CPG-based locomotion generation in a Drosophila inspired legged robot

Eleonora Arena, Paolo Arena and Luca Patané

Abstract— In this paper a CPG approach to locomotion pattern generation and control in a Drosophila-like hexapodal structure was implemented. The CPG consisted of a two-layer network of nonlinear oscillators: the first layer is devoted to guarantee a stable locomotion pattern, whereas the second was designed according to the kinematic constraints of each leg. An accurate leg motion required the synchronization control in parallel neural networks where different oscillation frequencies have to co-exist. A strategy based on the use of an intermittent laplacian coupling was used to solve this issue. Numerical results are reported, which deserve further analytical inspection.

I. INTRODUCTION

The issue of motor control and motor learning in artificial systems is of primary importance to build efficient and highly adaptive machines. Since the last decade a huge effort has been paid to discover and model the rules that biological neural systems adopt to show the surprisingly efficient strategies for generating and controlling the gait in animals and manage the efficient transition among different patterns of locomotion. The activity presented in this paper is in line with a deep study on the insect brain architecture. In particular a huge effort has been paid recently to blocksize model a number of different parts of the fly Drosophila melanogaster brain, to try to attain perceptual capabilities and to transfer them to biorobots. Regarding the Neurobiological studies on the fly motor control, while it is already known where visually guided orientation control is resident, it is not clear how the high level controller acts at the low level, to finely modulate the neural circuitry in charge for handling the locomotion pattern, steering activities and so on. On the other side, behavioral experiments are in line with the idea that the fruit fly mainly adopts the Central Pattern Generator (CPG) scheme to generate and control its locomotion patterns. A plausible CPG based neural controller was then designed, able to generate the joint signals and the consequent stepping diagrams for the fruit fly. The network designed was used to control an artificial model of the fruit fly built using a dynamic simulation environment.

In literature several CPG-based central structures were developed and applied to different robotic platforms [13]. The use of dynamical oscillators is also commonly used 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 [5]. The various gait types are obtained imposing different phase displacements among the oscillators, which however, have to be synchronised. However, only a few works deal with the problem of stability of the obtained gait, which is indeed a crucial issue. In the proposed work a network of coupled oscillators is used to control the 18 DOFs of a drosophila-like structure. At the aim to create a stable gait generator, a two layer structure is used to uncouple the gait generation issue to the low level actuation of the legs that present different peculiar kinematics structures. To guarantee the stability of the locomotion gaits, the partial contraction theory [1] has been suitably applied. The interesting aspects, exploited in the paper, refer to the proof of convergence to every imposed gait thanks to the tree structure of the proposed network. Moreover, controlling the single legs, designed so as to kinematically mimick the fly limbs, implies the needs of hosting in the same network, oscillators with different frequencies, which need to be synchronised. This poses a new methodological problem, neved faced in literature. In this paper a pulse-based laplacian connection is introduced to handle with the phase-locking of different oscillation frequencies within the network. The numerical results reported deserve further mathematical analysis.

II. THE NEURAL NETWORK FOR LOCOMOTION CONTROL

The neural network driving locomotion in our model is hierarchically organised in two different interconnected layers: a lattice of neurons devoted to the gait generation through the definition of the desired phase displacements among the legs and a layer constituted by several motor neuron structures, as illustrated in Fig. 1.



Fig. 1. Neural network scheme: the top layer generates a stable gait pattern, whereas the bottom layer is constituted by additional sub-networks generating the specific reference signals for the leg joints.

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The basic cell characterizing the CPG architecture is described by the following equations:

$$\begin{cases} \dot{x}_{1,i} = -x_{1,i} + (i + \mu + \varepsilon)y_{1,i} - s_1y_{2,i} + i_1 \\ \dot{x}_{2,i} = -x_{2,i} + s_2y_{1,i} + (i + \mu - \varepsilon)y_{2,i} + i_2 \end{cases}$$
(1)

with $y_i = tanh(x_i)$ and the parameters used to perform a stable *limit cycle* for each cell are: $\mu = 0.23$, $\varepsilon = 0$, $s_1 = s_2 = 1$, $i_1 = i_2 = 0$ [2]. Note that the μ value is chosen to make the ratio between the slow and the fast part of the dynamics of the limit cycle next to one, to approximate a harmonic oscillator. The dynamical behavior of the CPG network is determined by connecting adjacent cells through links defined through rotational matrices $R(\phi)$, according to the global equation:

$$\dot{x}_i = f(x_i, t) + k \sum_{j \neq i} (R(\phi_{i,j})x_j - x_i) \text{ with } i, j = 1, \cdots, n$$
(2)

where the summation is extended to all the neurons j immediately adjacent to the neuron i; n indicates the total number of cells; $f(x_i, t)$ represents the dynamic of the i-th uncoupled oscillator and k is a parameter determining the *strength* of the connections. Moreover, the sum of terms performs diffusive couplings among adjacent cells and induces phase-locking directly depending on the imposed rotational matrices [1]. On the basis of equation (2), the dynamics of the whole system performing the phase-shift synchronization can be written as:

$$\dot{x} = f(x) - k \cdot L \cdot x \tag{3}$$

where x is the state variables vector $(x_1, \dots, x_{mn})^T$, with m is the order of a single cell (m = 2 in the treated case); $f(x) = [f(x), \dots, f(x_{2n})]^T$ is the dynamics of the uncoupled system; L is the coupling matrix built up of blocks $L_{ij} \in \mathbb{R}^{mXm}$, defined through the following relations:

- 1) $L_{ij} = -R(\phi_{ij})$ if the *i*-th node propagates the diffusion to the adjacent *j*-th node;
- L_{ji} = -R(-φ_{ji}) and L_{ij} = -R(φ_{ij}) in case of bidirectional connections (as in the network in Section II-A), L_{ji} = 0 otherwise (as in the network of Section II-B);
- 3) $L_{ij} = L_{ji} = 0$ if nodes *i* and *j* are unconnected;
- 4) $L_{ii} = d_i \cdot I_m$ $\forall i = 1, \dots, n$ where d_i is the unweighted degree of the *i*-th node.

Being the connection matrix L defined as a function of the imposed phase shift among the oscillators, L imposes a particular locomotion pattern through the associated *Flow Invariant Subspace M* (see [1], [3] for details).

A. High-level network for gait control

This network consists of a 9-neurons tree structure with bidirectional connections (see Fig. 1) in which a central neuron chain, acting as backbone, splits into a left and right side, recalling, in a topographical way, the anatomical symmetry of the 6-legs insect structure. As just demonstrated and widely discussed in previous works [3], the structure has a diffusive, undirected tree-graph configuration, which was demonstrated to guarantee asymptotic phase stability independently on the specific locomotion pattern. In fact, under these hypotheses, once the topology is fixed (in terms of nodes and links), the network converges exponentially to any arbitrary flow invariant subspace M if:

$$k \cdot \lambda_1 > \sup_{x_i, t} \lambda_{max} \left(\frac{\vartheta f}{\vartheta x}(x_i, t) \right)$$
 (4)

where λ_1 is the algebraic connectivity of the graph associated to the network [1]. This relation provides a sufficient constraint between the Jacobian dynamics of the uncoupled system and the coupling forces that assure a stable steady-state condition.

B. Low-level network for motor command generation

The high-level network in Fig. 1 refers to the gait control in a generic hexapodal structure; it is used to impose specific, stable phase displacements among the legs. On the other hand, the bottom layer is designed depending on the desired kinematic behavior, directly correlated to the morphology of the limb. The implemented approach is different with respect to the work in [4]. There, the highly symmetrical characteristics of the robot 3-DOF legs allowed to obtain the desired motion of each single leg segment, simply associating a neuron to each leg joint. The hexapodal structure here considered, while possessing 3-DoF legs, is asymmetrical and characterised by higher dexterity, so a further effort is requested. The low-level network controlling the limb motion is constituted by a certain set of motor neuron oscillators, characterised by different frequencies, that directly innervate the muscle fibers. As in the biological case, the motion of a leg is the result of a number of different neural subnetworks, acting as motor units innervating single muscular units [6]. The overall dynamics of these neural groups generates a kind of motor primitives whose combination leads to the emergence of the desired leg motion. Within the low-level network, neurons are organised in groups of isofrequential oscillators: coupling among these groups takes place through monodirectinal connections, either descending from a specific node of the high-level CPG structure acting as driver, or coming from another isofrequential group: this monodirectional link allows maintaining each group with its own oscillation frequency. The choice of using here monodirectional rather than bidirectional connections, unlike the CPG network, allows to maintain the asymptotically stable synchronization of the CPG neurons, guaranteed by the Partial Contraction Theory [1]. This is a need for our aim, since, when analysing the behavioral motion of the different joints in an accurate leg model, some of them move at multiples of a given basic frequency, maintaining, at the same time, a specific phase locked synchronization at particular time instants. This can be observed also in real insect motion.

In particular, let us suppose that the low-level network is characterized by two subnets of neuron oscillating at different frequencies. Let A and B be the root neurons for each subnet, and let f_A and f_B their frequencies, respectively, as depicted in Fig. 2. The neuron A acts as the

'master', and it is desired to be synchronised with neuron B, (the 'slave'). We suppose that the only link between two sub-networks is that one connecting neuron A and B, unidirectionally. Experimental results, reported in Fig. 2 refer to the case when nodes A and B are characterised by frequencies $f_B = 2f_A$. The upper panel of the figure reports the numerical simulation results: for a suitable value of the connection gain $k_{A,B}$, it is possible to synchronise the two neurons (and so the two subnetworks) with the two different frequencies, if we allow the Laplacian effect to take place only when the amplitude of the unit A signal overcomes a given threshold. This gives rise to a quasi-impulsive coupling action, and therefore the action of one oscillator on the other approximates that one of a spiking neuron. Fig. 2 shows the two limit cycles phase locked in the highest amplitude region of the master signal. More in details, the equations characterizing the dynamics of the motor-neurons A and Bare:

$$\dot{x}_{A} = f(x_{A}) + k \cdot (R_{0} \cdot x_{CPG} - x_{A}) \dot{x}_{B} = f(x_{B}) + k_{A,B} \cdot (R_{0} \cdot x_{A} - x_{B}) \cdot T(x_{A})$$
(5)

where

$$T(x_A) = \begin{cases} 1 & \text{if } x_{1,A} \ge \theta \\ 0 & \text{otherwise} \end{cases}$$
(6)

with $\theta = 0.95$, where $x_A(x_B)$ is the state vector of neuron A(B), x_{CPG} is the driving signal coming from the CPG network, and $k_{A,B}$ is the control gain. As a whole, this leads to a new particular form of Laplacian connection that we could define as 'intermittent Laplacian'.



Fig. 2. Neurons with different frequencies $(f_B = 2f_A)$ can be synchronized in phase using an intermittent laplacian connection.

In addition, both strategies of considering monodirectional connections and of adopting an intermittent laplacian coupling, allow to preserve the natural frequency within each subnet. When neurons are coupled with bidirectional links, instead, due to the effect of the imposed phases, the different frequencies tend to be compensated and the network globally reaches an average oscillation frequency. In previous studies [7], the interest was devoted to find the relation between the intensity of the frequency of a driver node and the consequent re-adaption of the network in terms of frequency and phase displacements among the neurons. The Partial Contraction Theory gives a mathematical tool to establish the sufficient condition to reach the convergence to a desired flow invariant subspace among neurons with the same frequency. Here, we deal with groups of neurons with different frequencies where a master-slave topology is considered to avoid the convergence towards a mean frequency value in the whole network. For this reason we apply monodirectional and intermittent connections. Regarding the phase synchronization among neural nets possessing different oscillation frequencies, actually we have no analytical proof. However, in literature similar problems were dealt with [8] referring to phase resetting oscillators where the phase dynamics is related linearly to the state variable dynamics. In that case it was possible to derive analytical conditions for the trapping of the various frequencies within one unique oscillation period. This is not our aim, but nevertheless the following concept of instantaneous synchronization can be adopted.

"Definition [Instantaneous Synchronization] [8]: two oscillators A and B are defined to be instantaneously synchronized if their phases return to zero at some point in time, i.e. $\phi_A|_t = 0 \Leftrightarrow \phi_B|_t = 0$."

This definition states that the synchronization will occur in all the time instants when the slower oscillator resets. In our case we do not have resetting oscillators, but nevertheless we can select a small portion of the slower oscillator and impose synchronization only in that small time interval. Numerical results confirm the existence of a suitable gain K for which the instantaneous synchronization succeeds. We are actually investigating on analytical conditions.

III. DESIGN OF THE MOTOR NEURAL NETWORKS

As introduced above, the low level networks are built up by a certain number of synchronization groups, each one characterized by a given frequency, coupled through intermittent laplacian connections. The weights associated to the interneural links, the biases and the gain parameters are selected to obtain the desired leg kinematic motion. Some of these parameters could be learned to obtain adaptive locomotion strategies, starting from the basic gait here studied. In the next subsections we describe firstly the real morphology of the fly and the expected kinematics of the limbs compatible with behavioral observation. Subsequently, the configuration of the whole low-level network performing the desired dynamics is discussed.

A. Mechanical model and Kinematics of the structure

The mechanical scheme controlled by the neural clusters in the bottom layer (Fig.1) is inspired by the biological structure of the fruit fly *Drosophila megalonaster*, depicted in Fig. 3. Differently from the work reported in [4] here the legs are fairly different one another, to perform different functions: targeting through the anterior legs, support through the median legs and forward thrust through the hind legs. All legs are connected to the body thorax, in the three thoracic sections. As also shown in Fig.3 and Table I, the key aspects of the design regard the morphology of each limb, i.e. the size of the coxa, femur and tibia leg sections, and the other characteristics like the angular position of the limbs with respect to the body, the orientation and movements of the joints and the maximum extension reachable for each joint. It can be drawn that to perform an efficient protraction, the front legs have to be oriented forwardly of about 27°; to help support and equilibrium of the structure the middle legs are maintained orthogonally to the central axis of the body and to facilitate the forward pushing the rear legs are oriented backwards.

Moreover, in the experimental observations schematically reported in Fig. 3 (a), the trajectories of the stance phase for the *Drosophila* have a direction roughly parallel to the body orientation and the trajectories of the three legs develop at different distances from the body axis: the limit cycles spanned by the tips of the front and hind legs are closer to the body, whereas that one of the middle leg is further outside. The accurate design of the kinematics of the legs allowed to obtain the regular oscillations for each leg reported in Fig. 3 (b) (c) and (d). The design was performed in Matlab. Each leg is made up of the *coxa* (the basal segment), the *femur* (the largest segment) and the *tibia* (the most distal segment). The sizes of the model elements are scaled on the real structure and are reported in table I for each thoracic segment.

The articulation of the leg is controlled by the three joints, connecting the body-coxa, coxa-femur and femur-tibia links. The coordination among the joints of the same leg is directly dependent on the structure of the limbs, with higher complexity for the fore and hind legs, these being more inclined towards the body reference than the median one.

Link	Front legs length	Middle legs length	Hind legs length
Coxa	0.1	0.1	0.1
Femur	0.3793	0.4167	0.4065
Tibia	0.46	0.6	0.67

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LENGTH (IN MM) OF THE THREE LEG SEGMENTS (COXA, FEMUR AND TIBIA) FOR THE DIFFERENT THORACIC SECTIONS.

Fig. 3 outlines the trajectories during the stance and the swing phases. For each limb, the stance phase, developing from the Anterior Extreme Position (AEP) to the Posterior Extreme Position (PEP), and the swing phase, from the PEP to the AEP, take both the 50% of the period of a complete cycle, recalling the basic locomotion cycle of the real insect.

From the kinematics of each leg, an accurate inverse kinematic analysis was performed to inspect the corresponding joint signals that will be used as control references. The results are reported in Fig. 4. Analyzing the trend of these signals, it is evident that different activation frequencies underlie the action of the joints.

In particular, starting from the simplest configuration in Fig. 4(b), the kinematics of the middle leg is characterized by the effect of a periodic signal driving the coxa joint and two other signals, the femur and the tibia one, the latter having double the coxa frequency. It is important to notice from 4 that coxa signal evolution identifies the stance phase during the rising edge and the swing phase during the falling edge, whereas the femur and tibia joints synchronize



Fig. 3. (a) Arrows approximate the trajectories of the limb tip during the stance phase in forward locomotion. The circles and the rectangles indicate, respectively, the AEP and the PEP and thus the start of the stance and swing phases. It can be noticed the different kinematic configuration required for the legs in the three thoracic segments. (b)-(d) Limit cycles obtained for the anterior (b), median (c) and hind (d) leg. The duty cycle between stance and swing phase is about 50% to guarantee a sufficient support phase also with fast gaits such as the alternating tripod.

the articulation of the couple femur-tibia during these semiperiods. The articulation of the femur joint, connecting the coxa and femur links, must be approximately constant during the stance phase to maintain a constant clearance, whereas it can have higher excursions during the swing phase to allow the median leg position to fly back towards the AEP. The tibia joint, connecting femur and tibia, instead, is activated by a sinusoidal function reaching the maximum value in correspondence of half period of both the stance and the swing phases. It consequently reaches the minimum value during the transition from the stance to the swing phase and vice versa. This signal has therefore twice the frequency of the coxa joint motion. The movement of the middle legs, connected to the L2 and R2 neurons of the top layer network, will be stimulated by the concurrent action of the coxa, femur and tibia joints. The desired kinematics of the front limbs is obtained by the joint control signals reported in Fig. 4(a). Similarly to the previous case, the harmonic movement of the coxa defines the duration of the stance and swing phase, but this configuration is more complex than the median one since in this case the legs are forwardly inclined. Femur and tibia control signals, in fact, are built in order to perform a wider extension of the limbs when moving between the AEP and the stance Middle Position (MP) than in the remaining path to the PEP. Let us focus at first on the desired trajectory during the stance phase. In the path from AEP to MP, the edge of the femur control signal falls to be closer to the body, whereas in the phase between MP and the PEP, the same signal must be approximately constant to maintain



Fig. 4. Input signals for the coxa, femur and tibia joints in the front (a), median (b) and hind (c) legs. The coxa signals are harmonic and isofrequential in the three legs whereas the femur and tibia signals are the result of the composition of signals at different frequencies. The gain on the amplitudes and the phase displacement among the joint signals depend on both the working space of each joint and the desired kinematic behaviour.

the trajectory parallel to the body. The signal activating the femur-tibia link, instead, grows during all stance phase but with different slopes. In particular, in the AEP-MP phase the signal grows faster than in the MP-PEP path. Observing now the swing phase, it can be noticed that in the PEP-MP path the femur and the tibia trends are similar, whereas in the MP-AEP path the extension of the two joints are complementary.

Similar considerations hold in the case of the middle leg inverse kinematics (Fig. 4(b)) where the presence of multiple frequencies can be clearly appreciated. Finally, the kinematics of the hind leg is determined by the signal joints reported in Fig. 4(c). As for the other legs, the coxa joint acts as the reference signal for the stance and the swing phase. The pushing role of the posterior legs leads to design the femur and tibia control signals isofrequential to the coxa joint. In fact, during the stance phase, from the AEP to the PEP, the femur articulation follows the trend of the coxa, whereas the tibia articulation is in opposite phase with respect to the coxa control signal. During the swing phase, instead, the femur continues to follow the coxa trend, though with different slopes.

B. Muscle Fibers Activation by Synaptic Activity

After these results the next step was to design a neural architecture able to generate the joint signals for each leg, leaving the coordination among the legs to the CPG network already designed. In order to obtain the kinematic behavior illustrated in the Fig.4, the following primitive functions PFs have been designed as control signals coming from

the neural networks associated to the front, middle and hind limbs:

$$\begin{cases}
PF_{A,C} = I_{A,C} + a_{A,C} \\
PF_{A,F} = I_{A,F} + (a1_{A,F} + a2_{A,F} + a3_{A,F} + a4_{A,F}) \\
PF_{A,T} = I_{A,T} + (a1_{A,T} + a2_{A,T}) \\
PF_{M,C} = I_{M,C} + a_{M,C} \\
PF_{M,F} = I_{M,F} + (a1_{M,F} + a2_{M,F}) \\
PF_{M,T} = I_{M,T} + (a_{M,T}) \\
PF_{P,C} = I_{H,C} + a_{H,C} \\
PF_{P,F} = I_{H,F} + (a1_{H,F} + a2_{H,F} + a3_{H,F} + a4_{H,F}) \\
PF_{P,T} = I_{H,T} + (a1_{H,T} + a2_{H,T})
\end{cases}$$
(7)

where

$$\begin{split} a_{A,C} &= K_{A,C} * X_{f,A} \\ a_{1A,F} &= (K_{1A,F} * X_{2f,A,\phi_2} + B_{1A,F}) * (H(-X_A)) * H(dX_A) \\ a_{2A,F} &= (K_{2A,F} * X_{2f,A,\phi_1} + B_{2A,F}) * H(X_A) * (H(-dX_A)) \\ a_{3A,F} &= (K_{3A,F} * H(X_A) * H(dX_A) \\ a_{4A,F} &= (K_{4A,F} * X_{2f,A,\phi_2} + B_{4A,F}) * (H(-X_A)) * (H(-dX_A)) \\ a_{1A,T} &= (K_{1A,T} * X_{2f,A,\phi_1} + B_{1A,T}) * (H(-X_A)) \\ a_{2A,T} &= (K_{2A,T} * X_{f,A} + B_{2A,T}) * H(X_A) \\ a_{M,C} &= K_{1M,C} * X_{f,M} \\ a_{1M,F} &= (K_{1M,F} * X_{2f,M,\phi_3} + B_{1M,F}) * H(dX_M) \\ a_{2M,F} &= (K_{2M,F} * X_{2f,M,\phi_4} + B_{2M,F}) * (H(-dX_M)) \\ a_{M,T} &= K_{1M,T} * X_{2f,M,\phi_5} + B_{1M,T} \\ a_{H,C} &= K_{H,C} * X_{f,H} \\ a_{1H,F} &= (K_{1H,F} * X_{f,H} + B_{1H,F}) * H(X_H) * H(dX_H) \\ a_{2H,F} &= (K_{2H,F} * X_{f,H} + B_{2H,F}) * (H(-dX_H)) \\ a_{3H,F} &= (K_{3H,F} * X_{f,H} + B_{3H,F}) * (H(-dX_H)) * H(X_H) \\ a_{4H,F} &= (K_{4H,F} * X_{f,H} + B_{1H,T}) * H(X_H) \\ a_{2H,T} &= (K_{2H,T} * X_{f,H} + B_{1H,T}) * H(X_H) \\ a_{2H,T} &= (K_{2H,T} * X_{f,H} + B_{1H,T}) * H(X_H) \\ a_{2H,T} &= (K_{2H,T} * X_{f,H} + B_{2H,T}) * (H(-X_H)) \\ \end{split}$$

where the subscripts A,M and H indicate, respectively, Anterior, Middle and Hind thoracic segment, the subscripts C, F and T refer to the Coxa, Femur and Tibia segments of each limb. X is the signal coming from the high-level network node corresponding to that limb. This is the reference signal, imposing the frequency at which the neurons belonging to the same synchronization group have to work. In the same way, each limb subnet is enslaved to a neuron in the CPG layer: this imposes the overall phase shift, thus preserving the locomotion pattern stability. H indicates the Heaviside function of the reference signals, such that if $X \ge 0$ then H(X) = 1, else H(X) = 0. The bias and gain values, identified by the K, A and B parameters, respectively, are weights related to the working space of the joints. The term d stands for the time derivative operator.

It has to be noticed that these purely mathematical signals can be simply produced as neuron outputs, following our approach with phase rotation matrices: for example the time derivative is a 90° phase shift, the Heaviside function is realised by a threshold interneuron, its complementary by another threshold interneuron phase shifted by 180° .

All these functions describe the cumulative effect of the interaction among the neurons of the low-level network with strong dependence with the temporal evolution of the reference nodes. In the low-level network, in fact, each subnetwork is synchronized with the reference node associated to a specific limb (as illustrated for R3 in Fig. 1) in order to maintain the imposed stable locomotion pattern. Two different frequencies coexist in the subnet. In particular, focusing upon the median limb, the neural network performing the primitive functions for each joint is constituted by two subnetworks: one with the same frequency as the higher layer CPG network and directly connected to it (grey filled neurons

in Fig.5), and another subnetwork having double frequency (orange neurons).



Fig. 5. Neural Network innervating the middle leg. Two subnets with different frequencies are instantaneously synchronized through a pulse laplacian connection with zero phase delay (dashed arrow). The other rotational matrices lock at given phases the connected neurons. The Primitive Functions (PF_M) represent the driving signals for the corresponding coxa (C), femur (F) and Tibia (T) joint, respectively.

C. Remarks and conclusions

To artificially reproduce the accurate kinematic motion of each leg, a large number of parameters were identified, each one controlling a specific portion of the resulting Primitive function. In view of adaptive and learning locomotion strategies, some of these parameters can remain constant, some others can be adjusted at the level of local reflex, some others can derive from specific brain areas, like the Central Complex for orientation and step length control [10]. Moreover, differently to [4], the control signals are not directly obtained from the state variables of the corresponding neurons: they are the result of the interaction of a set of neurons belonging to the neural groups that innervate a given muscle. Also $PF_{M,F}$ in Fig. 5 results as a combination of the sign of the X signal derivative, through the Heaviside function and its complementary. These two functions are mutually exclusive and govern the dynamics of the femur and tibia joints during protraction and retraction, respectively. So they remind the activation of the flexor and extensor antagonist muscles acting on the femur and tibia joint, as in the biological counterpart. The modulation of the associated parameters could therefore be took into account for a fine tuning of the leg dynamics. Therefore the network designed, in spite of its apparent complexity, can allow a high degree of adaptability: in fact the high level CPG is unaffected if one or more legs are temporarily disconnected, to face with low level sub tasks, like obstacle avoidance or searching for ground support: this is assured by the monodirectional connections. Moreover, the last subtask can be efficiently solved modulating some of the parameters of the primitive functions, like the offsets $(I_{M,C}, I_{M,F}, I_{M,T})$ or the other gains. Once solved the subtask, the leg can be restored to

the default cyclic behavior and connected to the high level CPG. So the CPG could be able to show the advantages of a decentralised locomotion control.

Very recently, light begun to be shed on the details of the architecture of the fly leg motorneurons [6]. The spatial organization of these neurons is highly correlated with muscle innervation, making a myotopic map, in which, among the others, it was discovered that motorneurons innervating antagonistic muscles group together in clusters of activity, reinforcing our implementation of the concurrent and mutually exclusive activation of motorneurons, alternatively controlling flexion and extension within the same cluster.

Summarizing, in this paper a CPG approach to locomotion pattern generation and control in a *Drosophila*-like hexapodal structure was implemented. The peculiarity of the design dealt with the highly unsymmetrical structure of the leg shapes and arrangement throughout the body. Each leg was kinematically modelled, a neural controller was designed which revealed similarities with very recent neurobiological findings in the fly motor neuron organization. Another peculiarity consisted the presence of different frequencies in oscillators used for joint control. The stability of the locomotion pattern generator is theoretically guaranteed through the partial contraction theory. A control strategy using an intermittent Laplacian connection between neurons is adopted for the synchronization of neurons with different frequencies.

ACKNOWLEDGEMENT

Work supported by EU Project EMICAB (N 270182).

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