{3}$$

where K_s is the coefficient for proportional control and γ a phenomenological damping constant. The results presented are for critical damping. We assume with (3), that the target position s_t for the actuator is directly proportional to the neuronal activity $y = y(t)$. As a result, one has a sensori-motor feedback loop [3,6], with the actuator trying to reach a continuously updated target position. Biologically, muscles may exert force only when contracting, but not when expanding. This corresponds to the substitution $F \to F\big[1-\theta(F)\big]$, where we use the Heaviside step function $\theta(x)$ to set the force to zero when $s_t > s$, viz when the length s would be increased.

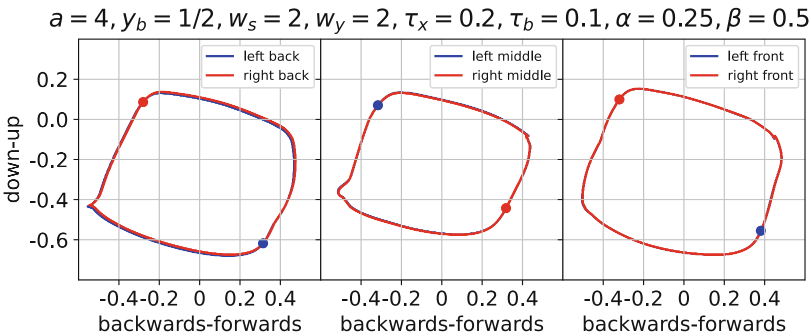

Fig. 2. The angle (in radians) of the legs of the robot shown in Fig. 1, viewed from the left side of the robot walking to the right after the initial synchronization phase. The dots show the position of the respective leg at the last time step, showcasing a tripod gait with the middle legs being in opposite phases to the front and back legs. The blue trajectory of the left legs can hardly be seen because the left/right trajectories align almost perfectly

Attractoring. The autonomous system, attained by setting $w_s = 0$ in (1), shows a super-critical Hopf transition at

$$w_y = \frac{4}{a} + \frac{\tau_x}{\tau_b}, \tag{4}$$

which holds for $y_b = 1/2$. When w_y and/or a is large, the system oscillates spontaneously, acting as a central pattern generator (CPG). In this regime, the additional feedback $w_s s_{\text{rel}}$ corresponds to a modulator. Here we concentrate on the case that the isolated neuron does not oscillate on its own, viz that w_y and/or a is too small for (4) to be fulfilled. Locomotion is generated consequently only when the feedback from the actuator is strong enough for an embodied limit cycle to emerge. We call this regime 'attractoring', which has been found to allow for increased behavioural flexibility [6]. Locomotion is embodied in the sense that the phase space of the resulting limit cycle contains the degrees of freedom of the body in addition to $x(t)$ and $b(t)$. We note in this context that it is important to use force signals for both real-world and simulated actuators, as the respective default PID controllers tend to be stiff.

Force Mediated Inter-muscle Coupling. The desired movement for a leg with two pairs of antagonstic muscles (up-down; left-right) is up-forwards-down-backwards. For this we expand (3) as

$$s_{t,1} = s_{\min} + (s_{\max} - s_{\min}) \cdot ((1-\alpha)y_1 + \alpha y_2), \qquad \alpha \in [0,1] \tag{5}$$

which corresponds to an embodied coupling via force superposition. The activity y_2 of a second neuron of the same leg influences the target position (and hence the force) generated by the first neuron, but not the first neuron directly. The order of coupling between the four muscles of a single leg is taken to be circular. The same principle is used for (indirect) inter-leg coupling,

$$s_{t,1} = s_{\min} + (s_{\max} - s_{\min}) \cdot ((1-\alpha-\beta)y_1 + \alpha y_2 + \beta y_3), \qquad \alpha + \beta \leq 1\,, \tag{6}$$

where y_3 is now the activity of a neuron from another leg. For the six-legged robot shown in Fig. 1, the contralateral pairs of legs are coupled via the up-down muscles for producing steps, while the inter-leg phase blocking is mediated solely via the upper muscles. We call this coupling principle 'force-mediated' coupling.

2 Results

For parameters in the attractoring regime, we present in Fig. 2 the time evolution of the positions of the six legs. One observes a stable tripod gait [Link to the video], which emerges without the direct coupling of the controlling neurons. A conceptually similar result has also been achieved by using pressure sensors and motors [5], albeit relying on CPGs for controlling the individual legs. Note that here oscillations would not be generated without feedback from the body and no forces are exerted when the muscles relax, so in this sense the locomotion is fully self-organized.

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