Neural Control and Learning for Versatile, Adaptive, Autonomous Behavior of Walking Machines

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Abstract

This article presents two different types of walking machines: an insect-like robot and a biped robot which have been developed during last years. Both walking machines are attractive in the way that they now combine three key aspects: versatility, adaptivity, and autonomy. Versatility in this sense means a variety of reactive behaviors, while adaptivity implies to online learning capabilities, and autonomy is an ability to function without continuous human guidance. These three key elements are achieved under neural control and an online learning mechanism. In addition, this contribution will point out that such control technique is shown to be a power method of solving sensor-motor coordination problems of high complexity systems.

1. Introduction

Living creatures like walking animals and humans have found fascinating solutions for the problem of legged locomotion in the way that their movements give the impression of elegance and smoothness. They are able to move around not only on flat terrains but also on rough terrains and even to perform a variety of walking behaviors. Furthermore, they can adapt themselves to environmental changes in order to survive. Neurophysiological and ethological studies have revealed that solving such tasks basically results from coupling appropriate *biomechanics* [1] with *neural control* [2]. For instance, walking animals (e.g., insects, cats) can walk forward, backward, and in lateral directions and perform self-stabilization to minor disturbances (stumbling) because of their appropriate biomechanical design. Neural control, on the other hand, plays a role in generating different walking behaviors as well as adaptivity. Therefore, during the last few decades several roboticists have begun actively to look to the biological sciences for the constructions (biomechanics) and the controller (neural control) de-

sign of robotic systems in particular walking machines to approach the living creatures in their levels of performance.

The diverse researches in the domain of biologically-inspired walking machines have been ongoing for over 20 years [3, 4]. Most of them have focused on the mechanical design to have animal-like properties and perform efficient locomotion [5]. Others have concentrated on the generation of locomotion based on engineering technologies [6] as well as biological principles [7]. While impressive in their own right, the versatility (behavioral repertoire) of these systems is much smaller. Typically they are not adaptive (learning capabilities) and most of them still fail to be autonomous (function without continuous human guidance). From this point of view, during last years we have developed two different types of walking machines (an insect-like robot [8, 9] and a biped robot [10]) where they now combine the three key aspects (versatility, adaptivity, and autonomy) under neural sensor-motor control and an online learning mechanism. The description of the development of each walking machine system and its performance is presented in the following.

2. AMOS: Insect-Like Hexapod

AMOS is an advanced mobility sensor-driven walking device (see Fig. 1a). It consists of a two-part body, at which six identical legs and one tail are attached. Each leg has three joints (three degrees of freedom) controlled by analog servo motors: the thoraco-coxal joint enables forward (+) and backward (−) movements, the coxa-trochanteral joint enables elevation (+) and depression (−) of the leg, and the femur-tibia joint enables extension (+) and flexion (−) of the tibia [9]. The morphology of these multi-jointed legs is modeled on the basis of a cockroach leg [8]. Each tibia contains a spring compliant element to absorb impact force as well as to measure ground contact during walking. The body of AMOS consists of two segments: a front segment where two forelegs are installed and a central body seg-
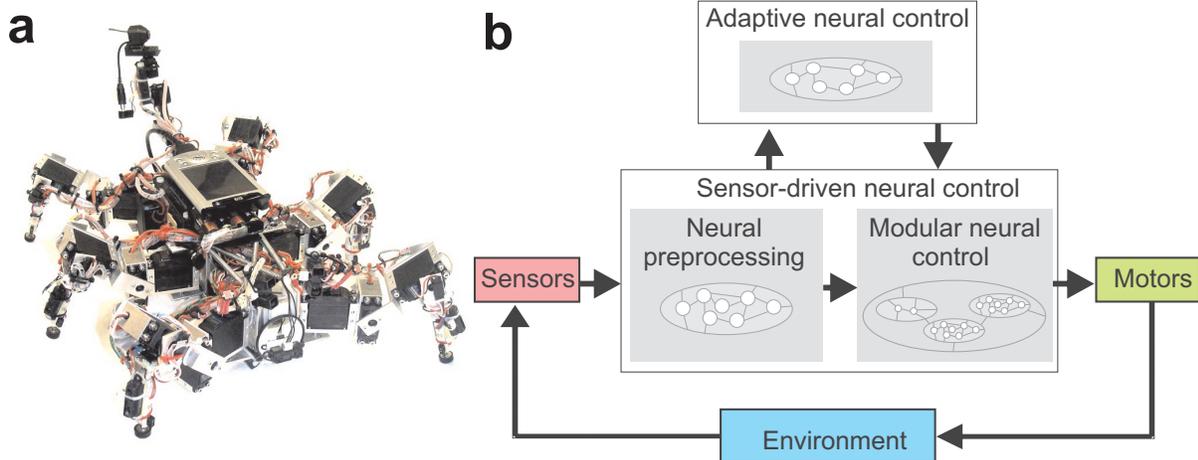
Figure 1. **a**, The physical insect-like hexapod AMOS (see [9] for the details of the location of the sensors on AMOS). **b**, The diagram of the neural controller of AMOS. The controller acts as an artificial perception-action system; i.e., the sensor signals are passed through the neural preprocessing unit into the modular neural control unit which directly drives the actuators. In addition, the adaptive neural control functions as high level control. It is used for learning capability. As a result, the hexapod's behavior is generated by the interaction with its physical environment in a sensorimotor loop.

ment where the two middle and the two hind legs are attached. They are connected by one active backbone joint inspired by the invertebrate morphology of the American cockroach's trunk [8]. This backbone joint driven by a digital servo motor is for up- and downward bending, which allows the walking machine to climb over obstacles. Moreover, a tail with two degrees of freedom, rotating around a horizontal and a vertical axis, is implemented in the center on the back of the trunk. On this actively moveable tail, which can be manually controlled, a mini wireless camera is installed for monitoring the environment while the machine is walking. This walking machine has a multitude of sensors: six foot contact sensors, six reflexive optical sensors, eight infra-red sensors, two light dependent resistor sensors, one upside-down detector sensor, one gyro sensor, one inclinometer sensor, and one auditory-wind detector sensor. The hexapod receives 26 sensory inputs, and controls 19 motors to achieve a broad behavioral repertoire including foothold searching, elevator reflex (swinging a leg over obstacles), self-protective reflex (standing in an upside-down position), obstacle avoidance, auditory- and wind-evoked escape responses, phototaxis (turn towards a light source), climbing over obstacles, and five different gaits.

These complex autonomous behaviors are generated through a so-called sensor-driven neural controller consisting of a neural preprocessing unit and a modular neural control unit (Fig. 1b). The neural preprocessing unit filters sensory noise, combines, and shapes sensory data to drive corresponding behaviors. On the other hand, the modular neural control unit is used for locomotive generation. It consists of three subordinate networks or modules: a neural os-

cillator network, two velocity regulating networks (VRNs), and a phase switching network (PSN). A simple neural oscillator network serves as a central pattern generator [11] (CPG) producing the basic rhythmic leg movements and regulates walking speed. Other modules, like the velocity regulating and the phase switching networks, enhance the walking capability of the machine to walk in omnidirection. Furthermore, adaptive neural control using a correlation based differential Hebbian learning rule (see Section 4 and [12] for details) has been implemented. It allows the hexapod to learn to respond to a conditioned stimulus, e.g., predator-recognition learning. As a result, all reactive and adaptive behaviors of the hexapod are accomplished by interacting with a physical environment through a sensorimotor loop (see [8, 9] for more details). The results of the real robot walking experiments can be seen as video clips at http://www.nld.ds.mpg.de/~poramate/AMOSWD06.html.

3. RunBot: Planar Dynamic Biped

RunBot is a planar dynamic biped robot (see Fig. 2a). It consists of four actuated joints: left hip, right hip, left knee and right knee. Each joint is driven by a modified servo motor where the built-in pulse width modulation (PWM) control circuit is disconnected, while its built-in potentiometer is used to measure the joint angles. RunBot has no actuated ankle joints, resulting in very light feet and efficiency for fast walking. Its feet were designed having a small circular form (4.5 cm long). Each foot is equipped with a switch sensor to detect ground contact events. A mechanical stop-
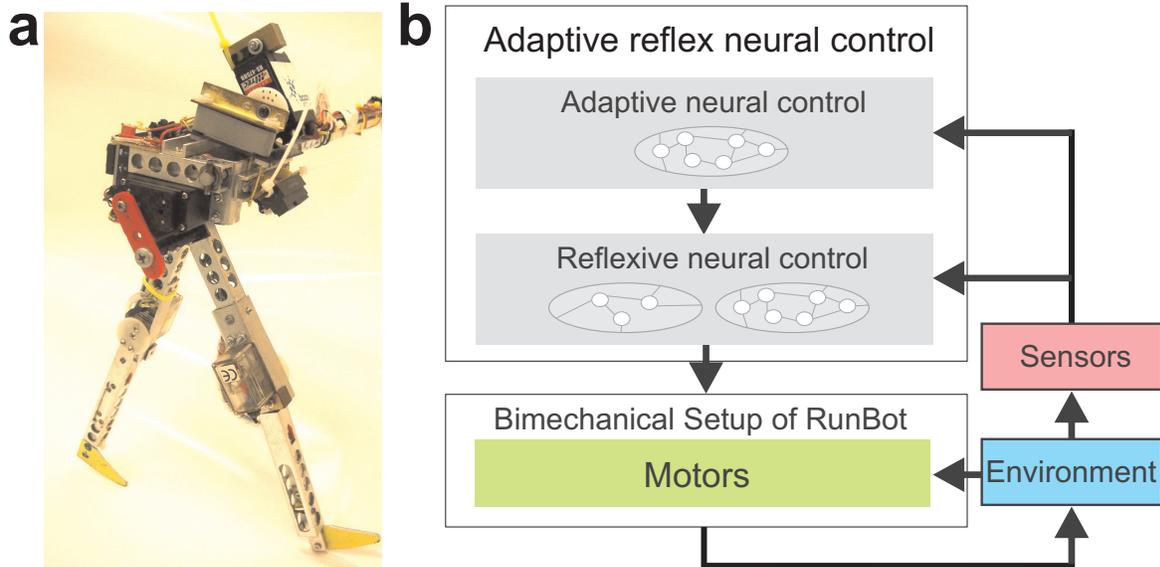
Figure 2. **a**, The planar dynamic biped robot RunBot (see [10] for the details of the location of the sensors on RunBot). **b**, The diagram of the neural controller of RunBot where the adaptive network is implemented on top as high level control to modulate the reflexive networks (lower level) through learner neurons (not shown but see [10] for details). Accordingly, the adaptive dynamic walking behavior of RunBot is achieved by the interaction with its physical environment in a sensorimotor loop.

per is implemented on each knee joint to prevent it from going into hyperextension. Approximately seventy percent of the robot's weight is concentrated on its trunk and the parts of the trunk are assembled in a way that its center of mass is located forward of the hip axis. In addition, it has an upper body component, which can be actively moved to shift the center of mass backward or forward for walking on different terrains, e.g., level floor versus up or down a ramp. It leans backward during walking on a level floor (see Fig. 2a) and this position is also suitable for walking down a ramp while it will lean forward (reflex action) when RunBot falls backward or after it successfully learned to walk up a ramp. The corresponding reflex is controlled by an accelerometer sensor (AS). The AS is installed on top of the right hip joint. Additionally, one infrared (IR) sensor is implemented at the front part of RunBot pointing downwards to detect a ramp. These IR and AS sensory signals are used for adaptive control (see [10] for details). As described here, the biomechanical design of RunBot has the following special features that distinguish it from other powered biped robots and that facilitate high-speed walking and exploitation of natural dynamics [10]: (a) small, curved feet allowing for rolling action; (b) unactuated, hence light, ankles; (c) lightweight structure; (d) light and fast motors; (e) proper mass distribution of the limbs; and (f) properly positioned mass center of the trunk. Utilizing all these properties, RunBot can perform self-stabilization of gaits [10] and it also exhibits passive walking characteristics [10] reflected

by the fact that during one quarter of its step cycle all motor voltages remain zero.

RunBot's locomotion is driven by adaptive reflex neural control (see Fig. 2b) which doesn't employ any trajectory control. It consists of two main circuits: adaptive and reflexive neural control circuits including signal preprocessing. The reflexive neural control based on reflex mechanisms uses proprioceptor signals (sensory feedback) coming from ground contact sensors, stretch receptors, and joint angle sensors to generate dynamic stable gaits while its AS sensor is used to trigger the body reflex. In the adaptive neural control where the correlation based differential Hebbian learning rule (see Section 4 and [12] for details) is applied, it serves for gait and posture adaptation during walking up a ramp. As a consequence, through the tight coupling of biomechanics with neural control, RunBot can autonomously walk with a high speed (> 3.0 leg length/s), self-adapting to minor disturbances, and reacting in a robust way to abruptly induced gait changes [10]. At the same time, it can learn walking on different terrains, requiring only few learning experiences [10]. The results of the real robot walking experiments can be seen as video clips at http://www.nld.ds.mpg.de/~poramate/Runbot.html.

4. Learning Algorithm

It is known that neurons can change their synaptic strength according to the order of the arriving inputs. That

is, if a predictive input u_1 (conditioned stimulus (CS), see Fig. 3) is followed by a reflex input u_0 (unconditioned stimulus (US), see Fig. 3), the plastic synapse of the predictive input gets strengthened ρ_1 but it will get weakened if the order is reversed. Hence, this form of plasticity depends on the timing of correlated neural signals (STDP, spike timing-dependent plasticity). This rule will lead to weight stabilization as soon as $u_0 = 0$ [12], meaning that the reflex has successfully been avoided. As a result, we obtain behavioral and synaptic stability at the same time without any additional weight-control mechanisms. In this learning rule (see Fig. 3), only the plastic synapse ρ_1 is allowed to change while the synapse of the reflex input ρ_0 is set to a positive value, e.g., 1.0.
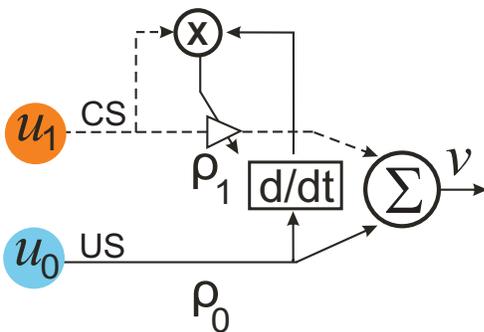

Figure 3. Correlation based differential Hebbian learning mechanism. In the terminology of conditioning, CS = conditioned stimulus, US = unconditioned stimulus.

Formally, we have

$$v = \rho_0 u_0 + \rho_1 u_1 \qquad (1)$$

as the neuron output driven by inputs (u_0, u_1). The plastic synapse ρ_1 gets changed by differential Hebbian learning using the cross-correlation between both inputs u_0 and u_1. It is given by:

$$\frac{d\rho_1}{dt} = \mu u_1 \frac{du_0}{dt}. \qquad (2)$$

μ is the learning rate which will define how fast a system can learn.

5. Conclusions

Taken together, this article gives two main contributions. On the one hand, it shows that neural control and learning can be successful for complex sensori-motor control problems in systems with a large numbers of sensors and motors. On the other hand, it guides that the biologically-inspired walking machines are fascinating technology to study with respect to their biomechanical design including sensor and actuator systems as well as the realizations of control concepts. For example, they can serve as scientific tools for better understanding and solving the sensorimotor coordination problems of many degrees of freedom, for performing experiments with neural controllers, and for the development of versatile artificial perception-action systems. In particular, the biped walking robot can serve as an experimental device in order to understand human walking which is a formidable challenge and which has been addressed through physiological studies as well as robotics research. Moreover, this walking machine technology is shown to be a highly interdisciplinary technology, uniting contributions from several areas as diverse as biology, biomechanics, material science, neuroscience, engineering, and computer science.

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