Biological Inspiration for Mechanical Design and Control of Autonomous Walking Robots: Towards Life-Like Robots

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ABSTRACT

Nature apparently has succeeded in evolving biomechanics and creating neural mechanisms that allow living systems like walking animals to perform various sophisticated behaviors, e.g., different gaits, climbing, turning, orienting, obstacle avoidance, attraction, anticipation. This shows that general principles of nature can provide biological inspiration for robotic designs or give useful hints of what is possible and design ideas that may have escaped our consideration. Instead of starting from scratch, this article presents how the biological principles can be used for mechanical design and control of walking robots, in order to approach living creatures in their level of performance. Employing this strategy allows us to successfully develop versatile, adaptive, and autonomous walking robots. Versatility in this sense means a variety of reactive behaviors including memory guidance, while adaptivity implies online learning capabilities. Autonomy is an ability to function without continuous human guidance. These three key elements are achieved under modular neural control and learning. In addition, the presented neural control technique is shown to be a powerful method of solving sensor-motor coordination problems of high complexity systems.

Keywords: Neural control, Biomechanics, Reactive behavior, Memory-guided behavior, Predictive behavior

1. INTRODUCTION

Living creatures like walking animals impress observers with the elegance and smoothness of their movements. They can perform versatile behaviors including reactive, proactive, and memory-guided behaviors (Fig. 1). They can even learn to adapt themselves to environmental changes in order to survive. All these sophisticated behaviors are basically driven by internal and external stimuli through interactions with the environment. From this point of view, during the last few decades several roboticists have begun to actively look into biological systems as blueprints for the design of multi sensori motor robotic systems, in particular walking robots, to approach their levels of performance. However, the achievements of complexity level comparable to that of the biological systems in artificial agents (i.e., robots) are still far from being realized or implemented. This is due to the fact that complex motor behavior requires combining information from a multitude of sensors while simultaneously providing coordinated outputs to a large number of motor units. To be efficient, this needs to include not only reactive (mostly used in existing walking robots) but also (anticipatory) predictive mechanisms.

The diverse researches in the domain of biologically-inspired walking robots have been ongoing for over 20 years [1, 2]. Most of them have focused on the mechanical design to achieve animal-like properties and perform efficient locomotion [3, 4]. Others have concentrated on the generation of locomotion based on engineering technologies [5] as well as biological principles [6, 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).

To tackle this highly challenging robotic field we have developed walking robots including their mechanics and neural sensori motor control based on a modular concept and an incremental synthetic process. As a result, we have now successfully produced diverse biologically-inspired complex behaviors (Fig. 1) including versatile reactive behaviors, predictive behaviors (or called proactive behaviors), and memory-guided behaviors for our walking robots. Thus, the purpose of this article is to present our achievements where biological systems have been used as blueprints for structural, control, and behavior designs.

In the following section, we will give a short overview of the biological systems in term of their diverse behaviors together with neural mechanisms. Afterwards we will describe the development of our

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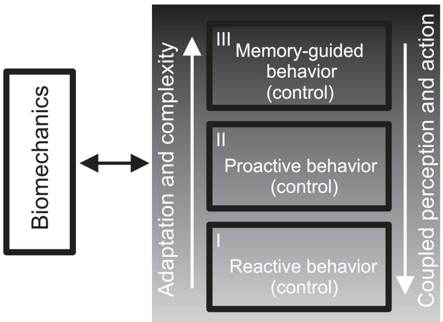

Fig.1: *Spectrum of artificial and biological behaviors where the high intensity (dark) area implies a high degree of adaptation and complexity of behavior and control but loosely coupled perception-action processes, and vice versa for low intensity. Each behavior level is driven by neural control coupled with biomechanics. Note that here we divide complex behaviors of biological and artificial systems into three major classes: reactive behavior, proactive behavior, and memory-guided behavior (delayed responses). Beyond the memory-guided behavior we find ourselves at the level of goal-directed behavior which will not be concerned here. Reactive behavior has a tight coupling between perception and action where the information from sensor activation patterns directly trigger reactions, resulting in immediate responses. In contrast, proactive behavior involving learning of a temporal association of subsequent cues allows animals to react to an early cue (predictive signal) instead of a later cue (reflex-triggering signal), leading to accelerated responses. Memory-guided behavior involving short-term memory (STM) is the development of behavior beyond reactive and proactive behaviors. Animals and robots have to memorize states, environmental conditions, or other information to fulfill a task, even in the temporal absence of essential sensory information. In other words, they have to remember the stimulus in order to keep on performing or to later use the stimulus information after a delay as an internal drive to fulfill their task. These behaviors lead to indirectly coupled perception-action processes.*

walking robots where their performances are often being presented alongside the structural elements from which they mainly derive. Finally, we will give a discussion and conclusions.

2. BIOLOGICAL BACKGROUND

Animals or even insects can perform diverse behaviors including reactive behaviors [8-12], memory guidance [13], and complex action planning [14, 15]. They enjoy complete freedom to control their actions within the environment to which they have been adapted. Solving these tasks basically results from coupling biomechanics with neural control.

Biomechanics: Animals use their biomechanically optimized legs (Fig. 2(a)) to support their body during standing, walking, turning, climbing, or other behaviors. In some insects, the leg structure is specialized for particular functions, e.g., digging, grasping, prey capture or jumping. Furthermore, the legs allow increased dynamic stability and minor disturbance rejection through a mechanical feedback loop (self-stabilization) [16, 17] while walking over irregular terrain. They also enable them to perform a variety of motion patterns (walking in different direction, climbing) while spending minimal energy during locomotion. In addition to the legs, body geometry and structure play a role in locomotion as well [17]. In general, the body of invertebrates (e.g., cockroach) is subdivided in segments (Fig. 2(b)) while the body of vertebrates consists of muscles propagating along a backbone (musculature, Fig. 2(c)). These body structures allow more flexible and faster motions and aid in climbing.

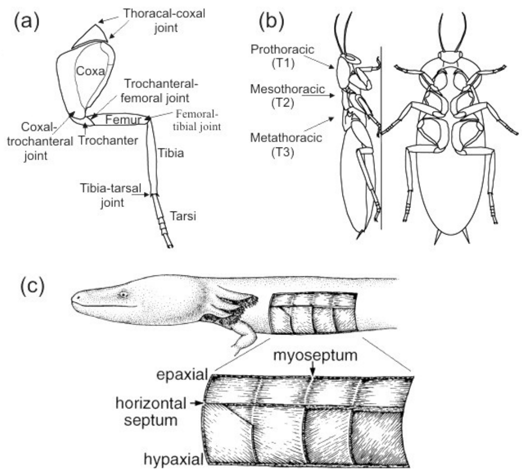

Fig.2: *(a), (b) Biomechanical legs of a cockroach and the orientation of the legs around its trunk (modified from [18]). The segmental body allows a cockroach to climb over large obstacles. It can bend its trunk downward at the joint between the first (T1) and second (T2) thoracic to keep the legs close to the top surface of the obstacles for an optimum climbing position and even to prevent unstable actions. (c) Axial musculature of an aquatic salamander, Necturus maculosus (modified from [19]). This muscular structure enables the salamander to perform more flexible and faster motions and aids in climbing. Generally, during locomotion on land, its trunk bends to one side causing an increase in the step length of the two diagonally opposite lifted limbs which are pushed forward while the other two limbs are pushed backward simultaneously.*

Neural locomotion control and reactive behaviors: Besides biomechanics, neural control generates appropriate natural movements by combining information from a multitude of external stimuli covering different sensor modalities and from internal stimuli (e.g., memory induced). These circuits finally provide coordinated outputs to motor neuron pools.

In many animals, the coordination of movement patterns is believed to be mediated by networks of neurons called central pattern generators (CPGs) [20-22] at the level of the spinal cord of vertebrates or the sensori motor ganglia of invertebrates [23, 24]. Above the spinal cord or local ganglia level, there are neural circuits in higher brain centers allowing the animals to react, memorize, and learn. These lead to reactive and proactive behaviors including ability to plan their actions in advance (prediction). Different reactive behavioral responses are commonly found, such as orientating toward (positive tropism [10, 11, 25]) or away (negative tropism [8, 26, 27]) from a stimulus. For instance, female crickets perform phonotaxis during courtship, that is they turn toward the direction of the calling of a male [10]. Negative tropism can be found in, for example, an obstacle avoidance behavior during navigation or exploration in insects [8]. They try to turn away from an obstacle perceived by their sensing systems (e.g. hairs, antennae).

Predictive behaviors and memory guidance:
In addition to reactive behaviors, animals can learn to act in advance of a future situation, rather than solely reacting. Rodents can learn the danger-predicting meaning of predator bird calls through a temporal association of cues which are an aversive stimulus (reflex signal) and the acoustic stimulus (predictive signal) [28]. As a consequence, they will react to the predictive signal, which they can detect earlier, for a safe escape. In general this mode of learning concerns presentations of a neutral stimulus (predictive signal) along with a stimulus of some significance (reflex signal). Once these two stimuli become associated, animals begin to perform a behavioral response to the predictive signal instead of the reflex signal. The fruit flies Drosophila melanogaster [14, 29] also demonstrate key aspects of predictive behavior where they always reposition their legs during the approach of a looming visual stimulus (predictive signal). This behavior, which effectively plans the direction of take-off, occurs approximately 100 ms earlier than all previously identified components of the escape response, and it is not reflexively coupled to flight initiation because a fly can prepare for an escape without taking off. More complex behaviors like memory guidance (also called delayed responses) involving short-term memory (STM) have been reported in some insects and mammals. For instance, cockroaches use their cercal filiform hairs (wind sensitive hairs) to elicit the so-called *wind-evoked escape behavior* [8], i.e., they run away from a wind puff to their cerci generated by a lunging predator. Another kind of memory guidance is also evident in the flying cricket Teleogryllus oceanicus. It uses sound sensitive organs to elicit *auditory-evoked escape behavior* [26] involving a fast movement away from abrupt, intense (loud), and unexpected stimuli. In general, such escape behaviors last longer than the stimulus itself. Once the actions have been activated, they will be performed even if the activating stimulus is removed to ensure a safe escape from the attack. Thus, these actions reflect not only reactive responses but also simple memory-guided behaviors (internal drive) known as fixed action patterns [30].

3. BIOLOGICALLY INSPIRED WALKING ROBOTS

Inspired by biomechanics of animals (mentioned in Sect. 2) we have developed different types of animal-like walking robots: four, six, and eight legs (see Figs. 3, 4 and 5, respectively). They have been employed as hardware platforms for studying the coordination of many degrees of freedom, for performing experiments with neural controllers, and for the development of artificial perception-action systems employing embodied control techniques. Moreover, such robots are more attractive compared to wheeled robots because they can behave somewhat like animals and they are still a challenge for locomotion control due to their complex sensori motor coordination.

The salamander-like robot AMOS-WD04: [1]
The AMOS-WD04 [31, 32] is a four-legged walking robot inspired by a salamander (Fig. 3). Each leg is designed to have two joints (two degrees of freedom (DOF)) based on the basic principle of movement of a salamander leg. The upper joint of the legs, called the thoracic joint, can move the leg forward (protraction) and backward (retraction) and the lower one, called the basal joint, can move it up (elevation) and down (depression) (see [31, 32] for more details of the leg configuration). The robot was constructed with a backbone joint which can rotate around a vertical axis (Fig. 3). It facilitates a more flexible and faster motion[2] as a salamander. The backbone joint is also used to connect the trunk, where two hind legs are attached, with the front part where two forelegs are installed. This robot has two infrared sensors to detect obstacles and two mini-microphone sensors to detect sound. These sensors are used to drive obstacle avoidance behavior and phonotaxis.

The cockroach-like robot AMOS-WD06:
The AMOS-WD06 [31, 33] is a six-legged walking robot inspired by the cockroach Blaberus discoidalis (Fig. 4). Each leg has three joints (three DOF, see Fig. 2(a)): the thoracal-coxal (TC-) joint en-

[1] Advanced MObility Sensor driven-Walking Device.
[2] To see an advantage of activating this active backbone joint during locomotion, we refer the reader to a video clip at http://www.manoonpong.com/AMOS/SalamanderLikeWalking.mpg.

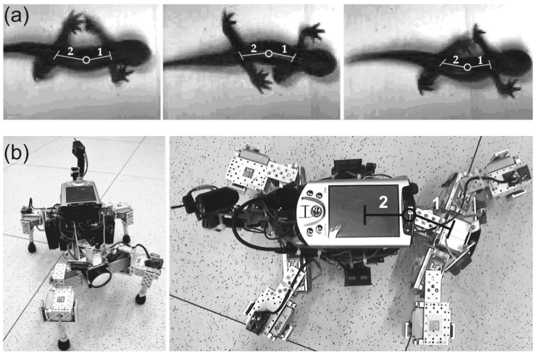

Fig.3: *(a) The locomotion of a salamander (from left to right). An open circle in each photo represents to a backbone joint which connects the first segment (1) to the second segment (2) and makes an active bending movement of a trunk for locomotion (Courtesy of J.S. Kauer (Kauer Lab at Tufts University)). (b) The four-legged walking robot AMOS-WD04.*

ables forward and backward movements, the coxal-trochanteral (CTr-) joint enables elevation and depression of the leg, and the femoral-tibial (FTi-) joint enables extension and flexion of the tibia (see [31] for more details of the leg configuration). The morphology of this multi-jointed leg is modeled on the basis of a cockroach leg but the trochanteral-femoral joint and the tarsal segments are ignored. Furthermore, to mimic biomechanical properties of the cockroach leg, we installed a spring damped compliant element in each tibia part of the robot. By doing so, these spring legs enable the robot to perform better self-stabilization and absorb a large impulse at touchdown. The body of the AMOS-WD06 consists of two parts: a front part where two forelegs are installed and a central body part where two middle legs and two hind legs are attached. They are connected by one active backbone joint which can be activated to rotate around the lateral or transverse axis (pitch axis) similar to the cockroach. It aids the robot to effectively climb over obstacles[3] (Fig. 4). This walking robot has a multitude of sensors: six foot contact sensors, six reflexive optical sensors, seven infrared sensors, two light dependent resistor sensors, one upside-down detector sensor, one gyro sensor, one inclinometer sensor, one auditory-wind detector sensor, and one current sensor. All these sensors are used to generate 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.

[3] To see the use of this active backbone joint in autonomous climbing over obstacles, we refer the reader to a video clip at http://www.manoonpong.com/AMOS/AMOSclimbing.mpg.

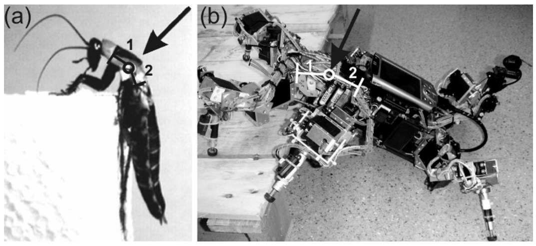

Fig.4: *(a) The cockroach Blaberus discoidalis climbs over a large obstacle. It bends its trunk downward at the joint between the first (1) and second (2) thoracic to keep the legs close to the top surface of the obstacles for an optimum climbing position and even to prevent unstable actions (modified from [34]). (b) The six-legged walking robot AMOS-WD06.*

The scorpion-like robot AMOS-WD08:
The AMOS-WD08 [35, 36] is an eight-legged walking robot inspired by the scorpion Pandinus cavimanus (Fig. 5). Its leg configuration is similar to that of the AMOS-WD06 except its tibiae where the spring element has not yet been implemented. The chassis design of the AMOS-WD08 follows the scorpion body contour but the tail part is ignored (Fig. 5). It is constructed with only one part where all legs are orientedly attached (Fig. 5(b)). In contrast to the AMOS-WD04 and -WD06 consisting of various exteroceptive sensors, the AMOS-WD08 has only proprioceptive sensors: potentiometer sensors for detecting the actual angle position of leg joints and photoresistor sensors in foot tips for measuring the ground contact. In general this robot has been designed to serve as a platform to investigate a role of proprioceptive sensing in locomotion [35].

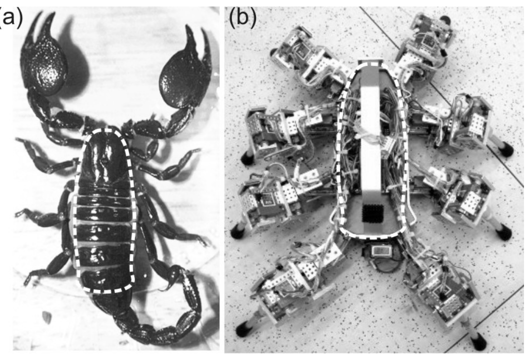

Fig.5: *(a) The scorpion Pandinus cavimanus (Copyright 1996 by R. David Gaban [37] and reproduced with permission). (b) The eight-legged walking robot AMOS-WD08. Dashed lines show a body contour.*

The control of all three walking robots is kept on a simple but powerful board, the Multi-Servo IO-Board (MBoard), which at a size of 125 mm × 42 mm can control up to 32 motors and has 36 analog sensor inputs. The MBoard can be interfaced with a personal computer (PC) or a personal digital assistant (PDA) via an RS232 serial connection at 57.6 kbits/s. The neural controllers however are first tested using a physical simulation environment "Yet Another Robot Simulator" (YARS) [38]. After the test on the simulator, the developed neural controllers are applied to the physical walking robots to evaluate their behaviors in real environments.

4. NEURAL CONTROL AND LEARNING

Inspired by the principles of locomotion control including behavior generation and learning capability of animals (cf. Sect. 2), we have developed neural sensori motor control and learning mechanisms for our walking robots (cf. Sect. 3) in a stepwise manner during the last years [31-33, 36, 39-42]. They now enable the robots to perform complex animal-like behaviors, i.e., versatile reactive, proactive (adaptive) and memory-guided behaviors (level I, II, and III, respectively, in Fig. 1). These neural mechanisms implemented using neural networks [31] can be divided into three main neuromodules (Fig. 6) having different functions. The first module is called the "modular neural locomotion control". It is based on central pattern generators (CPGs) [20-22] found in animals and here it is used to generate basic walking behaviors such as forward move, backward move, left turn and right turn. These walking behaviors are autonomously controlled by sensory signals. However, due to sensory noise and multiple sensor modalities, the signals need to be filtered, shaped and integrated through the second neuromodule called "neural sensory preprocessing" before activating the corresponding behaviors. The last neuromodule called "neural learning" is applied to allow the robots not only to react to environmental stimuli but also to adapt or to anticipate environmental changes. All neurons in the modules are modeled as standard additive non-spiking neurons. Their activity develops according to:

$$a_i(t+1) = \sum_{j=1}^{n} W_{ij} o_j(t) + B_i \quad i = 1, ..., n \qquad (1)$$

where n denotes the number of neurons and a_i is their activity. The variable B_i represents a fixed internal bias together with a stationary input of neuron i; W_{ij} is the synaptic strength of the connection from neuron j to neuron i, and o_j is the output of neuron j. In the neural sensory preprocessing and modular neural locomotion control units, the output neurons are given by the standard sigmoid transfer function $o_i(t) = \sigma(a_i(t)) = (1 + e^{-a_i(t)})^{-1}$ and the hyperbolic tangent transfer function $o_i(t) = \sigma(a_i(t)) = \tanh(a_i(t))$, respectively, while the output of the neural learning unit is governed by a linear transfer function. Input units, e.g., sensory neurons, are configured as linear buffers (see [31, 33, 36] for more details).

In the following, we provide a more detailed account on the development process of the modular neural locomotion control followed by the neural sensory preprocessing and finally the neural learning.

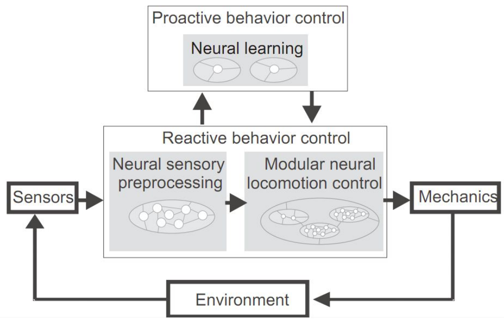

Fig.6: *Diagram of neural mechanisms of the walking robots. The sensor signals are passed through the neural preprocessing unit into the modular neural locomotion control unit which directly drives the actuators. In addition, the neural learning acts as high level control. It is used for enabling the robots to adapt to different situations. This neural learning mechanism leads to the generation of the proactive behaviors.*

A basic original neural locomotion controller (Fig. 7) has been evolved through an evolutionary algorithm [39]. The result of which shows that only one oscillator consisting of two neurons with full connectivity (central pattern generator, CPG (gray frame, Fig. 7(b))) is enough for basic locomotion, but oscillations need to be post-processed to arrive at more complex behaviors. This oscillator has been tested first on the hexapod robot Morpheus (Fig. 7(a)).

Based on the evolved neural locomotion control, the controller has been improved by adding the velocity regulating networks or VRNs (shaded box, Fig. 8) [31, 32]. The VRNs are feedforward neural networks. Each VRN controls the two or three ipsilateral TC-joints [4] on one side (Fig. 8). They are used to achieve more walking directions, like turning left and right as well as forwards and backwards movements (see experimental results at [31, 32]). Furthermore, the VRNs regulate walking speed of the robots by simply increasing or decreasing the amplitude of the periodic CPG signals. This improved neural locomotion control has been evaluated first on the YARS physical simulation environment [38] and then successfully transferred to the four- (AMOS-WD04) and six- (AMOS-WD06) legged walking robots. For demonstration, we refer to a

[4] The TC-joints enable forwards and backwards movement of legs.

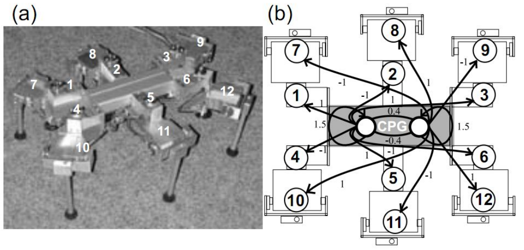

Fig. 7: *(a) The physical six-legged walking robot Morpheus; each leg has two DOF. (b) The evolved neural control with only two hidden neurons (shaded area) and symmetric output weights to motor neurons (small black numbers). It performs as a quasi-periodic oscillator or a CPG, enabling an efficient forwards movement [39]. Note that the large circled numbers indicate motor neurons (corresponding to the numbered location of actuators in (a)).*

video clip at *http://www.manoonpong.com/AMOS/ReactBehavior.mpg.*

After the developed neural locomotion control presented above has been successfully tested on the four- and six-legged walking robots, the controller has been further enhanced by adding a phase switching network or PSN (shaded box, Fig. 9) [36]. The PSN is a generic feedforward network that reverses the phase of the periodic signals driving the CTr- joints and the FTi- joints [5] of the six- (AMOS-WD06) and eight- (AMOS-WD08) legged walking robots. As a consequence, these periodic signals can be switched to either lead or lag behind each other in accordance with a sensory input. The PSN has been implemented to basically allow for sideways walking, e.g., for obstacle avoidance. The combination of CPG, VRNs, and PSN leads to a great multitude of walking patterns including turning with different radii or curve walking in forwards and backwards directions, forwards and backwards walking, diagonal walking, sideward walking, and their combinations (see experimental results at [36]). The controller has again been tested first on the YARS simulation [38] and finally verified on the six- and eight-legged walking robots. For this demonstration, we refer the reader to video clips at *http://www.manoonpong.com/AMOS/OmniS.mpg* and *http://www.manoonpong.com/AMOS/OmniR.mpg.*

In addition to the development of the modular neural locomotion control, we have developed the neural preprocessing module for different sensory signals (see Fig. 10). The preprocessing network is basically derived from a single recurrent neuron (Fig. 10(a)) and its combination (Figs. 10(b) and (c)). It shows an interesting neurodynamical property, namely the hysteresis effects [31, 36, 41] (Fig. 10(d)). This property is useful for filtering sensory noises and allows the robots to memorize a state (i.e., short-term memory) to perform a long-term task or to complete the task without continuous environmental feedback (Fig. 11). The combination of the neural sensory preprocessing network and the modular neural locomotion control leads to a so-called sensor-driven neural controller or reactive behavior control (lower loop in Fig. 6). As a result, it generates versatile reactive behaviors, e.g., phototaxis (Fig. 12(a)) [40], phonotaxis (Fig. 12(b)) [31], obstacle avoidance (Fig. 12) [32]. It also produces memory-guided behaviors such as auditory- and wind-evoked escape responses known as fixed action patterns[6] (Fig. 11) [31, 36, 41].

Although the developed neural preprocessing and control described above can autonomously generate various reactive behaviors including memory-guided behaviors, it still fails on adaptation since the link between sensory signals and walking patterns was preassigned. This results in a limited behavioral complexity. Furthermore, the controller can generate only one specific gait (typical tripod gait) while animals, like insects and cockroaches, use different gaits according to the environmental condition, e.g., for energy efficiency or danger avoidance. In order to obtain more complex behaviors including various gaits and adaptation, the controller has been modified by mainly replacing the original CPG oscillator (Figs. 7 - 9) with an adaptive neural chaos oscillator [33]. We also apply a neural learning mechanism based on a standard Widrow-Hoff rule [33] but keep other neural modules (VRN and PSN) unchanged (Fig. 9). The adaptive neural chaos oscillator is a simple chaotic two-neuron system controlled via an adaptive method for stabilizing unstable periodic orbits.

It generates distinct periodic orbits of different periods if controlled, otherwise it exhibits chaotic behavior. The different periods serve as the CPG output patterns determining different gaits of the robots, while chaos is functionally used for self-untrapping from a hole in the ground. This control strategy can quickly and reversibly adapt to novel situations, e.g., different gaits (Fig. 13) and additionally enable learning and synaptic long-term storage of behaviorally useful motor responses [33]. This novel neural control provides a simple way to self-organize versatile behaviors in autonomous walking robots (with many degrees of freedom). This has been verified on the AMOS-WD06. As a consequence, the robot can perform eleven basic behavioral patterns, e.g., orienting, taxis, self-protection, escaping, various gaits (Fig. 13), and their combinations. For demonstra-

[5] The CTr-joints enable elevation and depression of the leg and the FTi-joints allows the tibia of the leg to extend or flex.

[6] This is a time-extended response pattern activated by a stimulus, i.e., the action lasts longer than the stimulus itself. The intensity and duration of the response are not controlled by the strength and duration of the stimulus (See *http://www.manoonpong.com/ROBIO/* for video clips of the robot behavior and Section 2 for a comparison to animal behavior).

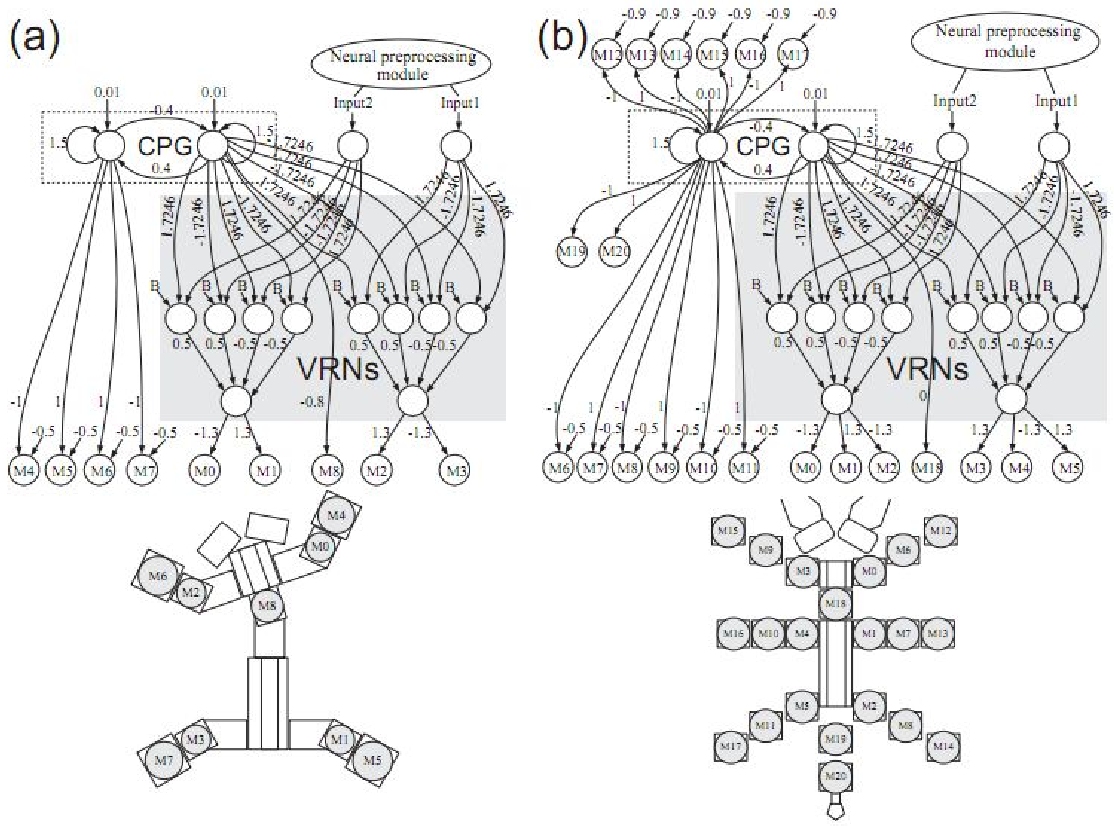

Fig.8: *(a) Modular neural locomotion control of the four- (AMOS-WD04) and six- (AMOS-WD06) legged walking robots (Figs 3(b) and 4(b)). It consists of two modules: CPG and VRNs. All connection strengths and bias terms are indicated by the small numbers except the bias terms of the VRN given by B = -2.48285. The location of motor neurons Mi on the walking robots is depicted below. We refer the reader to [31, 32] for more details of the controllers.*

tion of all these behaviors, we refer the reader to a video clip at http://www.manoonpong.com/AMOS/AMOSWD06.mpg.

Additionally it can learn to adapt its walking behavior to new situation to improve its performance. For example, it can learn to choose an energy saving gait during walking up a steep slope (Fig. 14). During learning (numbers 1 and 2 in Fig. 14) it randomly tries different gaits to find an appropriate one (number 3 in Fig. 14). And after learning (numbers 4, 5, and 6 in Fig. 14) it will directly select the right gait once it approaches the slope because the gait has been stored in a plastic synapse (ω , Fig. 14) as its long-term memory. Another kind of learning behavior called "acoustic predator-recognition learning" has been also implemented on the robot. The robot learns the association of a predictive acoustic signal (predator signal) and a reflex infrared signal (immediate danger signal). As a consequence, after learning it performs fast walking behavior when "hearing" an approaching predator from behind, leading to safely escape from the attack [42]. These adaptations are referred to proactive behaviors (level II, Fig. 1).

It is important to note that the presented neural network has four significant characteristics: (1) transferable, (2) generic, (3) neural and biological justifiable, and (4) robust.

Transferable: The CPG, PSN and VRN components so far have been successfully used in the four-, six- and eight-legged robots without changing its internal structure and parameters. Thus they do not require fine tuning and are transferable [32, 36].

Generic: Only few components (CPG, PSN, VRN) are required to achieve the very rich functionality presented. As suggested by their names, each module serves a general purpose (e.g., "phase switching") regardless of the robot's specific embodiment (see "transferable").

Neural and biological justifiable: The used networks (CPG, PSN, VRN) are directly related to similar functionalities in the networks of animals. For example, it is known that the basic locomotion and rhythm of stepping in many walking animals relies on CPGs (cf. Sect. 2). There is also strong evidence for phase switching functionality (i.e., PSN) from a study of Pearson and Iles [44] who have reported this property in inter-segmental neurons in a cockroach. More recent evidence suggests that neurons in a stick in-

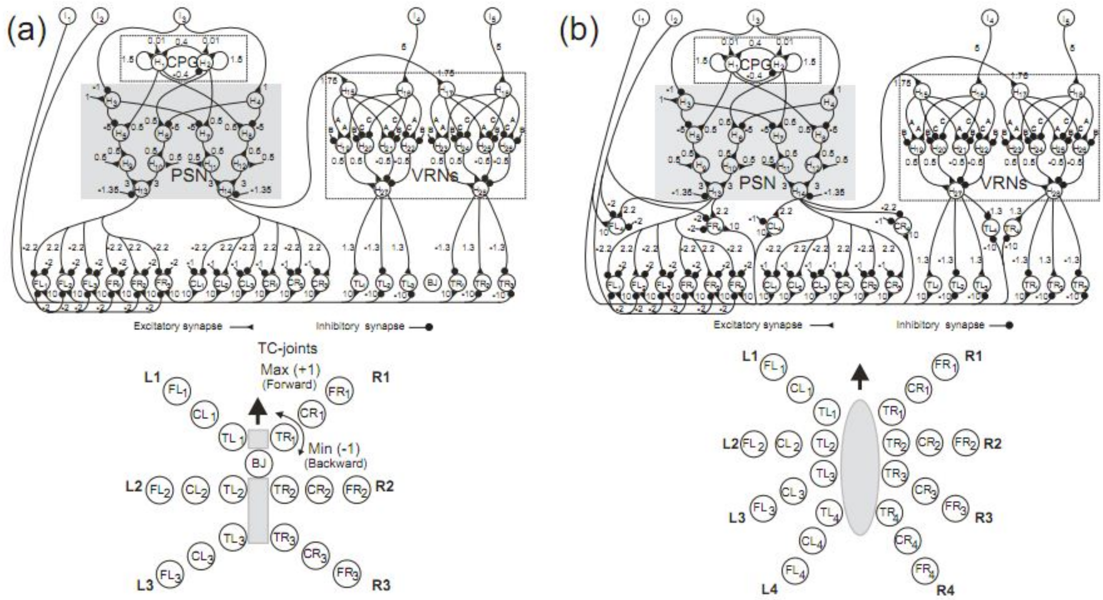

Fig.9: *(a) Modular neural locomotion control of the six- (AMOS-WD06) and eight- (AMOS-WD08) legged walking robots (Figs 4(b) and 5(b)) after enhancement. It now consists of three modules: CPG, VRNs and PSN. All connection strengths and bias terms are indicated by the small numbers except some parameters of the VRN given by A = 1.7246, B = -2.48285, C = -1.7246. The location of motor neurons (FLi, CLi, TLi, FRi, CRi, TRi, BJ) on the walking robots is depicted below. We refer the reader to [31, 36] for more details of the controllers.*

sect, which are active at stance-phase, receive synaptic input that modifies their activity according to the walking speed of the animal[43]. This input seems specific to only these neurons [45] and it arises via local pre-motor inter-neurons, which could be represented by the VRN inter-neurons suggested by the presented network.

Robust: The neural circuitry is not sensitive to changes of parameters and can be adjusted within large intervals, making any fine tuning unnecessary [36]. In addition, synaptic strengths can be substantially varied and even synaptic connections can be completely cut leading to graceful degradation of the agent's functionality.

5. DISCUSSION AND CONCLUSIONS

In this section, we conclude our accomplishments and discuss some remaining issues concerning the development of our animal-like robots while most of the relevant discussion points have been treated in the sections above.

Here, we employ biological principles to build our walking robots as well as their neural controllers. The controllers are systematically synthesized based on a modular structure such that the neuromodules are small and their structure-function relationship can be analyzed. This modular architecture is considered as a major advantage compared to many other controllers which were developed for walking robots, for instance, using genetic algorithms [46, 47] or evolutionary techniques [48-50]. In general, these controllers were too complex to be mathematically analyzed in detail, in particular if they consist of a massive recurrent connectivity structure. Most of them [46-50] have been created for a specific type of walking robots. Applying such controllers to other robots may require a modification of the network's internal parameters or structure.

In contrast, the neural controllers developed here can be successfully applied to physical four-, six- and eight-legged walking robots having different morphologies. They are also able to generate versatile reactive behaviors, proactive behaviors, and simple memory-guided behaviors (level I, II, and III in Fig. 1) without altering their internal parameters or structure of the CPG, VRN, and PSN. We believe that the developed neuromodules can serve as useful building blocks (generalizable and transferable) for other module-based neural control. This study also suggests that the employed modular neural design with an incremental synthetic process may be a way forward to solve coordination problems in other complex motor tasks, such as adaptivity and motor planning for active prosthetic and orthotic devices or in other autonomous robotic systems.

Taken together, our approach leads to a deeper understanding of the general control, memory, plasticity and predictive principles in embodied neural sensori motor function. In other words, it sharpens our un-

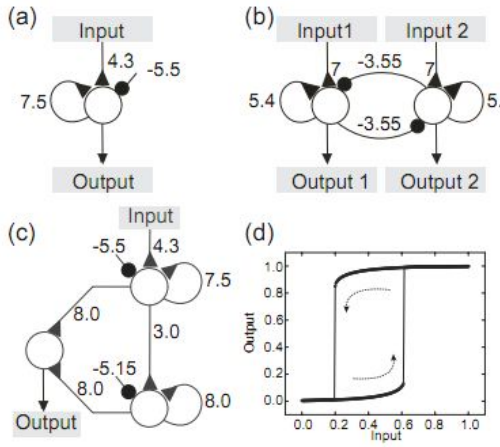

Fig.10: *Different types of neural sensory preprocessing. They act as simple short-term memories (STMs) for state memorization. (a) A single recurrent neuron [36]. (b) Two mutually inhibiting neurons with self-connection [36]. (c) A series of single recurrent neurons [41]. These neural preprocessing units receive inputs from sensors and provide outputs to drive different biologically inspired behaviors through the modular neural locomotion control (Figs. 8 and 9). Note that the small numbers in (a), (b), and (c) indicate connection strengths together with bias terms. (d) Example of hysteresis effect between the input and output deriving from the single recurrent neuron in (a). Although not shown, the other units in (b) and (c) have similar hysteresis patterns but with different loop sizes.*

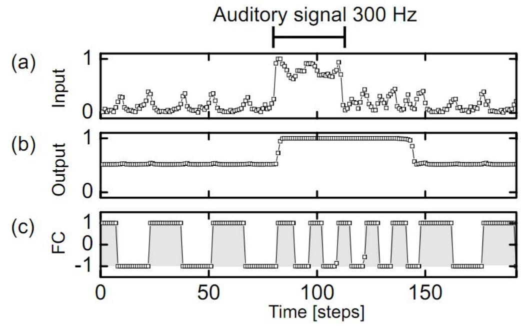

Fig.11: *Real time signals during the auditory-evoked escape behavior (cf. Sect. 2) of the AMOS-WD06 where a neural preprocessing unit shown in Fig. 10(c) is applied. (a) Raw input signal of an auditory sensor. (b) Preprocessed auditory signal (output signal from the neural preprocessing unit). (c) Foot contact sensor signal (FC) of the front right leg. It shows two walking phases: the swing and stance phases. During the swing phase, the foot has no ground contact where the sensor signal gives low activation (≈-1.0). During the stance phase (gray blocks), the foot touches the ground and the signal gives high activation (≈1.0). During around 80-150 time steps, the AMOS-WD06 performed the auditory-evoked escape behavior by increasing its walking speed up to 20 cm/s (as manifested through the high-frequency oscillation of the foot contact signal) while at other time steps it walked with its normal speed (≈6.5 cm/s). One can see that the AMOS-WD06 still kept fast walking after a certain period of time after a stimulus has been removed at around 110 time steps (i.e., input (a) shows low activation). This is because the hysteresis effect of the neural preprocessing prolongs the activation time of the sensory signal. This action implies to the memory-guided behavior (level III, Fig. 1).*

derstanding of how such a problem can be solved in not only reactive (mostly used in existing robots) but also adaptive self-organizing ways. This achievement can be viewed as a stepping stone towards true "Autonomous Intelligent Systems" in complex environments.

6. ACKNOWLEDGMENT

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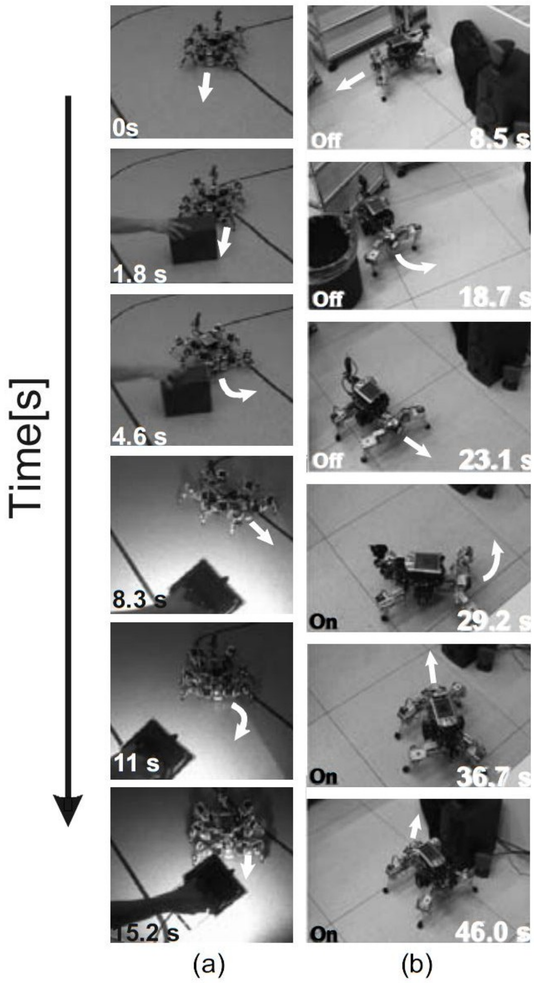

Fig.12: *Versatile biologically-inspired reactive behaviors (cf. level I, Fig. 1). (a) The phototaxis and obstacle avoidance behavior of the AMOS-WD06. It walked forwards at the beginning. At around 1.8 s, an obstacle was placed in front of it. The AMOS-WD06 then turned to the left to avoid the obstacle at around 4.6 s (obstacle avoidance behavior). After that, at around 8.3 s, a light source was provided. The robot turned towards the source at around 11 s. Eventually, it approached and stopped in front of the source. (b) The phonotaxis and obstacle avoidance behavior of the AMOS-WD04. At the first period, the source was switched off "Off" and the AMOS-WD04 was wandering around and avoiding obstacles if they were detected. The sound source then was switched on "On" to steer the AMOS-WD04 at around 29.2 s; consequently, it started to turn left and then walked forward and finally it stopped near the source at the end. For demonstration of these behaviors, we refer the reader to video clips at http://www.manoonpong.com/AMOS/PhotoTaxis.mpg and http://www.manoonpong.com/AMOS/ReactBehavior.mpg.*

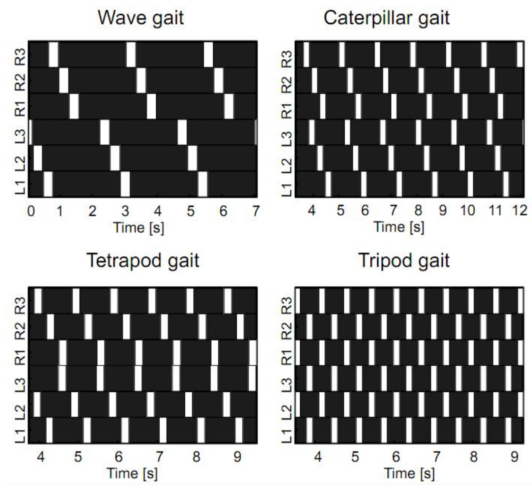

Fig.13: *Examples of four different gaits observed from the motor signals of the CTr-joints. Black areas indicate ground contact or stance phase and white areas refer to no ground contact during swing phase. These gaits are similar to those found in insects [43].*

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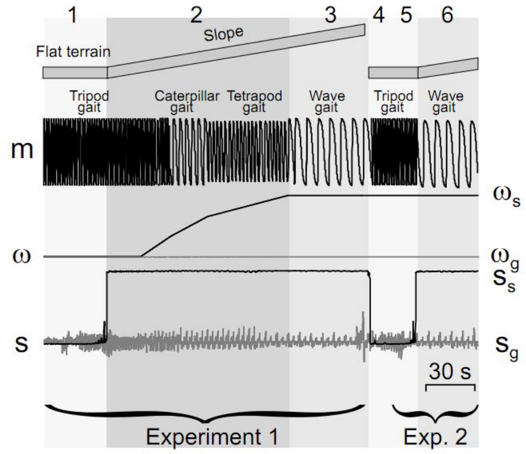

Fig.14: *Learning experiments demonstrating proactive behavior. In general the robot is preprogrammed to walk on flat terrain with a tripod gait while it needs to learn to find an appropriate gait by itself for other terrains (e.g., upward slope). From the experiments it shows that during learning the synaptic weight ω_s of the slope sensor S_s in a neural learning network [33] grows, whereas any uncorrelated synapse, for example ω_g from the gyro sensor S_g, remains unaffected. This means that only the relevant synapses learn. The output of the learning neuron (not shown but see [33]) follows these changes and determines different gaits. As soon as the energy-saving wave gait is selected, the error, which is the different between actual energy uptake during walking on the slope and the (low) energy uptake during walking on the flat terrain, drops to zero such that learning stops. As a result, the synapses are stabilized and thereby the gait is fixed. As the synaptic values remain stored, the next time the robot encounters this slope, the inclination sensor will immediately be triggered leading to the same output and again to the selection of the wave gait. Note that m shows a motor signal representing different gaits during the experiments. For this demonstration, we refer the reader to a video clip at http://www.manoonpong.com/AMOS/ ProactiveBehavior.mpg.*

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