Learning to walk in arbitrary legged morphologies

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1 Introduction

In mobile robots, a usually desired feature of the mobility is locomotion, which can be trivial e.g. in the case of wheeled robots, however legged robots often require more elaborate control methods. A common strategy to develop a locomotion controller is to create a model of the robot in simulation, define joint movement parameters and use an optimization method to find a suitable locomotion strategy. Reconfigurable modular robots (RMR) are a special type of robots that have the ability to be assembled into various morphologies according to a set of tasks, among which legged locomotion often is part of. While the controller development described above is also still applicable, it quickly can turn cumbersome as each new morphology requires a new model, parametrization and optimization. Our aim in this work is to explore a learning method coupled together with sensory feedback to develop a generic control strategy (i.e. the "spinal cord") able to make an arbitrary modular morphology locomote in *one shot*, i.e. a modular legged structure learns how to move on the fly. Once built, a structure first performs a series of discrete motor actions, so-called "Spontaneous Motor Activities" (SMA), that have been observed to occur during REM-sleep of mammals [1]. We use Hebbian learning as one of the basic biological unsupervised learning method to correlate these discrete motor actions with sensory feedback caused by them [2] to form a rough internal model of the robot with the goal of separating single limbs. We then implement phase oscillators in each limb to synchronize limb movements into an emergent gait through the clever use of force feedback, known as "tegotae". These processes are deployed into a customized modular robotic platform, and we present validation experiments as well as the first results of the learning procedure.

2 The ARBITER robotic platform

We use a customized version of the Bioloid-Kit[1]. The main components are 1 DoF hinged servo motors (Dynamixel AX-12+) and structural passive parts. Both components are equipped with custom designed male-female-male connectors that allow a flexible and fast assembly of almost arbitrary shape. The servo motors are controlled with a microcontroller (Robotis OpenCM9.04) and powered by a battery (Conrad energy BEC 11.1 V 1300 mAh 12 C). A 3-axis loadcell (LCT LAN-X1) measures linear forces in each limb at the foot level and an IMU (Sparkfun Razor IMU M0) measures linear accelerations (x, y, z) and rotational velocity in *yaw*. This data is collected by and processed on the microcontroller. The mechanics and electronics of the ARBITER platform are completely modular: a structure can contain as many servo motors and loadcells as desired and their location can be freely chosen; microcontroller, battery and IMU are bundled together as the "spinal cord" and must only be placed once into a structure. An example of a quadruped robot with the main components can be seen in Fig. 1.

[1] Bioloid comprehensive kit, http://www.robotis.com

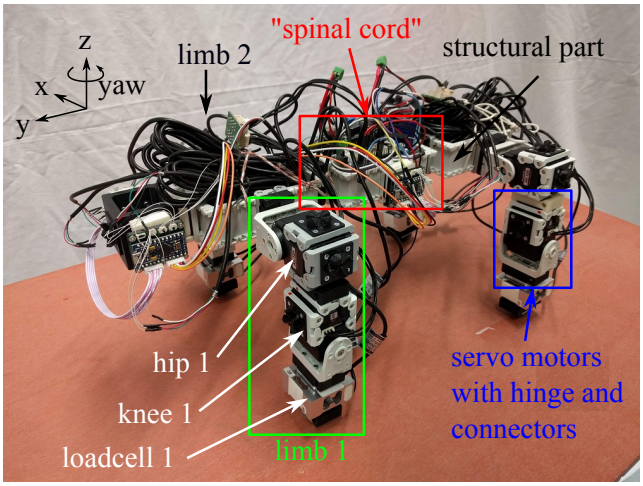

Figure 1: Quadruped prototype with the ARBITER platform.

3 Spontaneous Motor Activity and Hebbian Learning

Spontaneous Motor Activity, or *twitching*, occurs during REM sleep where a single muscle activates against a background of muscle atonia. This is thought to help the self-organization of motor synergies as the contraction induces movement in neighboring joints that is detected by those muscles [3]. These two effects (movement and sensory information) are causally related, allowing a correlation-based learning method such as Hebbian learning to create a map of how the musculoskeletal system is interconnected. We adapt this method for a robotic structure where the twitches consist of short bidirectional servo motor movements during which the position of all other servo motors, the force of all loadcells and the values of the IMU are recorded. This process repeats for every servo motor in the structure. We then use *differential hebbian learning* [4] to form the correlation matrix as the goal is to relate motor activity to the effects

of sensors, not their actual values. Using the Oja rule, the weight change is given by Eq. 1,

$$\Delta w_{i,j} = \eta \dot{m}_i (\dot{s}_j - \dot{m}_i w_{i,j}) \tag{1}$$

where $w_{i,j}$ is the connection between the servo motor i and sensor j, m_i is the servo motor position, s_j is the sensor activity, and η is the learning rate (set to $\eta = 1$ in our system). The correlation matrix contains data about how motors are connected together, and how their movement affects the force feedback. We intend to use this data to define separate limbs, and possibly extract basic kinematics of them.

4 Tegotae force feedback

Once limbs and their kinematics have been identified, a trajectory generator is needed to induce locomotion. We use a network of Central Pattern Generators (CPGs) to deploy one phase oscillator per limb to create a circular foot trajectory. The usual couplings between oscillators that are used to synchronize the system are replaced by the clever use of force feedback, called *tegotae* [5], provided by the loadcells. The phase progression $\dot{\phi}$ is described by Eq. 2

$$\dot{\phi}_i = \omega - \sigma N_i \cos(\phi_i) \tag{2}$$

where ω is the intrinsic angular velocity, σ is a positive gain and N_i is the ground reaction force acting on the ith limb during stance. The phase ϕ then is used to drive an oscillator, e.g. of the form $x = A\sin(\phi)$. Interestingly, tegotae can autonomously synchronize the leg movements by slightly accelerating or decelerating the stance phase of each leg. Although the limitations of this capability are unclear at the moment, it could have the potential to deal with an arbitrary number of legs. In [5], it was shown that if tegotae is applied to a hexapod robot, then Eq. 2 needs to be extended to take the state of the neighboring legs into account to create a stable leg synchronization. This extension seems to have been found empirically. Our approach aims at creating a systematic framework, leading to a generalized version of Eq. 2 that can immediately be used by the locomotion controller.

5 Validation of the platform and learning

The preliminary experiments include motor twitching, recording of sensor data and learning. We currently process the data also on an external computer in MATLAB for an easier analysis. Each servo motor twitches bidirectionally over a period of 500 ms per twitch with an amplitude of 7.5 deg, and the positions of all motors, forces of all loadcells and body accelerations are simultaneously recorded at roughly 28 Hz. We present the data collected by the system for a single motor. Fig. 2 top shows the motor position signal of the "hip 1" motor, twitching first in one and then the other direction, and the response in z-direction of the loadcell 1 at the foot. Fig. 2 bottom shows the derivatives of these signals with the learning happening in the shaded area. Fig. 3 shows the correlation map formed by the learning process, here for all three axes of loadcell 1 with the two motors of the same and the mirror limb (limb 1 and 2).

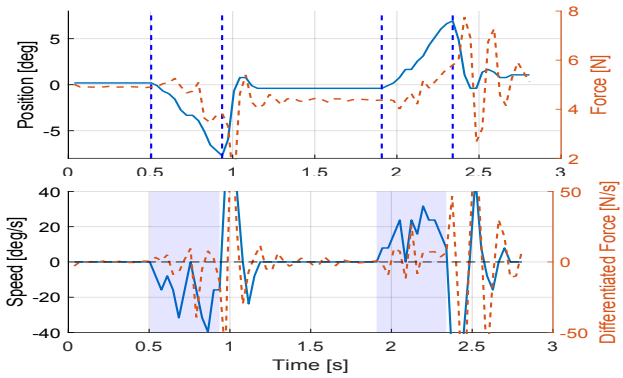

Figure 2: Signals of motor hip 1 and z of loadcell 1, raw (top) and derivatives (bottom; the shaded area is where hebbian learning happens).

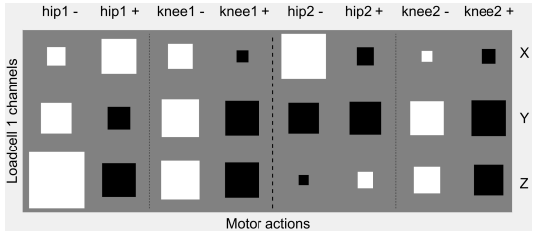

Figure 3: Correlation matrix of loadcell 1 and hip and knee motor of the same limb (limb 1) and hip and knee motor of the mirror limb (limb 2) for twitching in both directions (+ and −). Motors in limb 1 are closer to loadcell 1 and cause higher responses in it than motors in limb 2, giving information about the kinematics of the robot to form an internal model.

6 Conclusion and Future work

In this work, we propose a framework for locomotion control of arbitrary legged morphologies of a modular robotic platform. We present the first steps where a correlation map between motor activities (twitching) and sensory feedback (motor position, ground reaction forces and body accelerations) is created through differential hebbian learning. The map already shows promising features, e.g. which are the neighboring servo motors, which loadcell has the highest response in general (i.e. is closest), and which is the local kinematic effect of a servo motor movement. As the next steps, more work is needed on the raw signals (e.g. filtering); then the assignment of oscillators and tegotae needs to be implemented to assess the ability of our approach to create an emergent gait for any legged structure on the fly.

References

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