

Fly-inspired sensory feedback in a reaction-diffusion neural system for locomotion control in a hexapod robot

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Abstract—In this paper the implementation of a stable locomotion controller with sensory feedback on a hexapod robot structure is reported. Inspiration comes from recent results on the insect *Drosophila melanogaster* neural networks in charge for the control and modulation of basic crawling motion, where the role of sensory feedback is emphasized. A simple neural network, acting as a locomotion controller was designed and implemented. The phase stability, essential for a reliable gait generation, is assured exploiting tools from Partial contraction theory, whereas sensory feedback is used to locally modify the motor neuron dynamics to improve the robot dexterity in front of uneven terrains. Experimental results are reported in an autonomous hexapod robot, where the locomotion controller and sensory feedback are implemented in a commercial microcontroller low cost platform.

I. INTRODUCTION

THe control of walking robots is much more challenging than that of wheeled machines, but legged robots offer numerous advantages in terms of manoeuvrability and the areas they can access. Legged locomotion is the most common way in which animals move. For this reason, biologically inspired solutions have often been adopted to build legged robots [1], [2].

Animals walk in a stereotyped way, adopting rhythmic patterns of movement, called gaits. In a large variety of animals (from invertebrates to vertebrates [4]), the neural control of these stereotyped movements is hierarchically organized. The key point is the presence of a functional unit, called Central Pattern Generator (CPG), containing all the mechanisms needed to generate the rhythmic pattern of movements [3]. The CPG essentially provides the feedforward signals needed for locomotion even in the absence of sensory feedback and high-level control.

In literature several CPG-based structures were developed and applied to different robotic platforms [6], [7]. The use of dynamical oscillators is also common to represent the joint activity of a whole neural group and the different topological links among the oscillators give the opportunity to derive a rich variety of robot behaviors [10]. For our experiments we decided to use a network of non-linear oscillators synchronized each other using diffusive connections; the adopted structure represents a simplified version of the *Drosophila*-inspired model developed in [12], [14], [11]. By properly imposing a given phase shift-synchronization among the CPG neurons, we can coordinate the movements of the actuators and make the hexapod move with the desired gait.

Although the CPG paradigm is essentially an open loop approach to locomotion, in literature several feedback strategies were implemented to include closed loop signals.

The CPG paradigm, conceived as an open loop control scheme, acquires much more efficiency if coupled with signals coming from sensors which enable the overall structure to implement steering or adaptation strategies which increase the degree of adaptation to external constraints, making the CPG approach somewhat similar to a decentralised control. Here single leg motions are essentially independent, whereas the needed coordination is achieved through a series of rules, designed starting from behavioural observation on insects [26]. In Nature it is apparent that animals adopt mainly open loop control strategies whenever specific fast (for instance escaping) reactions are required, whereas more flexible adaptive strategies are used when moving in natural conditions and/or trying to move in highly uneven terrains. So the solution should be something in between the completely centralised and the decentralised approach [27]. On the other hand, it was recently found in Biology that insect nervous system modulates reflexes directly in individual legs in the adaptation of walking to specific tasks [20]. In particular the effect of the same reflex can be opposite (assistive or reversal) depending on the specific task, resulting in a considerable modulation of the overall CPG dynamics.

The authors were involved into both high level and low level approaches to feedback control in CPGs; the former involved visual sensors that were used to steer the robot motion, realising tactic or phobic behaviours [17]; the latter made use of contact sensors that were able to modify the equilibrium points of specific motor neurons driving the single leg [16]; the application of bionic antennae can be also considered [18]. In this paper a simple, low cost and effective strategy is used: feedback from the legs is exploited to modify the behaviour of the CPG neurons, with the aim to detect the presence of obstacles, or unexpected hindrances at different levels with respect to the ground and modify the movement of the robot accordingly. In this sense, the centralized approach tends towards the decentralised one by locally modulating the leg dynamics, as in [20]. This can take place without any need of additional complex sensory systems. Here the possibility to process feedback signals improves the robot performance in terms of adaptability to the environment state.

Moreover, going back to the roots of biological locomotion, crawling in worm-like animals or even in *Drosophila* larva involves the integration of CPG signals coming from the Central nervous system, motorneuron activity, muscle contraction and sensory feedback, at the level of peripheral

nervous system (PNS) [23]. Here, through genetic tools, it was found that specific multidendritic (MD) sensory neurons provide feedback, presumably mono synaptic, for controlling wave propagation, needed for a regular crawling. Inhibition of MD neurons causes defects in locomotion: without sensory feedback, contraction is generally too tight and exaggerated. The role of sensory neurons is to facilitate relaxation of a contracted segment in the larva, allowing a rapid forward wave propagation, boosting the much slower pattern inherent to the CPG alone. Once again, even if the CPG still runs without sensory feedback [24], this is a critical component for normal behaviour. The apparent local signal processing is believed to play a role in a smooth coordination of wave propagation. Specifically in the *Drosophila* larva, the primary role of MD sensory neurons is to report a signal after a successful contraction of a specific segment, inducing a muscle relaxation and a propagation of the contraction wave to neighbouring segments. In [23] authors suggest a four stage mechanism: first motoneuron firing takes place; this elicits the corresponding muscle contraction; sensory neurons respond to contraction signalling to the CNS; this in turn relaxes that muscle and lets the contraction wave propagate to the neighbouring segment.

This basic model of diffusion wave propagation was implemented in a very easy way in our robot prototype. This can be accomplished in two main ways using pressure sensors: the former could be to place the pressure sensors between two different joints in the leg, revealing contraction that can be used to modulate the gait; the latter is to use the pressure sensor as a proprio/exteroceptive sensor. In this case the pressure signal, posed in the tip of a leg, not only reports the load supported (typical of a proprioceptive signal), but also detects a reliable, successful contact with the ground. In our implementation the latter strategy was adopted for an efficient control of locomotion in rough terrains. To achieve this goal, we added 6 pressure sensors to the hexapod, one for each leg, placed in the end effectors of the legs, to obtain information about the extent of ground reaction force acting on each leg. By analysing the values acquired, we can detect if the legs are touching and which is the load at the impact. According to the values acquired, the leg behaviour is modified by modulating the dynamics of the corresponding motor neuron in the CPG. Of course, when the behaviour of some neurons of the CPG changes, the whole network can be influenced because of the interconnections the neurons, like in the *drosophila* larva case, where diffusion of the wave front to neighbours is facilitated.

II. THE STRATEGY ADOPTED

The CPG paradigm inspired a strategy for the control of robot locomotion based on Cellular Nonlinear Networks (CNNs) [8], [9]. The basic units of these artificial CPGs are nonlinear oscillators coupled together to form a network able to generate a pattern of synchronization used to coordinate the actuators of the robot.

The strategy adopted in this paper focusses to the problem of controlling the two phases of locomotion (stance and

swing) at the level of the single leg with application to a robot prototype. In the default locomotion the CPG imposes a given gait: in our case the fast gait (alternating tripod). The objective of our control strategy is to modulate the system dynamics differently in the stance and in the swing phase. In particular, the motoneuron oscillation frequency will be decreased when the leg is in stance. This is efficient for example, when dealing with highly unstructured terrains, where much more attention has to be paid to the stance than to the swing phase. Here in fact we have to prevent undesired phenomena, like slippery, for which complex models and control strategies were implemented [29]. Often in these cases the swing phase is simply a recovery to the subsequent stance phase. So, switching between the stance and the swing phase is detected and this signal used to modulate the local dynamics of the motoneurons associated with the leg into account.

The CPG scheme adopted will allow the possibility to the motoneurons to change their local dynamics still maintaining a given locomotion style. This is guaranteed by adopting parameters coming from a previous analysis through the partial contraction theory [14]. This is also in line with established literature results, which converge towards considering reflex signals coming from ground contact to modify the spiking rate of motoneurons, causing modulation in the overall locomotion patterns. In [21] a neuromechanical joint was accurately modelled and force feedback was analysed. Here, in a much simplified approach, the pressure signal is directly used to control the neural frequency of specific motoneurons, resulting in a simple yet efficient practical implementation.

III. THE CPG STRUCTURE

The CPG used to develop our control strategy is a hierarchical structure composed of ten neurons, disposed on multiple layers. The particular topology adopted allows also to consider the overall structure to belong to the class of reaction-diffusion Cellular Nonlinear Networks (CNNs), characterised by a local connectivity among the neurons. Among the different neuron models nowadays available, the authors already had introduced a neuron model that suitably matched the CNN basic cell [16]. Its equations are reported below:

$$\begin{cases} \dot{x}_{1,i} = \gamma(-x_{1,i} + (1 + \mu)y_{1,i} - s_1 y_{2,i} + i_1) \\ \dot{x}_{2,i} = \gamma(-x_{2,i} + s_2 y_{1,i} + (1 + \mu)y_{2,i} + i_2) \end{cases} \quad (1)$$

where $y_i = 0.5(|x_i + 1| - |x_i - 1|)$ with $i = \{1, 2\}$. For analytical reasons, the output nonlinearity will be substituted with its smooth hyperbolic tangent approximation. By using the following parameters for each cell: $\mu = 0.7$, $s_1 = s_2 = 1$, $i_1 = i_2 = 0$ the cell dynamics is able to show a stable *limit cycle* behaviour [19]. In this case, the μ value modulates the ratio between the slow and the fast part of the dynamics of the limit cycle. The parameter γ directly modulates the neuron frequency and this will be selected as the control parameter for feedback control.

The overall neural controller is made up of ten identical units (see Fig.1). The block D1-D2 represents the CPG, where the basic locomotion pattern is generated and imposed. In this implementation, oriented to a hardware demonstrator, the alternating tripod, the primary locomotion gait found in *Drosophila* was considered [25]. The two peripheral chains contain interneurons and motor neurons. Interneurons I1, I2, connect the drivers to the motor neurons for each leg. Motorneurons are called according to the leg they control (Right or Left, 1,2 or 3 for front, middle or rear leg). In particular the two state variables of one motor neuron drive coxa and femur of the associated leg. Tibia control is obtained from a modulation of the femur control signal. In details, its angle position is increased or decreased during movement by adding an opposite angle with respect to the one used for the femur, to keep the foot perpendicular to the ground. The two interneurons (I_1 I_2), one for each tripod, are controlled by the CPG neuron drivers (D_1 D_2). These establish the nominal frequency and impose a desired phase to the interneurons to realise the nominal feedforward locomotion.

The complete structure of the network is shown in Fig.1.

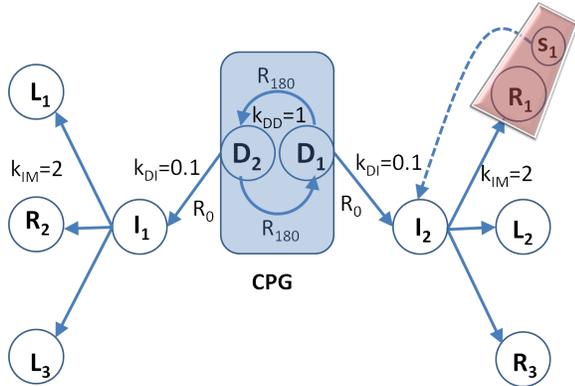


Fig. 1. Structure of the CPG composed by two drivers (D_1 D_2), two interneurons (I_1 I_2) and six motor neurons. Sensory signals acquired at the leg level, can be used to modulate the interneuron activity of the associated tripod.

By properly synchronizing the CPG neurons we can coordinate the movements of the actuators and make the hexapod move with the desired gait.

The dynamics of the CPG network, with the inclusion of the control parameters, is described by the following equation:

$$\dot{x}_i = \gamma f(x_i, t) + \gamma k \sum_{i \neq j; j \in N_r} (R_{ij} x_j - x_i) \quad (2)$$

where $f(x_i, t)$ represents the dynamics of the i^{th} uncoupled oscillator (1) and k is the feedback gain, whereas the argument of the sum represents the feedback error between the state variables of the i^{th} cell and the corresponding state variables of neuron j after those ones being phase-shifted with respect to neuron i of an angle ϕ_{ij} via the rotational matrix $R(\phi_{ij})$. Under these conditions, the two oscillators are

in reciprocal equilibrium only if the error term is zero, which implies *phase-shift synchronization*. For the implementation of the tripod gait we need that the two drivers in the CPG have to be phase shift synchronised of 180° , so that the stance phase in first tripod (left hand side of Fig.1) corresponds to the swing phase in the other one. The control parameters on the links of the network belong to two categories: the phase shifts, imposed through classical rotation matrices in the plane; the control gains, to assure that the imposed phase displacements are satisfied.

At this aim the network can be analysed in two parts: the part of the CPG composed by the drivers is first taken into account. This is a simple example of an undirected diffusive graph. In this case the Partial contraction theory can be exploited to find the minimum K gain value to assure sufficient conditions for global asymptotic stability of the imposed phase shift [13].

The gain K has to be chosen high enough to satisfy the sufficient conditions for achieving global exponential stability in the imposed phase 180° among the legs. This is needed to maintain the imposed locomotion gait.

Using the traditional formulation of a reaction-diffusion system, applied to the two drivers, the whole system becomes:

$$\dot{x} = f(x, t) - k \cdot L \cdot x \quad (3)$$

with: $x = [x_{1D_1}, x_{2D_1}, x_{1D_2}, x_{2D_2}]^T$, $f(x, t) = [f(x_{1D_1}, t), \dots, f(x_{2D_2}, t)]^T$, $L \in \mathbb{R}^{4 \times 4}$. In our case, the laplacian matrix L is the following:

$$L = \begin{bmatrix} I & -R(\phi_{180}) \\ -R(-\phi_{180}) & I \end{bmatrix} \quad (4)$$

For imposing stability constraints we refer to the Partial contraction Theory. The details on the methodology can be found in [14].

Partial contraction starts from the existence of a flow-invariant subspace \mathcal{M} and consequently, of its orthogonal complement \mathcal{V} . The subspace \mathcal{M} is a linear subspace acting as a limit set for the system trajectories: any trajectory starting in \mathcal{M} , remains trapped there forever. The methodology is based on the concept that if the diffusive side of the network system, projected on \mathcal{V} is sufficiently higher than the system autonomous incremental dynamics, then the system behavior will be trapped on \mathcal{M} . In our case, referring to the D1-D2 CPG network in Fig.1, the following dynamical constraints should be introduced: $x_{1D_1} = -x_{1D_2}$ $x_{2D_1} = -x_{2D_2}$. Then \mathcal{M} becomes:

$$\mathcal{M} = [R(\phi_{0^\circ}) \quad R(\phi_{180^\circ})]^T, \quad \mathcal{M} \in \mathbb{R}^4.$$

Here each block within \mathcal{M} describes the desired phase shift with respect to the reference node D_1 . One fundamental result from partial contraction, can be summarized in the following relation [14]:

$$k \cdot \lambda_1 > \sup_{x_i, t} \lambda_{max} \left(\frac{\partial f}{\partial x}(x_i, t) \right) \quad (5)$$

where

$$\lambda_1 = \lambda_{min}(L);$$

λ_1 being the algebraic connectivity of the graph. In our case it results: $\lambda_1 = 2$, $\sup_{x_i,t} \lambda_{max} \left(\frac{\partial f}{\partial x}(x_i,t) \right) = 0.64$, so that $k_{min} = 0.32$. We adopted the value $K_{DD} = 1$. It has to be noticed that, from results in [14], this value from k_{min} provides a sufficient condition for guaranteeing the global convergence to any imposed phase shift, so to any imposed locomotion gait. This gives us the possibility to change the phase shift without calculating a new gain value.

The other part of the network includes the interneurons and the motor neurons. Interneurons are enslaved to the CPG dynamics: in absence of sensory feedback $I1$ and $I2$ follow the same behaviour as the corresponding CPG drivers.

Feedback is generated from signals coming from sensory units which are assumed to send graded potentials related to the amount of pressure detected. These signals (for example from S_1 in Fig.1) directly modulate the γ value of the corresponding interneuron. This takes place in those portions of the limit cycle whenever the leg in stance phase. This forces the interneurons to temporarily deviate from the nominal frequency value, as imposed by the divers. This sensory feedback can be considered as an external disturbance on the the interneuron frequency, which acts persistently all times the sensors detect a reliable pressure with the ground. So, if the leg is in the stance phase, the control law decreases the oscillation frequency, and all the motor neurons associated with this interneuron have to follow the same dynamics, in order not to loose phase matching among motor neurons of the same tripod. Consequently, the gain from the driver has to be weak enough to compliant with this temporary frequency deviation. Instead the gain from the interneurons to the motor neurons has to be high in order to guarantee that this new frequency, imposed by sensory neurons, is adopted from all the motor neurons belonging to the same tripod. In this way the overall gait is still a tripod, whereas the stance phase is slew down. In this application $K_{DI} = 0.1$ from the drivers to $I1$ and $I2$, whereas $K_{IM} = 2$ for connections from the interneurons to the motor neurons.

Signals coming from numerical on board integration of the whole system equations provide references for each leg position thorough a suitable adaptation of the motor neuron dynamics ($L_1, L_2, L_3, R_1, R_2, R_3$). These signals are in fact converted into angle values within the range of movement of every servomotor. These values represent the angle, positive or negative, the motor has to move with respect to the actual position. Since the servomotor requires an absolute angle value, these angles are summed to a reference center position and the value obtained is sent to the motor to realize the desired movement.

IV. ARCHITECTURE DESCRIPTION

A. The control setup

A scheme of the control architecture embedded on the hexapod robot is shown in Fig. 2. The locomotion controller

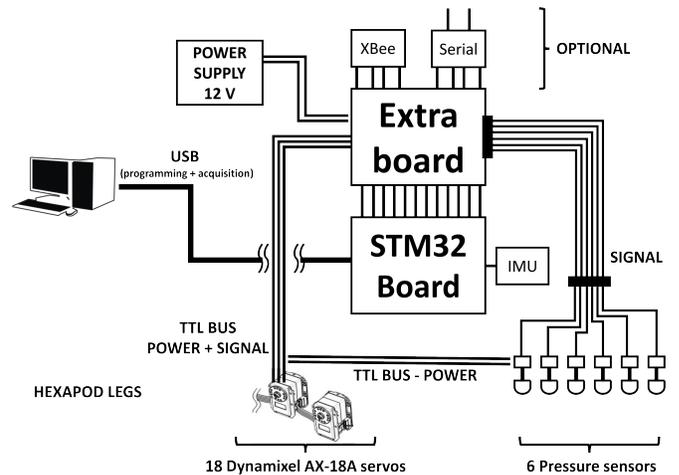


Fig. 2. Block scheme of the main elements constituting the control system of the hexapod robot.

is implemented on an ARM[®] Cortex[®] M4 STM32 microcontroller. In particular we used a commercial low cost development board, the STM32F4, which also contains an inertial module (IMU). A supplementary board, compatible with the STM32F4 pinout, was added to handle the I/O system: it acquires the analog signals coming from the six pressure sensors, allows external communication through serial port and Xbee and handles the bus for the robot motors. The power supply needed can be provided either through an external voltage generator or through an on-board LiPo battery at 12V. An USB connection with an external PC can be also used to program the microcontroller and to acquire the variable evolution during the experiments.

B. Robotic platform

The robot we used to realize our experiments is a modified version of a commercial hexapod, the PhantomX Hexapod Mark II of Interbotix Labs [22]. The hexapod robot is depicted in Fig. 3.

The reason behind this choice is that we needed to start with a reliable robotic platform ready to be used, to focus our attention only on some mechanical modifications. From the control side, attention was posed on the control algorithms for our experiments and on other hardware improvements to the structure. The hexapod was significantly modified both in the mechanical structure and in the hardware, to add our sensors and some more electronics. Of course, all the firmware code was totally rewritten.

Each leg of the hexapod is composed of 3 servomotors, to realize the coxa, femur and tibia joints. Hence, the robot has 18 actuators in total (18 Degrees Of Freedom). The servomotors used are the Dynamixel AX-18A.

The tibia links were substituted with new ones, appositely designed to host a pressure sensors and its conditioning electronics. At the end effector of each leg we have a structure similar to a pump, connected to the pressure sensor Freescale MPX5010GP through a small pipe (see Fig. 3). When passing from the swing phase to the stance phase the

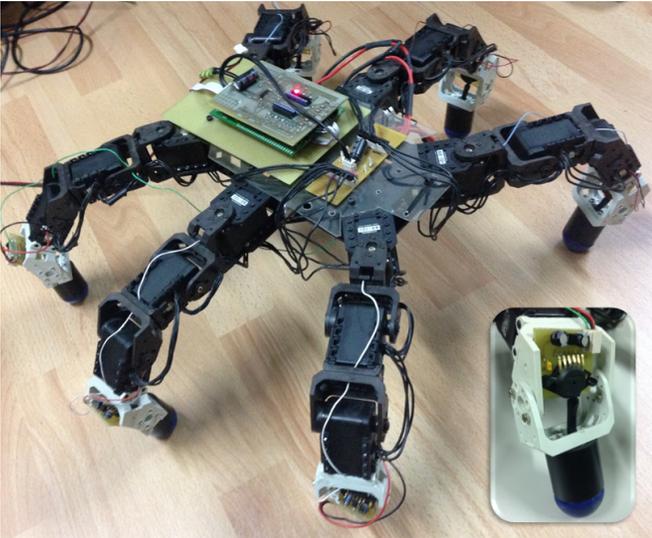


Fig. 3. Hexapod robot equipped with a microcontroller based board and six pressure sensors located on the tip of each leg. The insert shows the rearrangement of each tibia link: the tip of each leg contains a rubber ball connected with the pressure sensor. The electronic board used for conditioning purposes is also visible.

pressure signal provided by the sensor and acquired by the microcontroller is related to the entity of reliability of the contact with the ground or with an object.

The data acquired from the pressure sensor of the middle right leg during normal walking in open loop conditions are shown in Fig. 4. During an initial calibration procedure a threshold is identified to distinguish between the stance and swing phase of the leg cycle.

V. EXPERIMENTAL RESULTS

We noticed that network synchronizes very fast: in all the experiments the transient needed to let the net synchronize before moving the robot is negligible. At the beginning the stance phase, the pressure sensor signal overcomes the threshold; this is used to slow down of a factor 0.4 the nominal limit cycle frequency of the related interneuron, locally emphasising the slow-fast dynamics of the trajectory for all the legs of the considered tripod. The nominal oscillation frequency is restored when a lift off is detected and the swing phase is initiated.

A. Walking in open and closed loop

In a first experiment we made the hexapod walk in open loop, i.e. disabling feedback from all pressure sensors placed in the legs. Hence, signals coming from all the contact sensors were acquired but not included into the control loop.

Fig.4 depicts these conditions: the output (saturated) signal motor neuron R2 is shown, together with signal acquired by the pressure sensor placed in R2. The trend of the pressure sensor clearly detects the stance and swing status of the leg R2. However, no modulation in the motor neuron dynamics takes place. This phase is useful to test the reliability of the sensors and also to tune its threshold value.

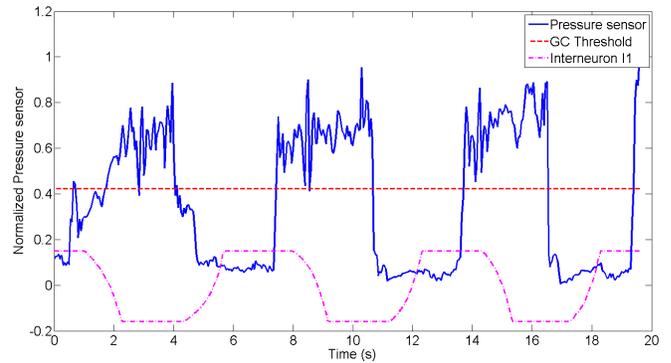


Fig. 4. Open loop conditions: normalized unfiltered data acquired from a pressure sensor placed on the leg R2 tip and the corresponding threshold used to evaluate the presence of a reliable Ground Contact state. Dashed line depicts the output of the motor neuron R2.

In the following experiment feedback was enabled from all pressure sensors placed in the legs.

Referring to each tripod, the strategy adopted was the following: when the value of the signal acquired by the pressure sensor of a leg of the tripod exceeds its threshold, this control signal acts on the corresponding interneuron (I1 for the tripod of R2 and I2 for the tripod of L2) decreasing its oscillation frequency. Due to the high gain value among the interneuron and the motor neurons of the corresponding tripod, all the legs of that tripod decrease their oscillation frequency and the stance phase takes place at a slow speed. When the pressure value decreases below the threshold for all of the legs belonging to the tripod, it is assumed that in this condition all the leg within the tripod released the ground and we are reliably in the swing phase. The sensor restores the oscillation frequency of the corresponding interneuron to the nominal value. The swing phase takes place at the nominal speed.

In Fig.5 the signals of the state variables of the interneurons I1 and I2 are shown, together with signals acquired by sensors of legs R2 and L2, in closed loop conditions. It is clear that when the pressure sensors reliably detect the ground contact, the dynamics of the corresponding interneuron is slowed down. Instead, during the swing phase, the oscillation frequency is restored to the nominal value. During the final time interval of Fig.5, the robot was lifted up for some seconds from the ground: the pressure sensor signals maintained below the threshold, no frequency modulation was imposed and the signals related to I1 and R2, and to I2 and L2 are fully matching. When the robot is on the ground, interneuron I1 (I2) imposes its dynamics on R2 (L2) through the feedback gain K_{IM} , so the dynamics of R2 (L2) is enslaved to that one of the corresponding interneuron.

The analysis of Fig.5 reveals that, even if the actual configuration is an alternating tripod, clearly when the robot is lifted up from the ground, feedback heavily modifies the phase displacement among the three tripods. In fact, according to specific conditions, we can have that sometimes all the legs are on the ground, as it can be seen from time window

around 35 – 45s.

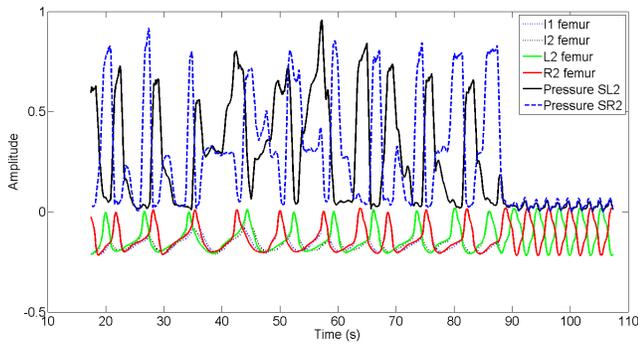


Fig. 5. State variables of the interneurons I1 and I2 and of the motor neurons L2 and R2; signals acquired by sensors of legs L2 and R2

B. Searching reflex experiment

The robot is allowed to walk on a simple path where a stair 6cm high was placed. It is asked to detect the presence of the stair through its pressure sensors and adapt the leg vertical displacement to search for a reliable contact with the ground. The scenario is reported in Fig.6.

The coordination of the robot legs during the experiments can be visualized through the stepping diagram reported in Fig. 7. The data were obtained comparing the signals acquired through the pressure sensors with the ground contact thresholds that have been computed during the initial calibration phase. The robot shows a basic tripod gait, modified by the influence of the pressure sensors, which, in turn, modulate the time constant of the dynamical equations governing the interneurons to emphasize the slow/fast dynamics during the stance/swing cycle.

The searching reflex can be appreciated in action looking at Fig.8, which shows the time evolution of the joint angular positions for the right side legs of the robot during a climbing experiment. Both the duration of the stance phase and the excursion of the femur joint are controlled by the information coming from the pressure sensors that are used to identify the touch down and lift off events. If, during the stance phase, the contact with the ground is missing (e.g. there is a hole in the ground or one leg misses the ground during climbing), or if a stair is met, the leg modulates its motion to compliant with the ground level. The searching reflex, in case of missing contact, continues until a contact is detected through the pressure sensors or until a lower limit on the joint motion is reached. This solution can extend and improve previous climbing results obtained with other robotic platforms [28].

The body posture, monitored through the inertial module, is reported in Fig. 9, showing the pitch and roll angle during the climbing scenario in closed loop and in open loop conditions. The inertial measurements are only monitored, i.e. the accelerometer is not used in the control loop. From the figure the added value of the searching reflex in smoothing the overall posture of the robot can be appreciated.



Fig. 6. Climbing scenario, the obstacle height is about 6cm.

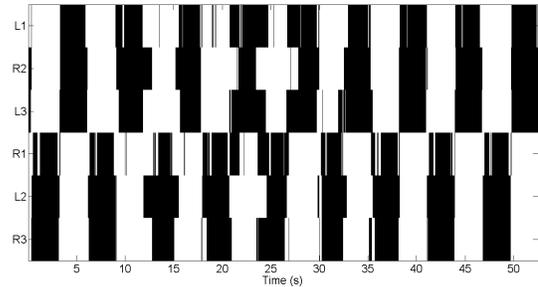


Fig. 7. Stepping diagram indicating the stance (white) and swing (black) phases during the step climbing experiment.

VI. REMARKS AND CONCLUSIONS

In this paper the implementation of a stable locomotion controller with sensory feedback on a hexapod robot structure is reported. Inspiration for this simple controller comes from recent results on *Drosophila* neural networks in charge for the control and modulation of basic crawling motion, where the role of sensory feedback is emphasized. The CPG implemented has the role of imposing a given locomotion pattern (the alternating tripod) to the legs, whereas the role of sensory feedback is to modulate the local dynamics of the motor neurons during the stance phase. Moreover, sensory signals are used to implement the searching reflex, fundamental to prevent the structure from loosing the posture. Posture signals, monitored through an inertial module hosted in the control board show that pressure sensors alone are sufficient to achieve a reliable attitude without needing to introduce the inertial sensors into the loop with additional control processing. The stability of the CPG is guaranteed through the selection of a suitable control gain in accordance with the partial contraction theory: the alternating tripod guarantees that at least three legs have to be in the stance phase. The results obtained further contribute to the idea that, even if the CPG paradigm is essentially an open loop strategy, the introduction of a really simple and low cost sensory feedback can heavily improve the quality of locomotion, adding flexibility and reliability. In this paper the signals coming from the pressure sensors are thresholded before being included into the control loop. An initial calibration procedure regulated single thresholds for each sensors as a function of the weight distribution of the robot. An improvement that is currently under implementation regards the

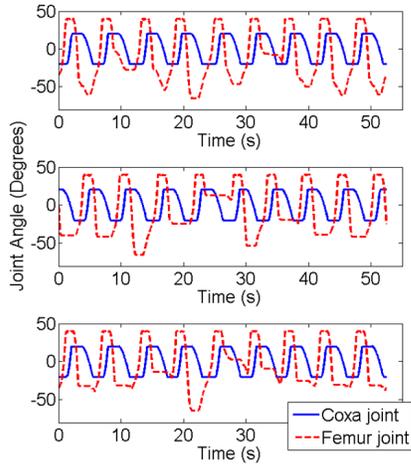
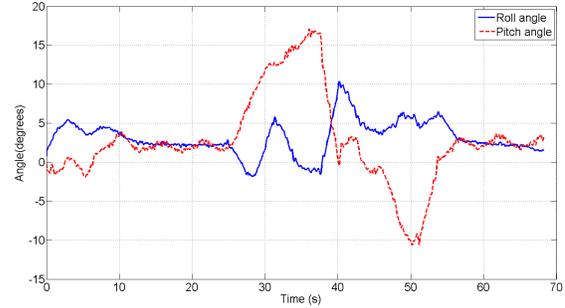


Fig. 8. Evolution of the angular positions of the coxa and femur joints of the right side legs during the climbing experiment. The femur joint position is guided by the pressure sensor to identify the touch down event.

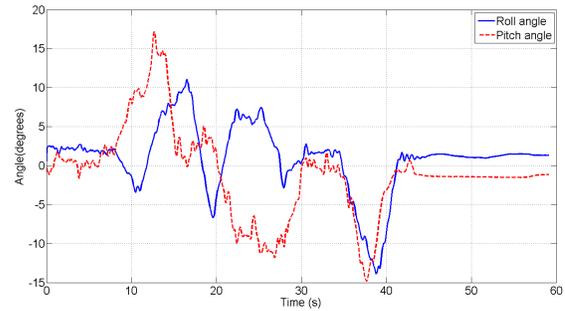
possibility to extract information from the pressure signal for more efficiently modulate local motion. In fact in literature complex adaptive locomotion strategies are implemented to control leg motion when dealing with different terrains [29]. The approach introduced in this paper can offer a valid low cost alternative to face with this issue. Moreover, the searching reflex was implemented allowing only a vertical movement for the leg. The strategy can be ameliorated with the addition of an oscillating input to the motor neuron controlling the leg involved in the searching phase: in these conditions the neuron undergoes chaotic dynamics, which can be exploited for implementing a more effective searching reflex. This work is currently in progress. In Biology the limitations of studying either the CPG or sensory system in isolation have become evident in recent years, and researchers are entering more and more in the details about the interconnections of the two systems. It is now clear that a complete understanding of pattern generation requires both aspects: pattern generators have probably to be considered integrated Central/Sensory Pattern Generators (CSPGs). Under this perspective, the CPG approach is going to be more and more related to the decentralised locomotion control (mainly reflex based), until now studied in specific insect species, like the stick insect: it is more and more evident that the CPG and the decentralised control live together within the same neural structure and take the lead in controlling motion upon specific needs. Finally, studying these details in simple creatures can provide a deep understanding of the basic recipes for a more and more neural-like locomotion control implementation in biorobotic structures.

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(a)



(b)

Fig. 9. Trend of the pitch and roll angle of the robot during the climbing experiment: (a) in closed loop and (b) in open loop. The raw sensor signal was filtered using a sliding window with size $w = 500ms$.

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