Modular Neural Control for a Reactive Behavior of Walking Machines

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***Abstract*— A small modular neural network is presented which is able to control the sensor-driven behavior of walking machines with many degrees of freedom. The controller is composed of a so called minimal recurrent controller (MRC) for sensory signal processing, a SO(2)–network as neural oscillator to generate the rhythmic leg movements, and a velocity regulating network (VRN) which expands the steering capabilities of the walking machine. This recurrent neurocontroller enables the machine to explore an in-door environment by avoiding obstacles. It was developed and tested using a physical simulation environment, and was then successfully transferred to the physical four-legged walking machine, called AMOS-WD02.**

I. Introduction

Research on biologically inspired walking machines is focused for the most part on the construction of such machines [7], [16], on a dynamic gait control [14], [17], and on the generation of an advanced locomotion control [4], [11], for instance on rough terrain [6], [10]. Most researches do not concentrate on the generation of a sensor-driven behavior of walking machines. In general, those walking machines are solely designed for the purpose of motions without sensing the surrounding environment. Two articles [1], [9] reported on neural controllers for locomotion and obstacle avoidance generated by an evolutionary algorithm. Both controllers use the same approach to avoid obstacles. They inhibit the neurons of the legs on the opposite side of a detected obstacle. The walking machines then turn in a slight curve, and the walking velocity is reduced. But these controllers sometimes have difficulties to avoid obstacles or when the walking towards a wall, because they are not able to turn around or even to walk backwards.

In this article, the modular approach for neural control of a reactive behavior is introduced, and the four-legged autonomous walking machine AMOS-WD02 is employed as a platform for testing the developed neural controller. Two simple infrared sensors are used to enable a sensor-driven reactive behavior. The neural controller generates the obstacle avoidance behavior by changing the rhythmic leg movements, also preventing the walking machine from getting stuck in corners or in a deadlock situation by applying hysteresis effects provided by the recurrent structure of the network.

The following section describes the technical specifications of the walking machine. Section 3 explains the neural perception-action system for reactive behavior. The experiments and results are discussed in section 4. Conclusions and an outlook on future research are given in the last section.

II. The walking machine AMOS-WD02

Inspired by morphology of the reptile's trunk and its motion, we design the four-legged walking machine AMOS-WD02 with a backbone joint at the trunk, which facilitates a more flexible and faster motion. The trunk is composed of the backbone joint which can rotate vertically, four identical legs, each with two degrees of freedom, and additionally an active tail with two degrees of freedom rotating in the horizontal and vertical axes (see Fig.1). All leg joints are driven by analog modelcraft servo motors producing a torque between 70 and 90 Ncm. The backbone joint is driven by a digital servo motor with a torque between 200 and 220 Ncm. For the active tail, micro-analog servo motors with a torque around 20 Ncm are selected. The height of the walking machine is 12 cm without its tail and its weight is approximately 3 kg. In addition, this machine has two infrared (IR) sensors, two integrated auditory-tactile sensors [15] for different reactive behavior; e.g. obstacle avoidance, protecting the legs from colliding with obstacles and sound tropism. On the active tail, a mini wireless camera with built in a microphone is installed for monitoring and observation while the machine is walking. All in all AMOS-WD02 has 11 active degrees of freedom and 4 sensors, and therefore it can serve as a reasonably complex platform for experiments concerning the functioning of neural perception-action systems.

The developed neural controller is finally programmed into a Personal Digital Assistant (PDA) which communicates with the Multi-Servo IO-Board (MBoard) to control the servo motors and to receive sensory input signals via an RS232 interface.

III. Neural perception-action systems

In order to create robust and effective neural controllers which are able to generate exploration and obstacle avoidance behaviors, the dynamical properties of recurrent

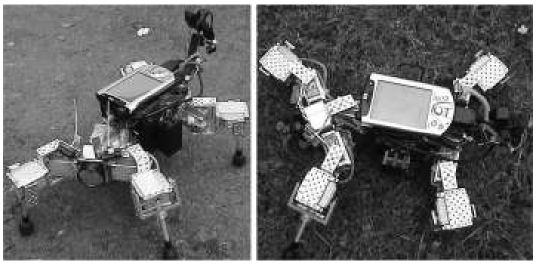

Fig. 1. Left: the 4-legged walking machine AMOS-WD02 with 11 active degrees of freedom. Right: top view of AMOS-WD02 showing the backbone joint corresponding to the morphology of the reptile's trunk.

neural networks are utilized. The standard additive neuron model with sigmoidal transfer function together with its time-discrete dynamics is given by

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

where n denotes the number of units, a_i their activities, B_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 is given by the sigmoid $o_i = \tanh(a_i)$. Input units are configured as linear buffers. This neural controller is divided into three subnetworks which are the *signal preprocessing* network, the *neural oscillator* network and the *velocity regulating* network. All networks are described in detail in the following sections. They have been tested first in a physical simulation environment, which simulates the walking machine in an environment with obstacles (compare Fig.2). The simulator is based on Open Dynamics Engine[1] (ODE) and it enables an implementation, which is faster than real time and which is precise enough to mirror corresponding behavior of a physical robot. This simulation environment is connected to the Integrated Structure Evolution Environment (ISEE) [13] which is the software platform for developing neural controllers. Eventually, a derived controller is downloaded into the walking machine and then tested in the in-door environment, e.g. a living room or an office. Especially, as in the simulator, the walking machine is able to avoid obstacles and to get out of corners and deadlock situations.

A. Preprocessing of the sensor inputs

The perception systems are driven by using two IR sensors. These sensors are used to detect obstacles in a distance between 10-30 cm. For the preprocessing of sensory signals, a neural structure called minimal recurrent controller (MRC) [12] is applied. This controller has been developed for a two wheeled miniature Khepera robot. On the background of its well understood functionality

[1]see also: http://opende.sourceforge.net/

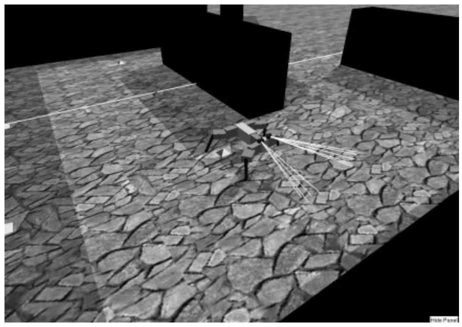

Fig. 2. The simulated walking machine performing obstacle avoidance and exploration behaviors.

the parameters were manually adjusted for using it in our approach. First, the weights $W_{1,2}$ from the input to the output units of both sides are set to a high value to eliminate the noise of the sensors, i.e. $W_{1,2} = 7$. Then the self-connection weights of the output neurons were manually adjusted to derive a reasonable hysteresis input interval. This effect determines the turning angle for avoiding obstacles. Both self-connections are set to 5.4 for convenience. Finally, the recurrent connections between output neurons were symmetrized and manually adjusted to the value -3.55. This guarantees the optimal functionality. The resulting neural network is shown in Fig.3.

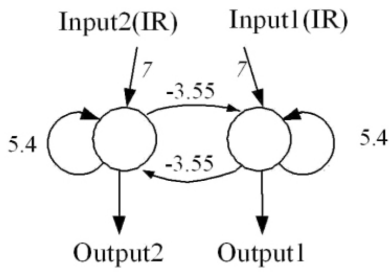

Fig. 3. The structure of a MRC with appropriate weights for this application.

The sensory signals are mapped onto the interval $[-\mathbf{1}, \mathbf{1}]$, with $-\mathbf{1}$ representing "no obstacles", and $\mathbf{1}$ "an obstacle is near". The signals are used as Input1 and Input2 of the neural controller. The output neurons of the MRC have "supercritical" self-connections which produce a hysteresis effect for both output signals. A strong excitatory self-connection (> 5) will hold the roughly constant output signal longer than a smaller one, resulting in a larger turning angle to avoid obstacles or corners. To visualize this phenomenon, the hysteresis effect is plotted in Fig.4, and the different weights of an excitatory self-connection can be compared.

In addition, there is a third hysteresis phenomenon involved which is associated to the even 2-loop between the two output neurons [2]. In general conditions, only one neuron at a time is able to get a positive output,

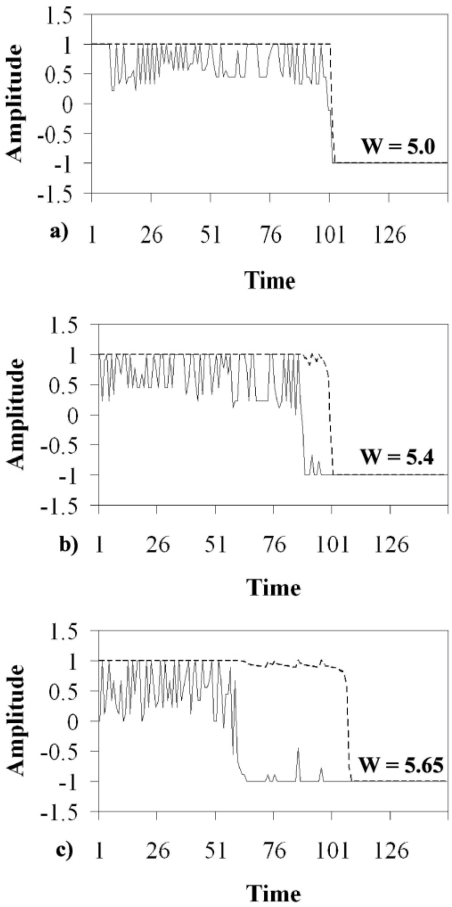

Fig. 4. Comparison of the “hysteresis effect” with different self-connection weights at the output neuron. a) shows that the output signal (smashed line) immediately decreases from 1 to -1 when the input signal (full line) is inactive (-1). b) shows that the output signal (smashed line) stays longer at 1 and then decreases to -1 when the input signal (full line) is inactive. c) shows that the output signal stays longest at 1 and then decreases to -1.

while the other one has a negative output, and vice versa. The phenomenon is presented in Fig.5. By applying these phenomena, the walking machine is enabled to avoid the obstacles, corners and deadlock situations. Finally, the output signals, output1 and output2 of the MRC together with the velocity regulating network described below, decide and switch the behavior of the walking machine; for instance, switching the behavior from “walking forward” to “turn left” when there are obstacles on the right, or the other way round. The MRC output also decides in which direction the walking machine should turn in corners or deadlock situations depending on which sensor has been previously active. In special situations, like walking towards a wall, both IR sensors might get positive outputs at the same time, and, because of the velocity regulating network, the walking machine is able to walk backwards and to leave the wall.

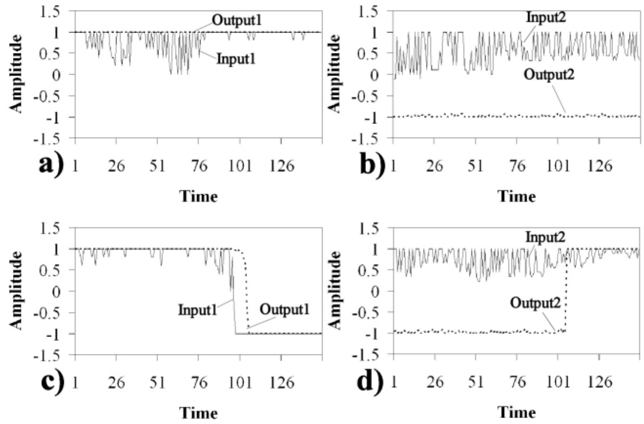

Fig. 5. a) to d) present the input signals (full line) of the IR sensors and the output signals (smashed line) of the output neurons. Because of the inhibitory synapses and the high activity of output1 (a), the output2 (b) is still inactive although input2 is active. c) and d) show the switching condition between output1 and output2 when the activity of input1 is low, meaning “no obstacles detected” and the activity of input2 is still high, meaning “obstacles detected”.

B. Neural oscillator network for rhythmic movements

The concept of neural oscillators for walking of quadrupeds has been studied e.g. by Hiroshi Kimura [5]. There, a neural oscillator network with four neurons is constructed by connecting four neural oscillator’s, each of which drives the hip joint of one of the legs. Here we use a so called SO(2)–network [3] to generate the rhythmic locomotion. It has already been implemented successfully as central pattern generator (CPG) in the six-legged walking machine Morpheus [9]. The same structure and weights are applied to control the four-legged walking machine AMOS-WD02.

The SO(2)–network consists of two neurons (compare Fig.6), where the sinusoidal neuron outputs correspond to a quasi-periodic attractor. They are used to drive the motors directly for generating the locomotion. This network is implemented on a PDA having a update frequency of 25.6 Hz and it generates a sinusoidal output with a frequency of approximately 0.8 Hz.

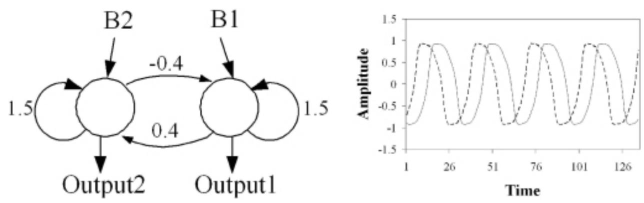

Fig. 6. Left: the structure of the SO(2)–network with the synaptic weights for our purpose. $B1$ and $B2$ are bias terms with $B1 = B2 = 0.01$. Right: the output signals of neurons 1 (smashed line) and 2 (full line) from the SO(2)–network. The output of neuron 1 is used to drive all thoracic joints and one backbone joint and the output of neuron 2 is used to drive all basal joints.

By using symmetric output weights a typical trot gait is obtained, which enabled an efficient motion. In a trot gait (see Fig.7), the diagonal legs are paired and move together.

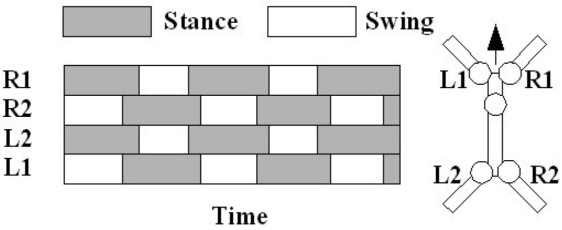

Fig. 7. Left: the typical trot gait. X-axis represents time and y-axis represents the legs. During the swing phase (white blocks) the feet have no ground contact. During the stance phase (gray blocks) the feet touch the ground. Right: the orientation of the legs.

C. The velocity regulating network

To change the motions, e.g. from walking forwards to backwards and to turning left and right, the simplest way is to perform a 180 degree phase shift of the sinusoidal signals which drive the thoracic joints. To do so, we introduce the velocity regulating network (VRN) which is described in [8]. It performs approximately a multiplication of two input values $x, y \in [-\mathbf{1}, \mathbf{1}]$. For our purpose the input x is the oscillating signal coming from the SO(2)–network to generate the locomotion and the input y is the sensory signal coming from the MRC network to drive the behavior. Fig.8 presents the network consisting of four hidden neurons and one output neuron. Fig.8 on the right shows that the output signal gets a phase shift of 180 degrees, when the sensory signal (input y) changes from -1 to 1.

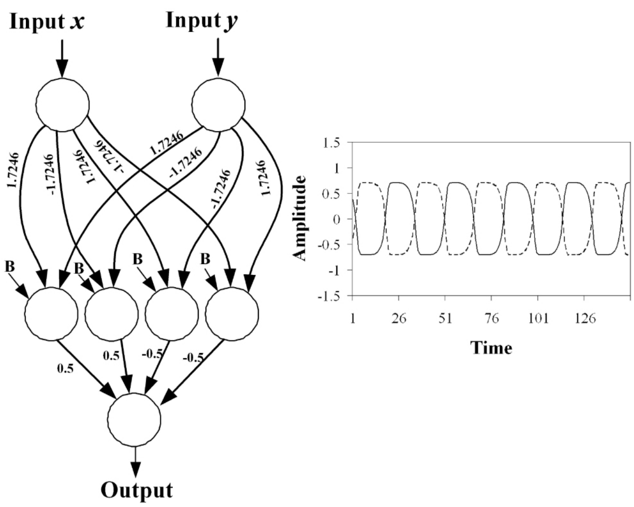

Fig. 8. Left: the VRN with four hidden neurons and the given bias terms B which are all equal to -2.48285. Right: the output signal (full line) when the input y is equal to 1 and the output signal (smashed line) when the input y is equal to -1.

D. The modular neural controller

The combination of all three networks leads to an effective neural network for reactive behavior control in changing environments. One oscillating output signal from the SO(2)–network is directly connected to all basal joints, while the other output is connected to the thoracic joints only indirectly, passing through all hidden neurons of the VRN through the so called x–input. In addition, for a more flexible and faster motion, the backbone joint can be activated by applying the first oscillating output signal (Output1 of the SO(2)–network). The output neurons of the MRC network are also connected to all hidden neurons of the VRN as y–inputs. This neural controller and the location of the corresponding motor neurons on the walking machine are shown in Fig.9.

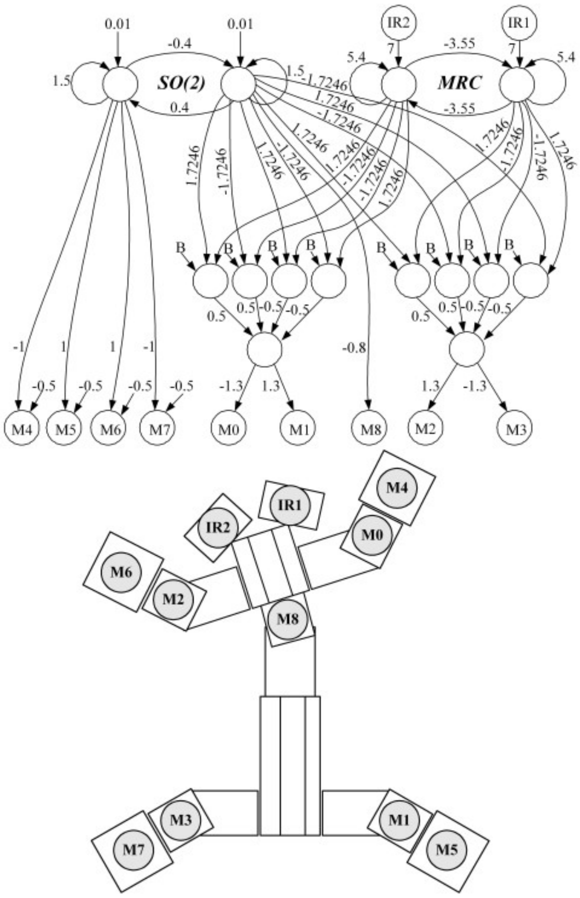

Fig. 9. This is the final modular neural controller. It generates a trot gait which is modified when obstacles appear. The bias terms B of the VRN are again all equal to -2.48285. Two infrared sensors are directly connected to the input neurons of the MRC network. If the obstacle is detected, the outputs of the MRC network make the walking machine turn because the VRN changes the quasi-periodic signals at the thoracic joints.

IV. EXPERIMENTS AND RESULTS

The performance of the network shown in Fig.9 is firstly tested on the physical simulation with a complex environment (see Fig.2), and then it is downloaded into the mobile processor of AMOS-WD02 for a test on the physical autonomous robot. The simulated walking machine and the physical walking machine behave almost similarly. The sensory information of IR sensors is used to modify the machine behavior as expected from a perception-action system. If the obstacles are presented on either the right or the left side, the controller will change the rhythmic movement of the legs, causing the walking machine to turn on the spot and immediately avoiding the obstacles.

In some situations, like approaching a corner and a deadlock situations, the MRC preprocessing network decides the turning direction, left or right. As shown in Fig.10, M0 and M1 of the thoracic joints (compare Fig.9) are turned into the opposite direction, if the left IR (IR2) detects the obstacle; correspondingly M2 and M3 of the thoracic joints are turning into the opposite direction when the right IR (IR1) is active. In special situations, e.g. walking towards a wall or detecting obstacles on both sides, both IR sensors are simultaneously active (see third column in Fig.10). Thus, M0, M1, M2 and M3 of the thoracic joints are turning into another directions which causes the walking machine to walk backwards and eventually it is able to leave the wall. Fig.11 is a series of photos of these example experiments[2] which show the reactive behavior of the walking machine. The photos on the left in Fig.11 show that the walking machine can avoid the unknown obstacle, and it can also leave a corner (middle column in Fig.11).

To compare the controller mentioned in [9] with the one described here, we implement that controller and test it with the same environments. The result is shown in the right column of photos. It can be seen that the controller [9] has difficulties to avoid and leave the corner. At first, the left IR sensor detects a side wall and then motors (M0 and M1 comparing Fig.12) are inhibited affecting the walking machine to turn right with a slight curve. After that it faces to the corner, both IR sensors are active, and then all motors (M0, M1, M2 and M3) are inhibited. Therefore the walking machine gets stuck in front of the corner. Fig.12 shows the motor signals as well as the signals from IR sensors. In all experiments, the walking cycle is approximately 1.25 s and the walking velocity without using the backbone joint is 10 cm/s.

V. Conclusions

The four-legged walking machine AMOS-WD02 is presented as a reasonably complex robot platform to test a neural controller generating the robust sensor-driven exploration and obstacle avoidance behaviors.

The modular neural controller was designed as a neural network composed of a preprocessing network (MRC), a two-neuron oscillator network for central pattern generation, and the velocity regulating network (VRN) for

[2]for more demonstrations see http://www.ais.fraunhofer.de/∼poramate

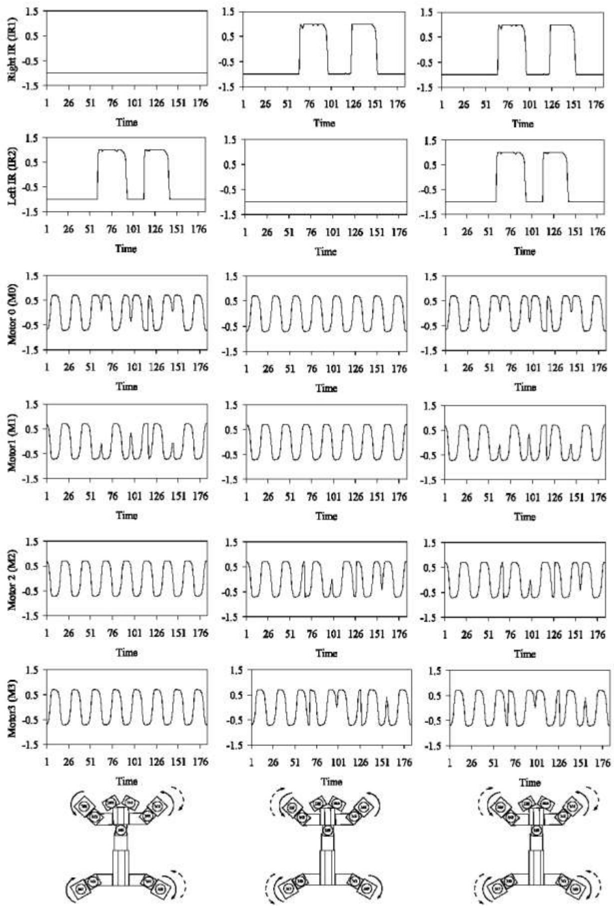

Fig. 10. Left: if the obstacles are presented on the left of the walking machine, then the two motors (M0, M1) on its right are changed into the opposite direction presented by the arrow smashed lines in the lower picture. Middle: if the obstacles are detected at the right of the walking machine, then two motors (M2, M3) on its left are reversed which is presented by the arrow smashed lines in the lower picture. Right: in this situation, the obstacles are simultaneously detected on both sides resulting in the reversion of all motors (M0, M1, M2 and M3). They are presented by the arrow smashed lines in the lower picture.

changing the locomotion appropriately. The controller is used to generate the walking gait and to perform the reactive behavior; for instance, exploring an in-door environment by wandering around, avoiding obstacles when they are detected, and leaving from a corner as well as from deadlock situations. In case of protecting the legs of the walking machine from hitting obstacles, like chair or desk legs, one can easily install more IR sensors on the legs, and all there signals can send to the corresponding input neurons of the MRC network. However, the controller has been tested successfully in the physical simulation environment as well as on the walking machine. Thus we were able to reproduce these basic behaviors, generally achieved for wheeled robots, also for a machine with many degrees of freedom. The generated behaviors are of course essential also for an autonomous walking machine. More demanding tasks will be related to the use of additional

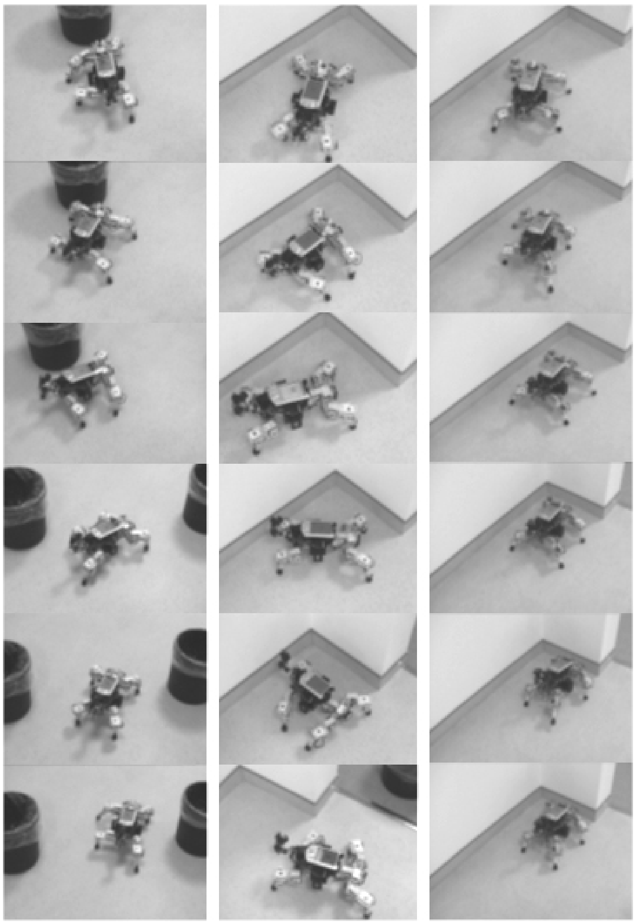

Fig. 11. Examples of the behavior driven by the two IR sensors of the four-legged walking machine AMOS-WD02. Left: the typical behavior avoiding obstacles. Middle: the walking machine is able to leave from the corner. Right: for comparison the controller described in [9] is implemented. The photos show that now the walking machine cannot avoid the wall and leave the corner. All photos are taken with the same time slot.

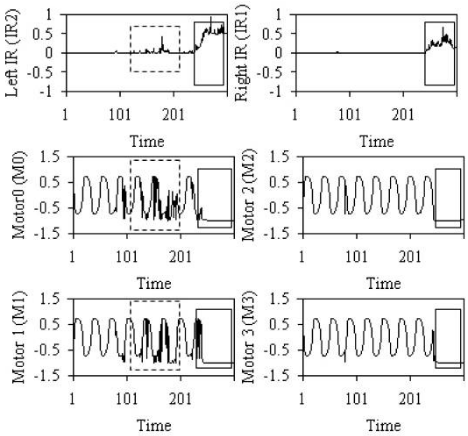

Fig. 12. First, obstacles are detected on the left of the walking machine and the two right motors (M0, M1) are effected by inhibition (smashed frames) while the others are still unaffected (because no obstacles are detected on the right side). Then, both IR sensors are detecting an obstacle (the wall) and all motors (M0, M1, M2 and M3) are inhibited (solid frames).

sensors. Therefore, future research we will make use of signals coming from combined auditory and tactile sensors, which are fixated on the two front legs. They will be used for protecting legs from colliding with obstacles using tactile information, and also for navigation based on sound tropism. Finally all these different reactive behaviors will be fused into one modular neural controller, where modules have to cooperate or compete as in versatile perception-action systems.

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