

Biologically Inspired Reactive Climbing Behavior of Hexapod Robots

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Abstract—Insects, e.g. cockroaches and stick insects, have found fascinating solutions for the problem of locomotion, especially climbing over a large variety of obstacles. Research on behavioral neurobiology has identified key behavioral patterns of these animals (i.e., body flexion, center of mass elevation, and local leg reflexes) necessary for climbing. Inspired by this finding, we develop a neural control mechanism for hexapod robots which generates basic walking behavior and especially enables them to effectively perform reactive climbing behavior. The mechanism is composed of three main neural circuits: locomotion control, reactive backbone joint control, and local leg reflex control. It was developed and tested using a physical simulation environment, and was then successfully transferred to a physical six-legged walking machine, called AMOS II. Experimental results show that the controller allows the robot to overcome obstacles of various heights (e.g., $\sim 75\%$ of its leg length, which are higher than those that other comparable legged robots have achieved so far). The generated climbing behavior is also comparable to the one observed in cockroaches.

I. INTRODUCTION

The concept of a fully autonomous and multi-mission-capable walking robot is one of the primary objectives in robotics. Often projects aim to design a biologically inspired robot with a conventional control system to perform locomotion. Most of them use a parametric model to control kinematics, dynamics and posture of the robot [1], [2]. Some works take inspiration from biological paradigms like Central Pattern Generators (CPGs) for basic walking generation and local leg reflexes for rough terrain locomotion and obstacle negotiation [3], [4]. In [5] and [6], biologically inspired compliant-legged robots have been developed to achieve a more stable and successful climbing. Especially in [5], they employed a body joint to improve the climbing capabilities of their robot. Another approach [7] implemented a “*sprawled posture*” on a robot hardware to obtain stability in climbing. More recent works on step climbing robots are mainly focussed on hybrid leg-wheeled mechanisms [8], [9] since they are easily controlled comparing with legged robots with

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many degrees of freedom. However, because of their reduced mobility these robots may have problems in negotiating very high steps as well as narrow stairs compared to legged robots. Besides all research and development related to such machines, existing robots still have not achieved a level similar to nature. Even the simplest forms of life are able to locomote autonomously through complex landscapes. Especially insects, e.g., cockroaches and stick insects, have the ability to negotiate obstacles relatively high with respect to their body scale. Research on behavioral neurobiology has identified key behaviors (i.e., body flexion, center of mass (CoM) elevation, and local leg reflexes) of insect climbing [10], [11], [12]. Only a few approaches have utilized parts of these key behaviors [3], [5], [7].

Inspired by behavioral neurobiology research, we developed a neural control mechanism for hexapod robots. It generates basic walking behavior and in particular reactive climbing behavior utilizing all mentioned key behaviors of insect climbing. Experimental results will not only demonstrate obstacle climbing capabilities but also show that the generated reactive climbing behavior is consistent with the one observed in insects.

The following section describes the key behaviors observed in insects. In section III, we introduce the hexapod walking machine AMOS II and the simulation toolkit *LpzRobots*. In section IV, the implementation of the neural control mechanism for climbing of hexapod robots is described. Section V presents experimental results of the climbing behavior of AMOS II. Finally, in section VI, we discuss the results and provide an outlook of possible future works.

II. BIOLOGICAL OBSERVATIONS

Research on behavioral neurobiology has identified at least three key behaviors necessary for climbing in insects: body flexion, CoM elevation and local leg reflexes.

A. Body flexion

Ritzmann et al. [10] investigated that the mobility of the two thoracic joints provides significant support for climbing of insects. For instance, cockroaches use their thoracic body flexion joint to support their locomotion over an object by tilting the prothorax down [10]. This specific behavior can be referred to as body flexion (see Fig. 6(a) in section V). It allows the forelegs a more powerful climbing movement and even more importantly it keeps the CoM near to the surface such that the cockroach does not fall down backwards.

B. CoM elevation

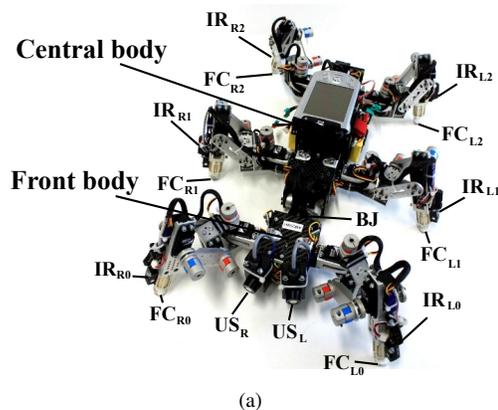
Watson *et al.* [11] investigated climbing locomotion of the deathhead cockroach (*Blaberus discoidalis*). Whilst climbing, the body requires an elevation of its center of mass (i.e., CoM elevation) to reach a higher altitude. This is done by a positive change of the body-substrate angle which is defined as the angle between ground and torso axis. Comparing climbing behaviors over obstacles of different heights, a difference of this positive change occurs. Cockroaches climb over obstacles smaller than the height of their front leg swing trajectory with no change of their walking gait. The front legs reach the obstacle's edge through walking. After the tarsi touches the top of the obstacle, the coxal-trochanteral (CTr) joint extends to push the front body from the ground. This leads to a positive change of the body-substrate angle. For higher obstacles the change is anticipated before the front legs reach the obstacle. This anticipatory change of behavior, moving the torso upwards, is called rearing phase [7]. To be able to fully climb the obstacle, a translation of the CoM above the obstacle is required. This is done through leg extension of each leg pair (see Fig. 6(c) in section V). This phase is named rising phase [7]. It appears that climbing does not require any remarkable dispositions from general walking control mechanisms, except the anticipatory behavior in the rearing phase. In addition, reacting to an obstacle the cockroach may require divisive sensory feedback (e.g. visual or antennae) as well as neural control mechanisms for leg reflex behaviors.

C. Local Leg Reflexes

Locomotion through complex landscapes causes many problems for legged animals, including holes in the ground as well as steps. Consequently, there is a high probability for legs to get stuck at such situations. The so-called searching and elevator reflexes observed in insects tend to solve such a problem leading to effective rough terrain locomotion and climbing over obstacles [13], [14], [15]. The searching reflex appears in situations in which legs lack ground contact, e.g. in a hole or a pit. The reflex then forces the respective leg to search for a foothold. It can be observed in certain insects, e.g. stick insects and locusts [12]. Uneven, complex landscapes are riddled with small obstacles such as rocks, roots or branches. Insects are able to avoid hitting an obstacle by triggering the elevator reflex [16]. During this reflex, the leg begins a further swing phase with a higher amplitude.

III. BIOLOGICALLY INSPIRED HEXAPOD ROBOT AMOS II

AMOS II (see Fig. 1(a)) is a biologically inspired hexapod robot developed to study neural control of locomotion of living creatures. The robot body is inspired by the morphology of cockroaches. Its six identical legs are connected to the trunk which consists of two thoracic jointed segments. Body flexibility is assured by an active backbone joint. The 19 active joints (three at each leg, one body joint) of AMOS II are driven by servomotors which are controlled in position mode. In addition, the body joint torque has been tripled by



(a)



(b)

Fig. 1. Experimental platforms. (a) Biologically inspired hexapod walking machine AMOS II. Symbols: BJ = backbone joint, FC = foot contact sensor, IR = infrared sensor, US = ultrasonic sensor. (b) Robot simulation toolkit *LpzRobots* with GUI.

using a gear to achieve a more powerful body joint motion (see Tab. I in Appendix). The thoracal-coxal (TC) joint controls forward/backward motion of the leg, the CTr joint has the role of extension and flexion of the second limb and the motion of the third limb (up and down) is driven by the femoral-tibial (FTi) joint. Besides the motors, AMOS II has 33 sensors perceiving its environment: nineteen joint angle sensors, two ultrasonic (US) sensors, six foot contact (FC) sensors, six infrared (IR) reflex sensors located at the front of each leg (see Fig. 1(a)). All in all, these sensors and motors are deployed for generating various behaviors (e.g., obstacle avoidance) [17], [18]. The simulation toolkit *LpzRobots* [19] based on the Open Dynamics Engine (ODE, see [20]) is used to simulate AMOS II (see Fig. 1(b)) and to test the developed reactive neural control before transferring it to the real robot. Since the simulation has the relevant properties of the real robot, it can accurately predict maximum obstacle or step heights that the robot can achieve. In addition, the tuned control parameters in the simulation can be directly tested on the real robot leading to almost identical behavior. Note that additional information of the dimensions, the mechanical and electrical properties of AMOS II is given in Tab. I in Appendix.

IV. CONTROL ARCHITECTURE FOR REACTIVE CLIMBING BEHAVIOR OF AMOS II

Inspired by behavioral neurobiology research discussed in section II, we extend the existing neural locomotion control of AMOS II (NLC [18], see Fig. 2) with two neural

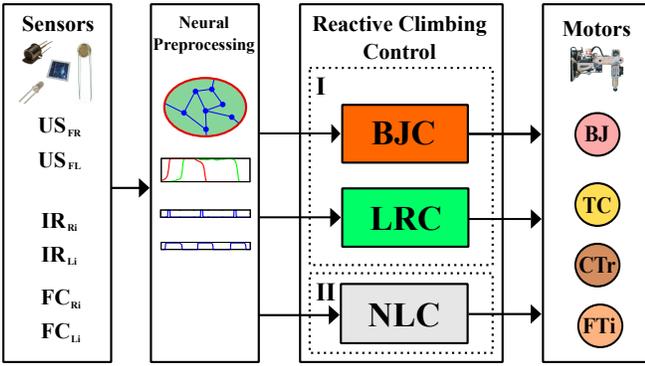


Fig. 2. Control architecture of AMOS II: the reactive climbing control composed of reactive backbone joint control (BJC), leg reflex control (LRC) and neural locomotion control (NLC). The BJC and LRC (I) control climbing key behavior while basic walking behavior including omnidirectional walking is achieved by NLC (II).

control units. This combination leads to so called Reactive Climbing Control (RCC). It allows the robot to effectively climb obstacles of various heights. The first extra unit is a reactive neural controller, called Backbone Joint Control (BJC), used to drive backbone joint motion. This controller enables the robot to negotiate obstacles higher than the ones existing robots have been able to negotiate. Inspired by neuroethological observations of stick insects and locusts [14], [15], we implement a second extra unit, called Leg Reflex Control (LRC), which generates local leg reflexes in order to avoid situations in which a leg might get stuck or lack ground contact.

All neurons applied in the networks are modelled as standard additive non-spiking neurons. The activity of a neuron i is given by $a_i(t+1) = \sum_{j=1}^n w_{ij} \sigma_j(a_j(t)) + \Theta_i$; $i = 1, \dots, n$, where n corresponds to the number of neurons, Θ_i is a constant input term, called bias, to the neuron i , and w_{ij} the synaptic weight of the connection from neuron j to neuron i . There are three types of transfer function of the neurons used here: the standard sigmoid $\sigma_i(a_i(t)) = (1 + \exp(-a_i(t)))^{-1}$, the hyperbolic tangent $\sigma_i(a_i(t)) = \tanh(a_i(t))$, and the linear (threshold) transfer function. Input units are linearly mapped onto the interval $[0, 1]$ (for sigmoid and linear) and $[-1, 1]$ (for hyperbolic tangent). Note that artificial neural networks are used here as robot control because they are conceptually close to biological systems [18] compared to any other solution. They can form as a modular structure where the entire controller consists of different functions as shown here. In addition, they also allow different off-line and on-line learning (not shown here but see [17], [18]).

A. Neural Preprocessing of Sensory Data

In order to generate biologically inspired reactive climbing behavior, we use foot contact (FC), infrared (IR) and ultrasonic (US) sensors. In this work, signal preprocessing is used for smoothing, filtering noise (i.e., random signal fluctuations) as well as prolongation of signals (see [21] for further study about neural preprocessing of sensory signals). This is done by applying the dynamical behavior of neural modules.

In particular, hysteresis effects of a recurrent neuron using a sigmoid transfer function are utilized to extend the activation time of the US signals [21]. This prolongation is required to control backbone joint motion (see below) longer than the stimulus itself is presented.

B. Reactive Backbone Joint Control (BJC)

Here, we present Reactive Backbone Joint Control (BJC) which supports the climbing behavior of the robot by emulating the body flexion observed in cockroaches. The neural network of the BJC is a hand-designed recurrent network with a behavior-based hierarchical order (see Fig. 3). There

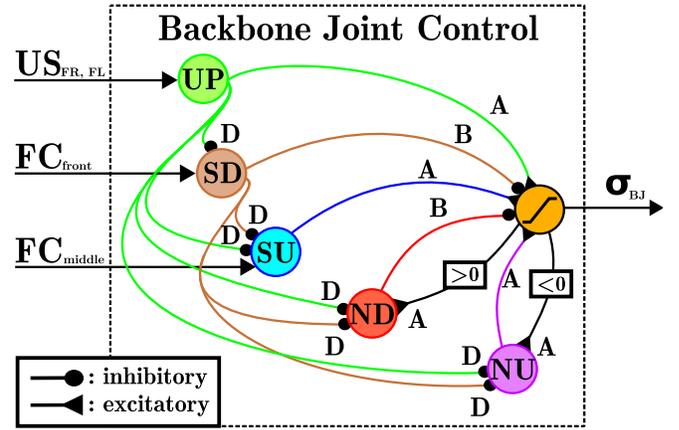


Fig. 3. Neural module for Backbone Joint Control (BJC). BJC receives preprocessed sensory data from different sensors (foot contact (FC) and ultrasonic (US) sensors). All neurons are modelled as standard additive neurons whose outputs are given by a linear transfer function. Input neurons are connected to a neuron whose output signal σ_{BJ} directly drives the backbone joint. Normalizing neurons ND and NU have a recurrent connection from the output neuron. Note that positive values of σ_{BJ} cause a normalizing downwards behavior, while negative values drive the backbone joint upwards to achieve normal position. The synaptic weights of the network are simply designed based on the hierarchical order of the control system. They have very strong connections (e.g., $C = -10.0$) from one behavior to another behavior to ensure fully inhibition. Other synaptic weights which combine all behaviors are set to smaller values (e.g., $A = 1.0$, $B = -1.0$) where positive and negative weights are used to drive the backbone joint up and down, respectively.

are five neurons with a linear threshold transfer function receiving preprocessed signals from different sensors (FC and US sensors). They are connected to an output neuron with a linear transfer function controlling the backbone joint. When activated, each of the five neurons causes different behaviors of the backbone joint. Leaning up (UP) the front body supports the robot before placing the front tarsi on the top of the obstacle (i.e., rearing phase). It is induced by US sensor signals. FC sensors of the front and the middle legs, respectively, are used for controlling reactive searching behaviors of the backbone joint. While downwards movements (SD) are useful for traversing an edge (i.e., transition of vertical/horizontal surface), upwards movements (SU) keep the middle legs to the ground when the robot locomotes through rough terrain. Normalizing behavior (ND, NU) is applied to drive the backbone joint to normal position after traversing an obstacle. Note that the interaction of

searching and normalizing behavior keeps the front body axis parallel to the surface.

C. Leg Reflex Control (LRC)

Besides the Backbone Joint Control, the Leg Reflex Control (LRC) is the second neural unit important for climbing. This sensor-driven control employs two leg reflex behaviors observed in insects. The first reflex is the searching reflex in which the leg searches a foothold when the foot has no ground contact, thus the foot contact signal σ_{fc} does not match the leg motor pattern. This reflex is implemented by using a neural module (see Fig. 4(a)) including a neural forward model [22]. The model transforms a motor command from a CPG (efference copy) into an expected foot contact signal σ_{forward} of normal walking. Describing the model in detail will go beyond the scope of this work. The output signal of the module is given by $\Delta = \sigma_{fc} - \sigma_{\text{forward}}$ and can be referred to as an error. The actual reflex is enforced by vertical shifting of the CTr and FTi signals using the accumulation of significant, positive errors: $\Delta^* = \sum_t |\Delta(t)|$; $\forall \Delta(t) \geq 0.15$. Consequently, the CTr/FTi signals are shifted when an error occurs, i.e., the respective leg searches for a foothold. The second reflex causes a leg elevation after the leg touches an obstacle during the swing phase. This reflex is called elevator reflex. It is induced by the infrared (IR) reflex sensors at the front of each leg. Using this sensory data as an input signal, a threshold neuron provides an output signal σ_e which shifts the CTr/FTi signals upwards, i.e., the leg is elevated. Note that this elevator reflex only occurs in the swing phase.

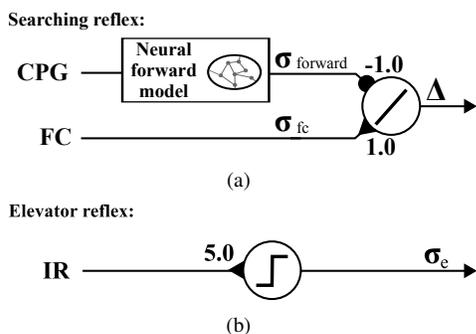


Fig. 4. Neural modules for local leg reflexes. (a) Searching reflex module. A neural forward model is applied to determine expected foot contact signal from leg motor pattern provided by the CPG. The additive neuron accumulates positive errors which cause vertical shifting of the CTr and FTi signals, resulting in searching reflex. (b) Elevator reflex module. A preprocessed infrared reflex signal are fed into a neuron using a linear threshold transfer function. The threshold is set to 0.01. The output signal σ_e shifts the CTr and FTi signals upwards. As a result, the leg is elevated. Note that each leg has its own searching and elevator reflex modules.

D. Neural Locomotion Control (NLC)

Neural locomotion control generates basic walking behavior including omnidirectional walking of the robot. This neural locomotion control has been presented in [17], [18]. Thus, here, we briefly discuss it. It consists of three modules:

- a Central Pattern Generator (CPG) including a postprocessing unit,

- a Phase Switching Network (PSN),
- two Velocity Regulation Networks (VRNs) working in parallel.

All neurons of these networks use a hyperbolic tangent transfer function. The CPG contributes periodic signals providing the leg rhythm of the robot. The PSN receives the CPG signals and directly drives the CTr and FTi joints. The VRNs, which receive an output signal from one neuron of the PSN and ultrasonic sensors, control the TC joints. While the CPG sets the rhythmic movements of the legs, the PSN and the VRNs provide a certain steering capability. Finally, the periodic signals provided by the neural modules are transferred to the motors using a delay line technique. This technique delays the output signal coming from the neural module about a certain delay $t_d = 0.8s$ for each following joint (from right hind to right front to left hind to left front). As a result, neural locomotion control enables AMOS II to move in different gaits as well as in any direction. Here only wave gait is used.

V. EXPERIMENTAL RESULTS

In the sequel, the efficiency of the applied climbing control has been tested by measuring the relative success of obstacle negotiation at five different altitudes (9-13 cm) using a wave gait. The relative success has been evaluated for 20 climbing trials per altitude. As a result, AMOS II negotiated obstacles with a height up to 13 cm (75% of its leg length) with a success rate of 100%. In addition, we measured input and output signals of the controller to illustrate the mechanism of our neural control (see Fig. 5). Besides climbing capabilities, the experiments reveal that AMOS II applies the same key behaviors as observed in cockroach climbing (see Fig. 6). Video clips of the climbing experiments can be seen at <http://www.manoonpong.com/AMOSII/Climbing>.

VI. DISCUSSION

This article demonstrates the reactive climbing behavior of the hexapod walking robot AMOS II which is generated by neural control. As a result, the physical robot was able to surmount obstacles with a maximum height of 13 cm which equals 75% of its leg length. As a comparison, Gregor I [7] was able to negotiate obstacles with a height of 65% of its leg length, while Scorpion IV [3] was able to negotiate obstacles with a height of 55% of its leg length. In [23], a quadruped robot successfully negotiated obstacles up to 40% of its leg length. The reference values were calculated using experimental videos of the respective robots which can be seen at <http://www.manoonpong.com/AMOSII/Climbing>. In addition, AMOS II displays three key behaviors (cf. sect. 2) which have been observed in insects. Therefore, the experiments not only show that AMOS II exhibits outstanding climbing capabilities, but its control system also generates climbing behavior similar to the behavior observed in insects. However, the presented behavior of AMOS II can be improved by:

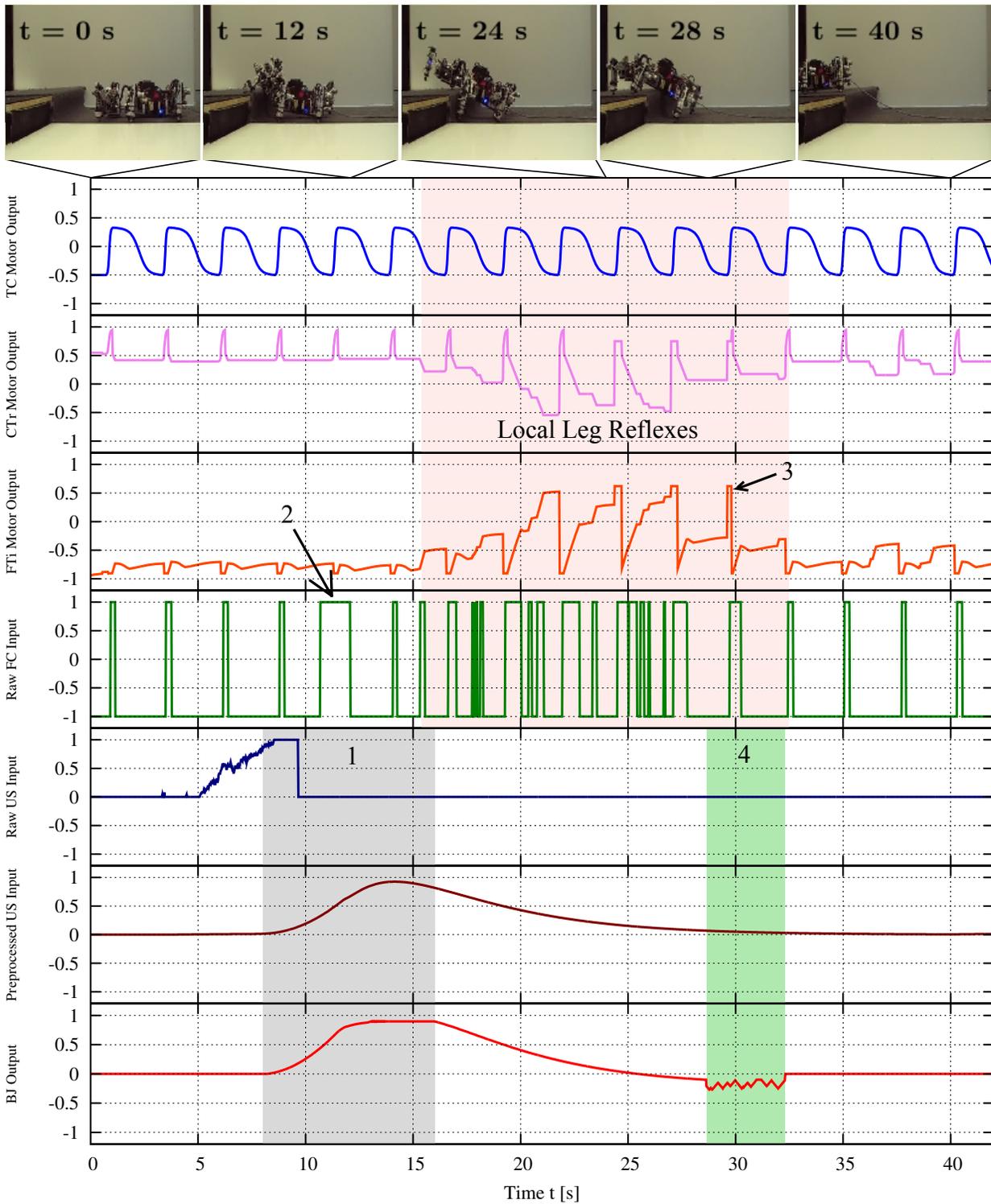


Fig. 5. Climbing behavior of AMOS II over a 13 cm high obstacle. In order to demonstrate the neural control mechanism we measured input (sensor) and output (motor) signal of the left front leg and the backbone joint (BJ). As AMOS II approached the obstacle, the US sensor detection activated the backbone joint control (BJC) and the BJ leant upwards ((1), see also gray colored area). Because the front legs had no ground contact at this period (2), the local leg reflex control drove the leg to search for a foothold (searching reflex, see rose colored area). Note that the peak of the FTi signal was induced by the elevator reflex in order to avoid the leg from hitting the obstacle (3). Local leg reflex control also generated the CoM elevation of AMOS II by extending the legs for support. At a certain time after the middle legs were on top of the obstacle, the front legs had no ground contact. BJC drove the backbone joint downwards to gain foot contact (body flexion). Additionally, the behavior-based hierarchy of the BJC tried to always keep the front body part parallel to the ground ((4), see also green colored area). Finally, AMOS II successfully negotiated the 13 cm high obstacle. Note that in this experiment body flexion can be recognized when the BJ motor signal (BJ Output) is nonzero. Indications of the y-axis: TC (+1 = forward, -1: backward), CTr (+1 = up, -1 = down), FTi (+1 = up, -1 = down), FC (+1 = no contact, -1 = contact), US (0 = no detection, +1 = full detection), BJ (+1 = up, -1 = down). Symbols: BJ = backbone joint, CTr = coxal-trochanteral joint, FC = foot contact sensor, FTi = femoral-tibial joint, TC = thoracal-coxal joint, US = ultrasonic sensor.

- integrating a learning mechanism into the controller such that the robot is able to adapt its body joint motion to an obstacle height as well as a selected gait,
- adjusting the hind legs while climbing,
- implementing switchable friction materials underneath the trunk of AMOS II to obtain sufficient levels of friction and adhesion during climbing.

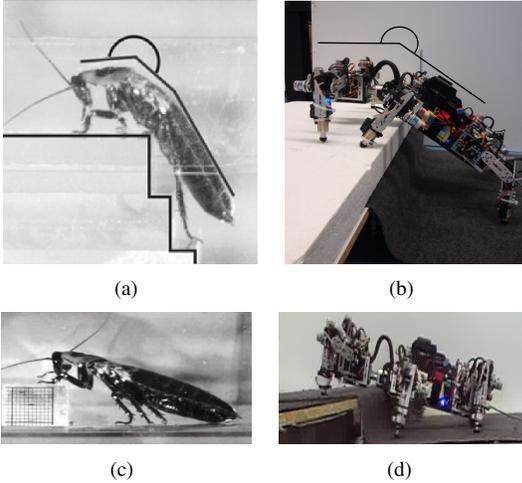


Fig. 6. Comparison of the climbing behavior of a cockroach and the robot: (a)-(b) body flexion and (c)-(d) CoM elevation observed in a cockroach and the robot. (a) and (c) modified from [24])

APPENDIX

TABLE I

DIMENSIONS, MECHANICAL AND ELECTRICAL PROPERTIES OF AMOS II.

Property	Description/ Value [Unit]
Robot front height	7.5 [cm]
Robot length	46 [cm]
Robot width	36 [cm]
Body height	7.1 [cm]
Body length	42 [cm]
Body width	6.6 [cm]
Leg length	17.5 [cm]
Coxa length	3.5 [cm]
Femur length	6 [cm]
Tibia length	11.5 [cm]
Weight	4.2 [kg] (with batteries)
Material	Carbon-fiber-reinforced polymer and Aluminum alloys AL5083184
Motors	HSP-5990 TG HMI Digital Robot Servo (torque: $\tau = 2.4 - 2.9$ Nm, for backbone joint three times larger via gear)
Ultrasound Sensor	UNDK 30U6103
Infrared Sensor	Sharp GP2Y0AH01K10F High Accuracy Distance Measuring Sensor (range: 0.45 - 0.6 cm)
Microcontroller	Multi-Servo IO-Board (Mboard)
Batteries	1x 11.1 V/3S-1P/3200 mAh (for servos), 2x 11.1 V/3S-1P/910 mAh (for MBoard/ sensors)

REFERENCES

[1] M. Fielding, R. Dunlop, and C. Damaren, "Hamlet: force/position controlled hexapod walker-design and systems," in *Control Applications, 2001.(CCA'01). Proceedings of the 2001 IEEE International Conference on*. IEEE, 2001, pp. 984–989.

[2] B. Gassmann, K. Scholl, *et al.*, "Behavior control of LAURON III for walking in unstructured terrain. intl," in *Conference on Climbing and Walking Robots (CLAWAR'01)*, Karlsruhe, Germany, 2001.

[3] B. Klaassen, R. Linnemann, D. Spenneberg, and F. Kirchner, "Biomimetic walking robot SCORPION: control and modeling," *Robotics and Autonomous Systems*, vol. 41, no. 2-3, pp. 69–76, 2002.

[4] K. S. Espenschied, R. D. Quinn, R. D. Beer, and H. J. Chiel, "Biologically based distributed control and local reflexes improve rough terrain locomotion in a hexapod robot," *Robotics and Autonomous Systems*, vol. 18, pp. 59–64, 1996.

[5] W. A. Lewinger, C. M. Harley, R. E. Ritzmann, M. S. Branicky, and R. D. Quinn, "Insect-like antennal sensing for climbing and tunneling behavior in a biologically-inspired mobile robot," in *Proc. IEEE Int. Conf. Robotics and Automation ICRA 2005*, 2005, pp. 4176–4181.

[6] U. Saranlı, M. Buehler, and D. Koditschek, "Rhex: A simple and highly mobile hexapod robot," *The International Journal of Robotics Research*, vol. 20, no. 7, p. 616, 2001.

[7] M. Pavone, P. Arena, L. Fortuna, M. Frasca, and L. Patané, "Climbing obstacle in bio-robots via CNN and adaptive attitude control," *International journal of circuit theory and applications*, vol. 34, no. 1, pp. 109–125, 2006.

[8] Y.-C. Chou, W.-S. Yu, K.-J. Huang, and P.-C. Lin, "Bio-inspired step crossing algorithm for a hexapod robot," in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, sept. 2011, pp. 1493–1498.

[9] S.-C. Chen, K. J. Huang, C.-H. Li, and P.-C. Lin, "Trajectory planning for stair climbing in the leg-wheel hybrid mobile robot quattroped," in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, may 2011, pp. 1229–1234.

[10] R. Ritzmann, R. Quinn, and M. Fischer, "Convergent evolution and locomotion through complex terrain by insects, vertebrates and robots," *Arthropod Structure & Development*, vol. 33, no. 3, pp. 361–379, 2004.

[11] J. T. Watson, R. E. Ritzmann, S. N. Zill, and A. J. Pollack, "Control of obstacle climbing in the cockroach, *blaberus discoidalis*: I. locomotion," *J Comp Physiol*, vol. 188, no. 1, pp. 39–53, 2002.

[12] H. Fischer, J. Schmidt, R. Haas, and A. Büschges, "Pattern generation for walking and searching movements of a stick insect leg. I. coordination of motor activity," *Journal of neurophysiology*, vol. 85, no. 1, p. 341, 2001.

[13] K. Pearson and R. Franklin, "Characteristics of leg movements and patterns of coordination in locusts walking on rough terrain," *The International Journal of Robotics Research*, vol. 3, no. 2, p. 101, 1984.

[14] U. Bässler, *Neural basis of elementary behavior in stick insects / Ulrich Bässler ; [translated from the German by Camilla Mok Zack Strausfeld]*. Springer-Verlag, Berlin ; New York :, 1983.

[15] H. Cruse, "The control of the anterior extreme position of the hindleg of a walking insect, *carausius morosus*," *Physiological Entomology*, vol. 4, no. 2, pp. 121–124, 1979.

[16] R. Franklin, *The locomotion of hexapods on rough ground*. Paul Parey, 1985, pp. 69–78.

[17] P. Manoonpong and F. Wörgötter, "Adaptive sensor-driven neural control for learning in walking machines," 16th International Conference on Neural Information Processing, 2009.

[18] S. Steingrube, M. Timme, F. Wörgötter, and P. Manoonpong, "Self-organized adaptation of simple neural circuits enables complex robot behavior," *Nature Physics*, vol. 6, pp. 224–230, 2010.

[19] G. Martius, F. Hesse, F. Güttler, and R. Der, "LpzRobots: A free and powerful robot simulator," <http://robot.informatik.uni-leipzig.de/software/>, 2012.

[20] Open dynamics engine official site. [Online]. Available: <http://www.ode.org/>

[21] P. Manoonpong, F. Wörgötter, and F. Pasemann, "Neural preprocessing of auditory-wind sensory signals and modular neural control for auditory-and wind-evoked escape responses of walking machines," in *Robotics and Biomimetics (ROBIO). IEEE International Conference on*. IEEE, 2008, pp. 786–793.

[22] P. Manoonpong, U. Parlitz, and F. Wörgötter, "Internal forward models with efference copies for state estimations in adaptive hexapod locomotion," in *Frontiers in Computational Neuroscience*. Bernstein Conference, 2012.

[23] H. Lee, Y. Shen, C.-H. Yu, G. Singh, and A. Y. Ng, "Quadruped robot obstacle negotiation via reinforcement learning," IEEE International Conference on Robotics and Automation, 2006.

[24] Ritzmann lab videos. [Online]. Available: roach.biol.cwru.edu/~ritzmann/