Neural Preprocessing of Auditory-Wind Sensory Signals and Modular Neural Control for Auditory- and Wind-Evoked Escape Responses of Walking Machines

Poramate Manoonpong and Florentin Wörgötter
Bernstein Center for Computational Neuroscience
University of Göttingen
Bunsenstr. 10, 37073 Göttingen, Germany
{poramate, worgott}@nld.ds.mpg.de

Frank Pasemann
Institute of Cognitive Science
University of Osnabrück
Albrechtstr. 28, 49069 Osnabrück, Germany
frank.pasemann@uni-osnabrueck.de

***Abstract*— The flying crickets $Teleogryllus\ oceanicus$ have sound sensitive organs to elicit an "acoustic startle response". Another kind of the startle response is also evident in the cockroaches $Periplaneta$ and the crickets $Gryllus\ bimaculatus$ where they use their cercal filiform hairs (wind sensitive hairs) to trigger so called "wind-evoked escape behavior". Similarly, in this paper a setup is described where an auditory-wind detector sensor and a neural preprocessing system together with a modular neural controller are used to simulate such animal behaviors in an abstract form on a six-legged walking machine. The neural preprocessing network acts as a low-pass filter and sensory shaping unit. In addition, the modular neural controller then generates the desired responses such that the machine performs a fast movement away from abrupt, intense, and unexpected auditory and/or wind stimulus in a physical environment.**

***Index Terms*— Biologically-inspired robots, Autonomous hexapod robots, Neural control, Recurrent neural networks.**

I. INTRODUCTION

Animals show a variety of fascinating behaviors driven by their sensing systems. For example, the flying crickets $Teleogryllus\ oceanicus$ have sound sensitive organs in their forelegs. Through this sensing system, the flying cricket exhibits a startle response called "acoustic startle response" [1] which is stereotyped escape behavior involving a fast movement away from abrupt, intense (loud), and unexpected stimuli. In brief, the pulses of suprathreshold ultrasound (e.g., 30 kHz at around 60 dB sound pressure level (SPL)) produced by predatory bats cause it to fly faster away from the ultrasound generator. Another kind of the startle response is also evident in the cockroaches $Periplaneta$ and the crickets $Gryllus\ bimaculatus$. They use their cercal filiform hairs (wind sensitive hairs) [2] to elicit so-called "wind-evoked escape behavior" [3]; i.e., they turn and then run away from a wind puff to their cerci generated by the lunging predator. All these startle responses are implicated in the context of escape responses or predator avoidance behaviors induced by warning signals, e.g., sound and/or a wind puff. Inspired by the acoustic startle response and wind-evoked escape behavior together with the corresponding sensing systems, we introduce here a simple combined auditory-wind detector sensor and its neural signal processor which is able to reproduce such animal behaviors in an abstract form on a walking machine through a locomotion generator called modular neural control.

There are several examples of experiments with robots that use auditory signals and/or wind puffs for generating reactive robot behaviors [4], [5], [6], [7]. These sensory information are practically obtained from different sensor channels. In other words, roboticists have not yet implemented these two sensor functions (detecting sound and wind puffs) into one sensor system to save electrical power consumption. In addition, the sensor signals are mostly analyzed by using principle engineering techniques, e.g., a Fast Fourier Transformation or diverse filter techniques [8]. Often these methods are too slow to generate reactive actions of machines, too complex, and computationally too expensive to achieve the optimal performance and to implement on mobile processors, e.g., a personal digital assistant (PDA).

In contrast, we make use of one sensor for obtaining both sound and wind puff information where the preprocessing of sensory signals is achieved by a simple and analyzable recurrent neural network. Together with modular neural control, this will enable our autonomous walking machine to react to high-intensity sound and a wind puff by simply running away from the sources[1] in a real environment.

However, the main purpose of this article is not only to

[1]The $high{-}intensity$ ultrasound generated by the predatory bats and the rapidly accelerating wind puff produced by the lunging predator are replaced by $high - intensity$ sound ($>$ 48 dB of 300 Hz) generated by stereo portable speakers and a wind puff produced by a computer fan, respectively.

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present the sensory system and demonstrate the walking machine performing the biologically-inspired reactive behavior but also to investigate the analyzable neural mechanisms underlying this approach in order to understand their inherent dynamical properties. Furthermore, in this study we will try to show that neural preprocessing and control can be a powerful technique to better understand and solve sensorimotor coordination problems of many degrees-of-freedom systems like sensor-driven walking machines.

The following sections (II and III) describe the technical specifications of the artificial auditory-wind detector sensor and the walking machine, respectively. Section IV explains the neural perception-action system for a reactive escape behavior. The experiments and results are discussed in Section V. Conclusions and an outlook on future research are given in the last section.

II. An artificial auditory-wind detector sensor

The artificial auditory-wind detector sensor is applied from [9], [10] where the use of the sensor for auditory and wind detection was not investigated. It is used here to detect auditory and wind puff stimuli which control auditory- and wind-evoked escape responses. The sensor is composed of a mini-microphone (0.6 cm diameter) built in an integrated amplifier circuit, a root and a whisker-shaped material taken from a whisker of a real mouse (3.0 cm long). The mouse whisker is selected for our purpose here because of its appropriate mechanical properties (elasticity, stiffness, moment of inertia) which have been investigated in [10]. Figure 1 shows the sensory components.

In order to construct this sensor, the mouse whisker was inserted into a root which was glued onto the diaphragm of a microphone. The main purpose of implementing the whisker here is to improve the response of the sensor to a wind puff (shown in Section V). That is the physical force of the whisker vibrates the diaphragm of the capacitor microphone, which results in a voltage signal. The signal is amplified via the integrated amplifier circuit where the maximum output voltage with respect to the given input signals, e.g., auditory[2] and wind puff stimuli, is around 5 volt DC. The raw sensory signals are presented in Fig. 2.

Fig. 1. (A) The real auditory-wind detector sensor including a preamplifier circuit installed at the rear part of the six-legged walking machine AMOS-WD06. (B) The drawing of assembly parts of the sensor.

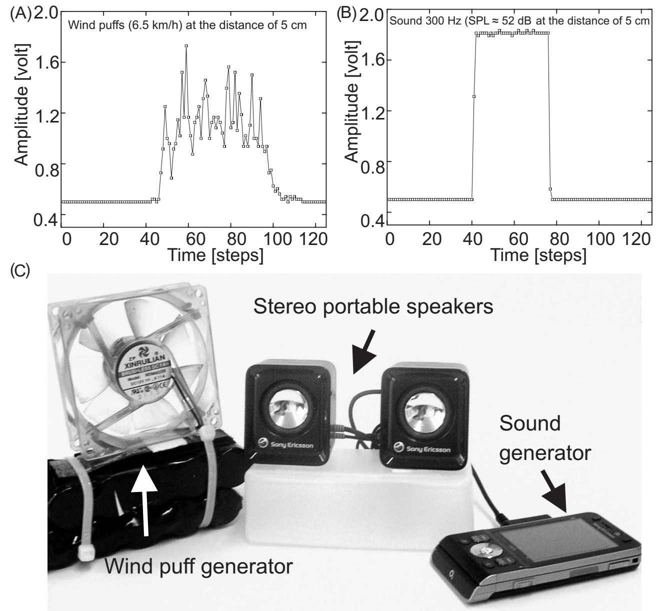

Fig. 2. (A) The response of the sensor to a wind puff which is generated by a small fan taken from a power unit of a personal computer (PC). (B) The response of the sensor to an auditory signal at a frequency of 300 Hz and a sound pressure level of around 52 dB which is generated by stereo portable speakers (Sony Ericsson MPS-70). Note that the sensor can detect only the amplitude of the sound because of a low sampling rate of the A/D converter board. However it is adequate to trigger the auditory escape response. (C) The fan and a mobile phone with the stereo portable speakers used to generate a wind puff and sound, respectively.

To obtain these sensory signals, the sensor is interfaced and digitized via the analog to digital channels of the Multi-Servo IO-Board (MBoard). Subsequently, the digital signals are here sent to a PDA through an RS232 interface at a transfer rate of 57.6 kbits/s for the purpose of monitoring and feeding the data afterwards into a neural preprocessor. The preprocessed sensory signals will enable our walking machine to autonomously perform the desired biologically inspired reactive behavior.

III. The reactive walking machine AMOS-WD06

The six-legged walking machine AMOS-WD06 (see Fig. 3) is a biologically-inspired hardware platform for studying the coordination of many degrees of freedom, for

[2]Due to the characteristics of the portable speakers which provide appropriate loudness at a frequency range of 300 to 500 Hz for our sensor system, we then select the auditory signal at the frequency of 300 Hz for testing the sensor and stimulating the auditory escape behavior.

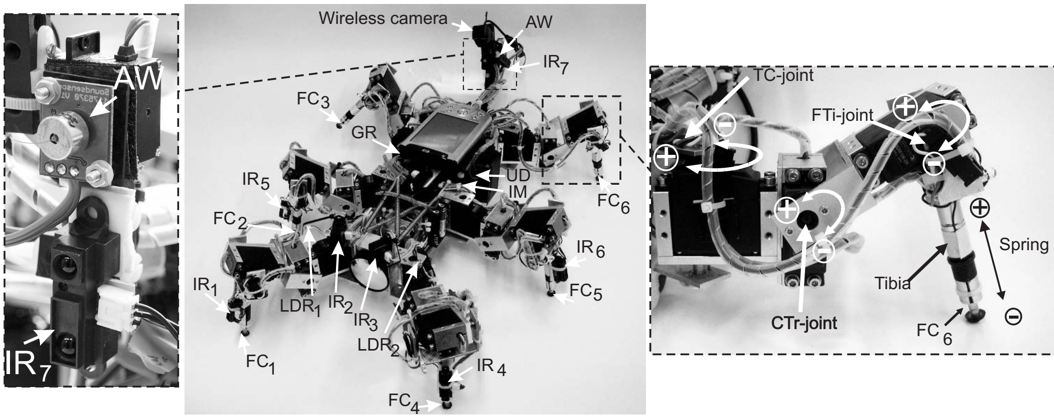

Fig. 3. The physical six-legged walking machine AMOS-WD06. A right dashed frame shows the leg configuration with three DOF of the AMOS-WD06 in close-up view and the left one presents the location of the auditory-wind detector sensor (AW) and the rear infrared sensor (IR_7).

performing experiments with neural controllers, and for the development of artificial perception-action systems employing embodied control techniques.

It consists of six identical legs. Each leg has three joints (three DOF): the thoraco-coxal (TC-) joint enables forward (+) and backward ($-$) movements, the coxa-trochanteral (CTr-) joint enables elevation (+) and depression ($-$) of the leg, and the femur-tibia (FTi-) joint enables extension (+) and flexion ($-$) of the tibia (see Fig. 3, right dashed frame). Each tibia segment has a spring-like compliant element to absorb impact force as well as to measure ground contact during walking. All leg joints are driven by analog servo motors. The machine is constructed with two body 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 driven by a digital servo motor. This machine has six foot contact ($FC_{1,...,6}$) sensors, seven infrared ($IR_{1,...,7}$) sensors, two light dependent resistor ($LDR_{1,2}$) sensors, one gyro (GR) sensor, one inclinometer (IM) sensor, one upside-down detector (UD) sensor, and one auditory-wind detector (AW) sensor (see Fig. 3). The foot contact sensors are for recording and analyzing the walking patterns [12]. The $IR_{1,...,7}$ sensors are used to elicit negative tropism, e.g., obstacle avoidance and escape response [12], while the $LDR_{1,2}$ sensors serve to activate positive tropism like phototaxis [13]. The GR and IM sensors apply to upward/downward slope detection. The UD sensor is employed to trigger a self-protective reflex behavior when the machine is turned into an upside-down position [12]. Moreover, the AW sensor is applied here for the auditory-wind application which is the main contribution of this manuscript. It will activate the auditory- and wind-evoked escape behavior of the walking machine. The control of this walking machine is programmed into a PDA interfaced with the MBoard. Electrical power supply of the whole systems is via battery packs which can run for experiments up to 35 minutes (see [11], [12] for more details of the walking machine system).

IV. A NEURAL PERCEPTION-ACTION SYSTEM

A neural perception-action system (see Fig. 4) generating the auditory- and wind-evoked escape responses is formed by two main components: a neural preprocessing unit and a modular neural control unit. The neural preprocessing unit filters sensory noise and shapes sensory data to drive the corresponding reactive behavior. The modular neural control unit, on the other hand, is used for locomotive generation of the walking machine. It coordinates leg movements, regulates walking speed, and generates omnidirectional walking. The details of these two neural units are described in the following sections.

The approach of signal preprocessing and locomotive generation utilizes dynamical properties of recurrent neural networks. The standard additive neuron model with sigmoidal transfer function together with its time-discrete dynamics is given by:

$$a_i(t+1) = \sum_{j=1}^{n} W_{ij}\sigma(a_j(t)) + \Theta_i \quad i = 1,\ldots,n \qquad (1)$$

where n denotes the number of units, a_i their activities, Θ_i represents a fixed internal bias term together with a stationary input to neuron i, and W_{ij} the synaptic strength of the connection from neuron j to neuron i. The output of the neurons in the neural preprocessing unit is given by the standard sigmoid $\sigma(a_i) = (1 + e^{-a_i})^{-1}$ while in the

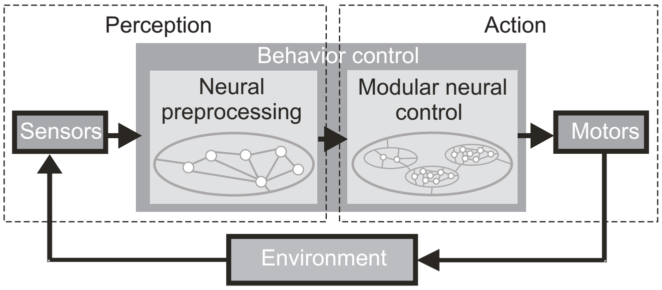

Fig. 4. The diagram of the neural perception-action system. The system acts as a behavior controller, i.e., the sensor signals are passed through the neural preprocessing unit into the modular neural control unit which directly drives the actuators. As a result, the walking machine's behavior is generated by the interaction with its (dynamic) environment in a sensorimotor loop.

modular neural control unit is governed by $\sigma(a_i) = \tanh(a_i)$. Input units are configured as linear buffers. They are linearly mapped onto the interval [0, 1] for all neurons in the neural preprocessing unit and $[-1, 1]$ for those in the modular neural control unit.

A. Neural preprocessing of auditory-wind sensory signals

The raw sensory signals coming from the auditory-wind detector sensor are used to trigger the reactive auditory- and wind-evoked escape behavior of the walking machine. These types of reactive behavior can be described as a fixed action pattern [11], which is a time-extended response pattern activated by a stimulus. That is, the action perseveres for longer than the stimulus itself. Once a fixed action pattern has been activated, it will be performed even if the activating stimulus is removed. To do so, a series of single recurrent neurons $H_{Np1,2}$ is employed. Their output is combined at an output neuron O_{Np} before feeding preprocessed signals to modular neural control for activating a corresponding reactive behavior. The complete neural preprocessing network is shown in Fig. 5A. This simple preprocessing network has a capability to eliminate unwanted noise, shape the sensory data, and prolong the activation time of sensory signals (see Fig. 6).

On the background of the well understood functionality of a single recurrent neuron [11], [14] we manually constructed the network according to dynamical properties of the recurrent neuron, i.e., hysteresis effect [11], [14]. The neural parameters of the network were manually adjusted as follows. We adjusted the raw sensory inputs $RAW - AW$ such that they will cross forward and backward through the hysteresis domain to mainly filter sensory noise. By doing so, we set a synaptic weight connecting between raw sensory inputs $RAW - AW$ and H_{Np1} to a positive value, i.e., 4.3, to amplify the signals. Afterwards, we shifted the amplified

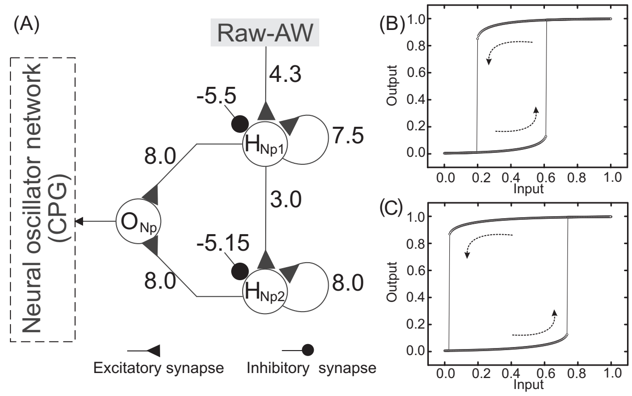

Fig. 5. (A) The structure of the neural preprocessing unit with appropriate weights. Note that one can optimize this network, for instance by using an evolutionary algorithm [15], but for the purposes of signal preprocessing and controlling the desired reactive behaviors, it is good enough. (B), (C) Hysteresis effects between the input and output of the recurrent neuron H_{Np1} and the recurrent neuron H_{Np2}, respectively. The $presynaptic$ input of all recurrent neurons $H_{Np1,2}$ varies between 0.0 and 1.0 while the output of H_{Np1} and H_{Np2} has low (≈ 0.0) and high (≈ 1.0) activations at different points. The output of H_{Np1} will show high activation when the input increases to values above 0.61. On the other hand, it will show low activation when the input decreases below 0.19. For the output of H_{Np2}, it will show high activation when the input increases to values above 0.73 while it will show low activation when the input decreases below 0.03.

signals by a negative bias term, i.e., -5.5. Consequently, the modified signals sweep over the input interval between -5.5 and -1.2. Finally, we tuned the self-connection weight of the neuron to derive a reasonable hysteresis interval on the input space; i.e., 7.5. This hysteresis effect allows the output to show high (≈ 1.0) and low (≈ 0.0) activations at different points (see Fig. 5B). By utilizing this feature, the recurrent hysteresis neuron H_{Np1} performs as a low pass filter which can eliminate unwanted noise, i.e., motor sound while the machine walks. The output of H_{Np1} (filtered signals) is fed into another neuron H_{Np2} where its structure was configured in the same manner as H_{Np1}. Only, the neural parameters were set differently. We chose them in the way that they derive a large hysteresis interval on the input space (see Fig. 5C) which will extend the duration of response (see Fig. 6). As a result, the connection weight between neurons, the bias term, and the self-connection weight are empirically set as 3.0, -5.15, and 8.0, respectively. With this setup, we obtain the appropriate long activation time of our robot system.

Eventually, the output of each recurrent neuron is amplified through a connection weight set to 8.0 before adding at the output neuron O_{Np}. Afterwards the output of O_{Np} is transmitted to modify all synaptic weights of a neural oscillator network in a modular neural control unit (see Figs. 5A and 7) described in the next section. As a result, the walking speed

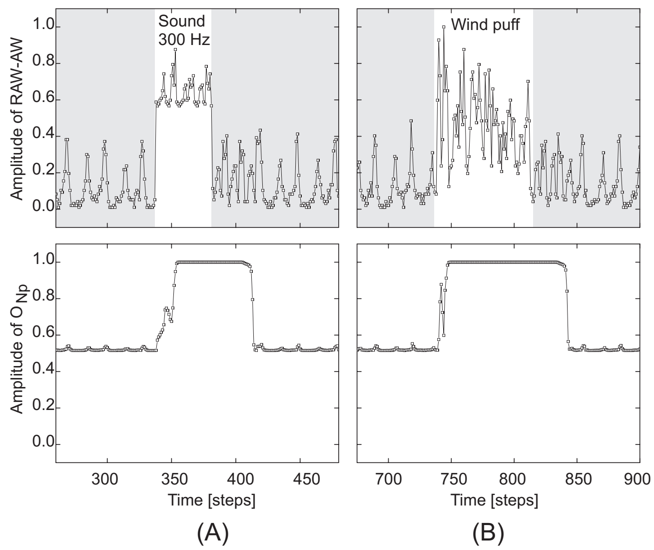

Fig. 6. (A), (B) The sound and wind puff signals before ($RAW - AW$) and after (O_{Np}) preprocessing. Gray areas show background noise while the machine walks. In order to obtain longer activation time, one can simply add more recurrent neurons H_{Np2} in series and combine their output at the output neuron O_{Np} in the same manner as shown in Fig. 5A.

of the machine will be increased as soon as a wind puff and/or an auditory signal are detected.

B. Modular neural control for a reactive behavior

Actions or walking behaviors of the machine are generated through modular neural control. This modular controller consists of three subordinate networks[3] (colored boxes in Fig. 7): a neural oscillator network, a phase switching network (PSN), and two velocity regulating networks (VRNs). The neural oscillator network, serving as a central pattern generator (CPG) [16], generates periodic output signals. These signals are provided to all CTr-joints and FTi-joints only indirectly passing through all hidden neurons of the PSN. TC-joints are regulated via the VRNs. Thus, the basic rhythmic leg movement is generated by the neural oscillator network and the steering capability of the walking machine is realized by the PSN and the VRNs.

The synaptic weights and bias terms of the neural oscillator network (see colored box A in Fig. 7) are selected in accordance with the dynamics of the 2-neuron system [17] staying near the Neimark-Sacker bifurcation where the quasi-periodic attractors occur. They are empirically adjusted through the Integrated Structure Evolution Environment (ISEE) [15] to acquire the optimal periodic output signals for generating locomotion of the walking machine. The example of periodic output signals having different frequencies resulting from different weights can be seen at [11], [12]. The network has the capability to generate various sinusoidal outputs depending on the weights. For instance, changing weights in a proportional way (see [12] for details), the system dynamics still stays near or beyond the Neimark-Sacker bifurcation [17], resulting in an increased frequency of the sinusoidal outputs of the network. Correspondingly, the amplitude of the signals will also slightly increase. Thus, we will use the preprocessed auditory and wind puff signals to modify all weights of the network determined by Eqs. 2, 3, 4:

$$w_{11,22} = 0.75 O_{Np} + 1.125, \quad (2)$$

$$w_{12} = 1.5 O_{Np} - 0.35, \quad (3)$$

$$w_{21} = -1.5 O_{Np} + 0.35, \quad (4)$$

As a consequence, walking speed of the machine can be increased by the activation of these signals, resulting in simple auditory- and wind-evoked escape responses.

The synaptic weights and bias terms of a phase switching network (PSN) (see colored box B in Fig. 7) were manually constructed (see [12] for details) while those parameters of the velocity regulating networks (VRNs) (see colored box C in Fig. 7) was partly constructed and partly trained by using the backpropagation rule (see [11], [18] for details).

Figure 7 shows the complete network structure together with the synaptic weights of the connections between the controller and the corresponding motor neurons as well as the bias term of each motor neuron. These synaptic weights and all bias terms were manually constructed and adjusted to obtain an optimal gait; i.e., a typical tripod gait where the diagonal legs are paired and move synchronously.

This modular neural control can generate more than 10 different walking patterns which are controlled by the four input neurons $I_{2,...,5}$ (see Fig. 7). Furthermore, a self-protective reflex[4] can be activated via the input neuron I_1 which will excite TR_1 and TL_1 joints and all CTr- and FTi- joints and inhibit the remaining TC-joints. Appropriate input parameter sets for the different walking patterns and the reflex behavior are presented in Table I where the first column describes the desired actions in accordance with five input parameters shown in the other columns. Abbreviations are: $FDiR$ and $BDiR$ = forward and backward diagonal motion to the right, $FDiL$ and $BDiL$ = forward and backward diagonal motion to the left, LaR and LaL = lateral motion to the right and the left. Note that marching is an action where all the legs

[3]Here, we discuss only main functions of the network. A more complete description of each subordinate network is given in [11], [12].

[4]The action is triggered when the machine is turned into an upside-down position. As a consequence, it stands still in this position as long as the stimulus (UD signal) is presented (not shown here but see [12] for details).

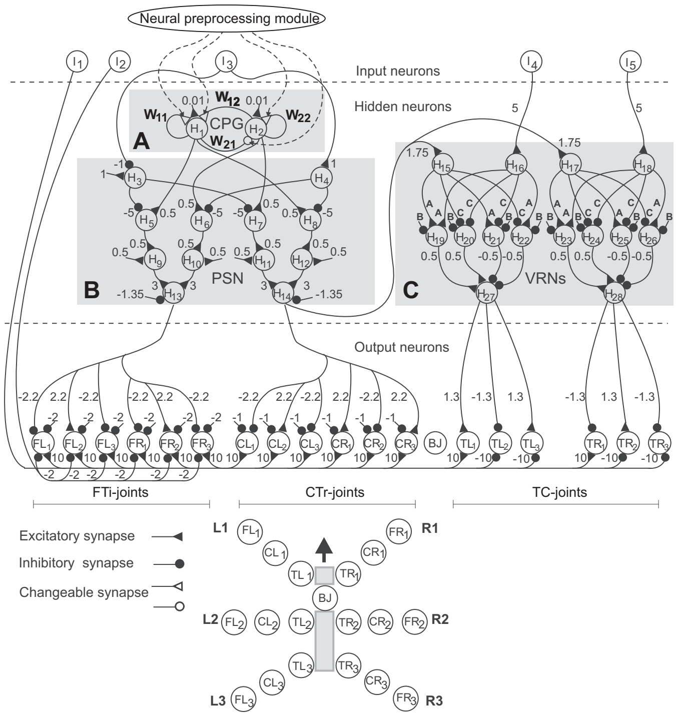

Fig. 7. The modular neural control of the six-legged walking machine AMOS-WD06 consists of three different neuron groups: input, hidden, and output. Input neurons I are the neurons used to control walking direction ($I_{2,\ldots,5}$) and to trigger the self-protective reflex (I_1). Hidden neurons H are divided into three modules (CPG, PSN, and VRNs (see [11], [12] for details)). Output neurons (TR, TL, CR, CL, FR, FL) directly command the position of servo motors. Abbreviations are: BJ = a backbone joint, TR(L) = TC-joints of right (left) legs, CR(L) = CTr-joints of right (left) legs, FR(L) = FTi-joints of right (left) legs. All connection strengths together with bias terms are indicated by the small numbers except some parameters of the VRNs given by A = 1.7246, B = -2.48285, C = -1.7246. W_{11}, W_{12}, W_{12}, and W_{21} are modifiable synapses governed by Eqs. 2, 3, 4. The location of the motor neurons on the AMOS-WD06 is shown in the lower picture. Note that describing the controller driving the machine also with the backbone joint will go beyond the scope of this article. Thus, the motor neuron controlling the backbone joint BJ is not activated; i.e., the backbone joint functions as a rigid connection. However, it can be modulated by the periodic signal via the PSN or VRNs to perform an appropriate motion, e.g., helping the machine during climbing over obstacles.

are positioned and held in a vertical position and support is switched between the two tripods.

In this article, we will simulate simple auditory- and wind-evoked escape responses; i.e., the walking machine will perform fast forward walking behavior as soon as it detects auditory and/or wind puff stimulus. Thus, the five input neurons $I_{1,\ldots,5}$ are here set to $I_1 = 0.0$, $I_2 = 1.0$, $I_3 = 1.0$, $I_4 = -1.0$, and $I_5 = -1.0$ allowing the machine to walk forward only. However, the values of all these input neurons can be controlled by sensory signals driving the machine to autonomously perform various reactive behaviors [11], [12].

TABLE I
INPUT PARAMETERS FOR THE DIFFERENT WALKING PATTERNS AND THE REFLEX BEHAVIOR.

Actions	I_1	I_2	I_3	I_4	I_5
Forward	0	1.0	1, 0	-1.0	-1.0
Backward	0	1.0	1, 0	1.0	1.0
Turn right	0	1.0	1, 0	-1.0	1.0
Turn left	0	1.0	1, 0	1.0	-1.0
Marching	0	1.0	1, 0	0.0	0.0
FDiR	0	0.0	0	-1.0	-1.0
BDiR	0	0.0	0	1.0	1.0
LaR	0	0.0	0	0.0	0.0
FDiL	0	0.0	1	-1.0	-1.0
BDiL	0	0.0	1	1.0	1.0
LaL	0	0.0	1	0.0	0.0
Reflex	1	0.0 ...1.0	1, 0	-1.0 ...1.0	-1.0 ...1.0

V. EXPERIMENTS AND RESULTS

This section describes experiments carried out to assess the ability of the sensory system[5] and the behavior controller (see Fig. 4). The first experiment was to investigate the effect of utilizing a whisker for wind detection. Thus the maximum distance at which the sensory system with and without the whisker are able to detect a wind puff was measured and compared. During the test, a wind puff was produced at different distances in front of the sensors embedded at the rear part of the walking machine. Figure 8 shows the detection rates of a wind puff; i.e., the number of detection divided by number of experiments. Here we performed 10 experiments at each of the different distances.

As a result, it shows that the sensor with the whisker can detect a wind puff at a longer distance (up to ≈ 17 cm or at wind speed higher than ≈ 2.5 km/s.) comparing with the one having no whisker. This concludes that the whisker can improve the performance of the sensor for wind puff detection. From this experimental results, we therefore make use of this whisker sensor to mainly detect wind for eliciting a wind-evoked escape response. Due to the sensory construction based on a microphone, it can also detect auditory signals. Hence, we will use high-intensity sound at the frequency of 300 Hz where the whisker sensor can detect at the distance up to ≈ 30 cm or at the sound pressure level higher than ≈ 48 dB to activate an auditory-evoked escape response.

The second task was to demonstrate the auditory- and wind-evoked escape responses of the walking machine AMOS-WD06 in the real environment. These reactions will be activated as soon as the sensor detects the stimuli. As a consequence, the AMOS-WD06 increases its walking

[5]The physical sensor (cf. Fig. 1) and its neural preprocessing (cf. Fig. 5).

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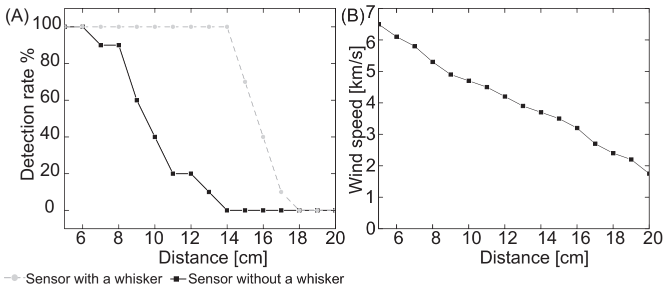

Fig. 8. (A) Detection rate of a wind puff from different distances. (B) Wind speed at different distances.

speed, as if it escapes from an attack. This action will be preserved for longer time steps even if the activating stimulus has already been removed. The results of the real robot walking experiments can be seen as video clips at http://www.nld.ds.mpg.de/∼poramate/ROBIO. Here we report the real-time sensory-motor data (see Fig. 9). As shown in Fig. 9, the AMOS-WD06 walked forward with its normal speed (≈ 6.5 cm/s) at the beginning. During walking forward, the CTr-joints and the TC-joints performed periodic movements while the FTi-joints were inhibited to stay in the flexed position. After around 80 time steps, the auditory signal was generated leading to high output activation of the sensor. The AMOS-WD06 then performed auditory escape running by increasing its walking speed up to ≈ 20 cm/s where the periodic signals of the motor neurons as well as the foot contact sensor signals oscillated at a higher frequency. Then it returned to its normal walking speed at around 150 time steps meaning that it was far enough from the stimulus. Furthermore, at around 250 time steps a wind puff was induced making the AMOS-WD06 again increases its walking speed reflecting the wind-evoked escape behavior and it eventually returns to the normal walking speed at around 310 time steps. From this experimental result, one can see that such a reactive behavior can be generated by the behavior controller (see Fig. 4) in the way that the RAW-AW signal is first preprocessed via the neural preprocessing unit (see Fig. 5). Then the preprocessed signal triggers the escape behavior by simply increasing the step frequency of the walking machine through the modular neural control unit.

VI. Conclusions

Inspired by the sensory system of invertebrates and their reactive behaviors, we constructed a simple auditory-wind detector sensor and embedded it on a physical six-legged walking machine in order to stimulate comparable behaviors. Using the auditory-wind detector sensor in analogy to sound sensitive organs of crickets and wind sensitive hairs of crickets and cockroaches the auditory and wind puff signals can be detected. They are preprocessed by a series of single recurrent neurons having a capability to filter unwanted noise (low-pass filter), shape the sensory data, and prolong the activation time of the sensory signals. Furthermore, to generate the biologically-inspired reactive behaviors of the walking machine, the modular neural controller is applied. It was constructed by integrating three different functional neural modules: the neural oscillator network, the velocity regulating networks, and the phase switching network. The neural oscillator network acts as a central pattern generator (CPG) for basic rhythmic leg movements while controlling different walking patterns is done by the velocity regulating and the phase switching networks. This modular neural control can produce more than 12 different actions by using five input neurons. Moreover, it can generate different walking speeds by modifying the strength of synaptic connections of the neural oscillator module. These synaptic weights are changed according to the preprocessed sensory signal of the auditory-wind detector sensor.

The experimental results illustrate that the proposed neural technique has been shown to be adequate for generating simple auditory- and wind-evoked escape responses; i.e., the walking machine can autonomously perform fast forward walking behavior as soon as it detects auditory and/or wind puff stimulus. To a certain extent the approach pursued here sharpens the understanding of how dynamical properties of a recurrent neural network (i.e., hysteresis effects) can benefit for filter design or other applications requiring high and low output activations at different points on the input space.

More demanding tasks will be the improvement of the neural preprocessing in the way that it will be able to distinguish between auditory and wind puff stimulus for driving different behaviors. To do so, an evolutionary algorithm [9], [15] will be applied to reconstruct and optimize this preprocessing unit. We also aim to implement more auditory-wind detector sensors together with an additional neural preprocessing network for the left and right detection [11] allowing the machine to sense the direction from which the stimuli came and then to orient its escape path away from the source.

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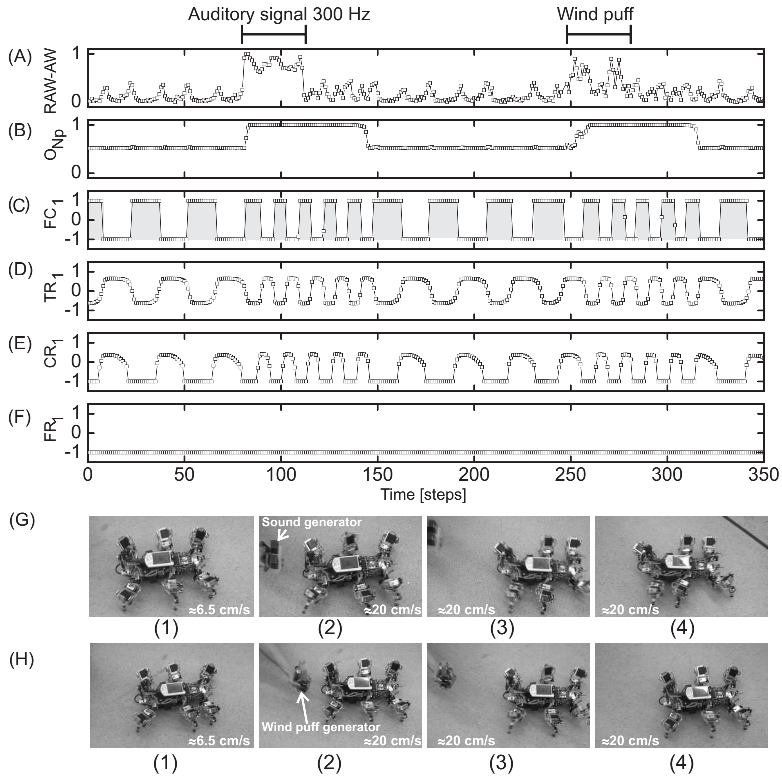

Fig. 9. (A) Raw signal of the auditory-wind detector sensor ($RAW - AW$). (B) Preprocessed auditory-wind detector sensor signal (O_{Np}). (C) Foot contact sensor signal of the front right leg (FC_1). It shows two walking phases: the swing and stance phases. During the swing phase the foot has no ground 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). (D), (E), (F) Motor neuron signals of the TC-joint (TR_1), the CTr-joint (CR_1), and the FTi-joint (FR_1) of the right front leg, respectively. (G) A series of photos ((1)-(4)) during around 0-150 time steps where the AMOS-WD06 performed the auditory-evoked escape behavior at around 80-150 time steps (photos (2)-(4)). (H) A series of photos ((1)-(4)) during around 150-310 time steps where the AMOS-WD06 performed the wind-evoked escape behavior at around 250-310 time steps (photos (2)-(4)). Note that an update frequency of the system is about 14 Hz.

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