# Modelling stepping strategies for steering in Insects

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**Abstract.** In this paper a minimal control strategy for the reproduction of steering strategies in insects is reported. The strategy is a further development of a control methodology for locomotion control based on the Central Pattern Generator and accompanied with rigorous stability analyses obtained exploiting the Partial Contraction Analysis method. The mathematical model was derived extending the CPG network already introduced by the authors with an additional degree of freedom in each leg of a simulated legged robot, augmenting the leg steering possibilities for better mimicking Neurobiological findings. The control methodology aims at implementing the steering strategy using, at the same time, a minimal number of control variables, which are related to the phase displacements among the oscillators of the femur and tibia of the robot legs. Experimental results carried out in a dynamic simulation environment are also reported.

**Keywords.** *Biorobotics, Central pattern Generator, dynamic simulations.*

## Introduction

The ability to move can be considered as one of the most important characteristics of animal life. Each motor behavior is characterized by its peculiar motor pattern, i.e. the sequence and degree of activation of specific muscles ensembles. One of the paradigms for the generation and control of locomotion in animals is the Central Pattern Generator (CPG), a neuronal network that can generate basic motion patterns even in the absence of sensory feedback. So, although sensory feedback is very important for shaping locomotion to the environment, the basic motion patterns are generated in an open loop manner: this gives the opportunity to the animal to efficiently move without caring about external signals, and this strategy is in many cases life saving, for example during the escape reactions. In the literature, the CPG paradigm was implemented in different ways. The authors have been involved in CPG design and implementation since many years, introducing new paradigms which exploited the parallel computational capabilities of nonlinear, locally connected, programmable analog circuits called Cellular Nonlinear networks (CNNs). The authors were involved in all the stages of the research: from the circuit design to the simulation, to the implementation in an analog VLSI programmable chip for locomotion control in multilegged structures [1]. Very recently the attention was focused toward the study of analytical results that could guarantee the stability of the obtained locomotion pattern under the form of phase stability schemes. Under particular network configurations it was recently demonstrated that, for any arbitrarily imposed locomotion gait, fixed through specific phase displacements among the leg actuators, sufficient conditions can be derived to guarantee the global exponential convergence to the flow invariant subspace of the state trajectories leading to the imposed phase [2].
In this paper the strategy is extended to consider the problem of the steering stepping

patterns in insects, that are necessary to implement efficient control strategies for trajectory planning in legged robots. The problem was faced with particular attention to two main issues: the first was to retain the stability conditions already gained for the feedforward locomotion patterns, and the second was to try to generate efficient steering strategies using a minimal number of control parameters.

## 1. Insect locomotion and steering

Many  traditional studies on curve walking in insects agree that there are two main strategies for negotiating a curve: by changing either step frequency or step length. This view is based on the assumption that the movements of each leg are caused by a protraction–retraction oscillator with adjustable frequency and amplitude. Cockroaches for example typically adopt the strategy of fast movements. During tripod running, they control orientation by adjusting the frequency of depressor and extensor motor neuron activity to control the relative force output on opposite sides of the body [3].

The stick insect possess a rather different behaviour: here changes of leg movements during curve walking can be related to the curvature of the walked path. Trajectories are largely parallel to the body axis during straight walking but of different length and orientation during curve walking. A behavioral model simulation of the stick insect walking system implemented turning tendency by a course control module that reduced/increased retraction amplitude in legs at the inner/outer side of the curvature [4]. Curve walking performance of this controller was quantified for different path curvatures and walking speeds [5]. In the fruit fly Drosophila melanogaster  as in straight walking, variation during turning is achieved by concomitant changes in step length and stepping frequency; turning is achieved exclusively by diminishing the step lengths on the inner side, whereas the number of steps per leg on the inner and the outer body side are identical. On the other side, the orientation of the body relative to the direction of progression is astonishingly variable [6]. Steering control based on frequency was already implemented in CPG based networks, but only numerical results were reported, since up to now no analytical conditions on the stability of gait during steering were demonstrated with this method [7]. So in this paper the approach related to the step length and orientation control for the different legs of the robot will be adopted, since in this way the stability conditions on the imposed phase are maintained, and also, as outlined below, a minimal number of control parameters can be used.

## 2. The neural Network for steering control

The CNN designed consisted in a topology matching the topographical distribution of the legs along the insect body. The CPG architecture imposes basic oscillation dynamics, and locomotion patterns (i.e. slow, medium and fast gait and their transitions in between) and turning are governed by synaptic activity. Diffusive couplings can be easily represented as CNN cloning templates.

In order to allow the suitable dexterity of the leg for an efficient steering strategy, each leg joint is controlled by one state variable (representing the membrane potential) of one specific neuron, having the following second-order dynamics:

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

with $y_i = \tanh(x_i)$.

The following parameters $\mu = 0.5$, $\varepsilon = 0$, $s_1 = s_2 = s = 1$, $i_1 = 0$, $i_2 = 0$, allow each cell to oscillate with a stable *limit cycle* [8].

The action of a given cell $i$ on the adjacent neurons $j$ is implemented through diffusive coupling terms, which, as in [9], are represented by rotational matrices $R_{ij} \in R^{2\times2}$. Moreover, $R_{ij} = R_{ji}^T$ in order to have a balanced and undirected network. The dynamical network is built up connecting $n_n$ identical cells in the following way:

$$\dot{x}_i = f(x_i) + k \sum_{j \neq i; j \in N_n} (R_{ij}x_j - x_i) \qquad i, j = 1,...,n_n \tag{2}$$

where $f(x_i, t)$ represents the intrinsic dynamic of the i-th uncoupled oscillator, $k$ is a parameter determining the "strength" of the connections and the sum of terms is given by the *diffusive* couplings between the i-th and j-th node and is extended only to nearest neighbors.

## 2.1. Sufficient conditions exponential convergence to walking and steering gaits

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 $(x_1, \cdots, x_{2n_n})^T$ (2 is the order of the single cell), $f(x) = [f(x_1), \cdots, f(x_{2n_n})]^T$, and L is the coupling matrix built up of $L_{ij}$ blocks $L_{ij} = \in R^{2\times2}$, 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;

2) $L_{ji} = -R(-\phi_{ji})$ if $L_{ij} = -R(\phi_{ij})$ to satisfy the phase periodicity conditions between nodes i and j;

3) $L_{ij} = L_{ji} = 0$ if no direct connection joins the i and j nodes;

4) $L_{ii} = d_i \cdot I_2 \quad \forall i = 1..n_n$, 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*. Extending the results reported in [9], in case of an undirected diffusive tree graph, like our case, sufficient conditions were found in order to guarantee global exponential convergence to any desired locomotion pattern (i.e. to any desired phase shift among the oscillators in the network), given the graph algebraic connectivity $\lambda_1$ and the maximum value of the largest eigenvalue of the Jacobian matrix of the unconnected cell, according to the following relation [2]:

$$k \cdot \lambda_1(V^T L V) > \sup_{x_i, t} \lambda_{\max}\left(\frac{\partial f}{\partial x}(x_i, t)\right) \tag{4}$$

where V is the orthogonal projection of the flow invariant subspace $M$ [2]. This relation describes how much the coupling forces need to be sufficiently "strong" in order to dominate the local dynamics of the uncoupled system and thus perform the desired phase-locked synchronization. This relation provides the minimum value for the k gain in order to assure the synchronization for any imposed phase shift, defined through $M$ and then through L. Please notice that both $\lambda_1$ and $\sup_{x_i,t} \lambda_{max}\left(\frac{\partial f}{\partial x}(x_i,t)\right)$ are a priori known, and therefore $k_{min}$ can thus be fixed consequently. Any desired locomotion pattern can be imposed, starting from one and then switching to the other.

We remark that the tree topology is essential, since this is one of the basic conditions to allow arbitrarily changing locomotion patterns while maintaining the stability conditions guaranteed by the Contraction Theory. In this paper we extend these results to deal also with steering patterns, since, as outlined below, arbitrary steering trajectories for each leg can be obtained modulating the phases in a neural network mimicking the insect topology and with a neuron number suitable to allow the degree of dexterity requested by the legs. Arbitrary turning trajectories in the walking robot can be obtained with a suitable phase control retaining the stability conditions on the overall neural structure.


## 3. Simulation Results

The overall motion structure proposed is shown in Fig.1. In Fig.1a the topological arrangement of the neural network is shown. It basically consists of a central neuron chain (the network backbone), and six different side chains, corresponding to the different legs. Each of these is made-up of three neurons, each one actuating the coxa, femur and tibia joint. respectively. In our approach the central part of the network (including the backbone, the coxa neurons and their synapses in Fig.1a) is used to fix the gait (slow, medium or fast) in terms of phase shifts in the stepping diagram, whereas the side layer (including the femur and tibia neurons for each leg) is associated to steering. In our minimal approach to steering, it will be shown that only by modulating the femur-tibia synaptic connections we are able to reproduce an efficient steering. The control will act in a complementary way between the opposite legs.

The steering control acting on the weight adaptation (i.e. phase displacements) among Femur and Tibia neurons was experimentally proved by using two different simulation environments. Firstly, the kinematic behavior of the insect legs has been designed using the Matlab Robotic Toolbox. Then the assessment of the steering control was performed in a dynamic simulation environment. The kinematic behavior resulted in a regular limit cycle described by the legs in the operative space (Fig.1b), in front of the stable limit cycle described by the dynamics of the neurons. Fig.1b shows the structure implemented and inspired by the insect leg (Fig.1a-insert), in particular taking into account the real dimensions of the fruit fly Drosophila melanogaster. Legs have been modeled considering the following three segments: the *coxa*, the basal segment of the leg, connected to the thorax; the *femur*, usually the largest segment; the *tibia*, the most distal segment of the leg.

The fore, mid and hind legs are identical, have the same orientation with respect to the body, and they are organized symmetrically to their contra lateral ones. Then we can focus on the kinematic of the right middle leg, indicated with R2.

As shown in Fig.1b the articulation of the leg is determined by the parameters of the links and by the Q1, Q2, Q3 joint variables connecting respectively the body-coxa, coxa-femur and femur-tibia links. The Qi are the first variables of the corresponding neurons actuating the joints. The leg is configured as serial-link having three joints with one rotational DOF each.
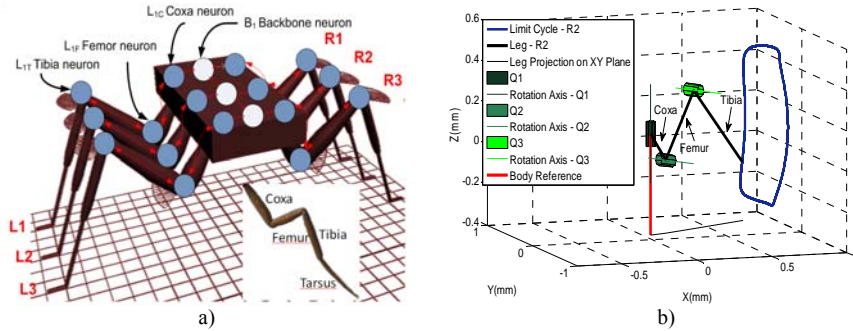


Fig 1: a) the neural network topology and the insect model structure; insert: insect leg structure; b) Structure of the leg in the kinematic model. The three segments coxa, femur and tibia are connected by the Q1,Q2,Q3 joint variables directly driven by the corresponding neurons depicted in a). Coxa length: 0.8mm, Femur length: 0.42mm; Tibia length: 0.8 mm. These dimensions were scaled on the Fly leg.

### 3.1. Steering control

Referring to Fig.1a, the nodes in the side chains of the network are associated to the joints connecting the leg segments. Thanks to the theoretical results demonstrated, any imposed phase displacement among the neurons is stable. Suitable phase displacements among the backbone and the coxa neurons (Fig1a) can be imposed so as to generate any desired locomotion pattern. Let us start from the slow forward gait configuration, characterized by the phase parameters reported in the second row of Table 1. In Fig.2a) the trajectory of the stance (protraction) phase in the XY-plane is depicted in solid line. The combination of the protraction and extension movements exhibits the regular limit cycle, as in Fig.1b, parallel to the orthogonal axis of the body (z-axis). Note that during the straight walking, the specific gait is fully determined by the central part of the network. In fact, Coxa-Femur and Femur-Tibia phases ($\Delta\phi_{C,F}$ and $\Delta\phi_{F,T}$ )are constant and equal on both sides, right and left, and then they do not influence the locomotion pattern as shown in the stepping diagram of Fig. 4a, derived when slow gait is imposed.

If a steering control is requested, the set of phase displacements as reported in Table 1 (second row) can be retained, with the addition of particular phase rotations only on the connections Femur-Tibia ($\Delta\phi_{F,T}$), as reported in the third row of Table 1. These rotations are related to the desired degree of steering in our structure. In particular, it is sufficient to act in complementary way between the inner and outer side of the steering direction: the approach makes use of only one control parameter: $\Delta\phi_{F,T}=\phi_{steering}$. Fig.2b) shows the relation between the phase displacement imposed on ($\Delta\phi_{F,T}$) and the radius of the curved trajectory made by the robot in the XY-plane. In

Fig.2a the XY-trajectory during stance phase, when $\phi_{steering} = 60°$ is applied on the left side and $\phi_{steering} = -60°$ is applied to the contralateral side is reported, in dotted line.

**Table** 1. *Phase Shift among joints during forward slow walking and left steering*

| | $\Delta\phi_{B1,L1C}$ | $\Delta\phi_{B2,R2C}$ | $\Delta\phi_{B3,L3C}$ | $\Delta\phi_{B1,R1C}$ | $\Delta\phi_{B2,L2C}$ | $\Delta\phi_{B3,R3C}$ | $\Delta\phi_{C,F}$ | Left $\Delta\phi_{F,T}$ | Right $\Delta\phi_{F,T}$ |
|---|---|---|---|---|---|---|---|---|---|
| Forward Slow Gait | 0° | 60° | 120° | 180° | 240° | 360° | 90° | 0° | 0° |
| Steering Left Gait | 0° | 60° | 120° | 180° | 240° | 360° | 90° | $+\phi_{steering}$ | $-\phi_{steering}$ |



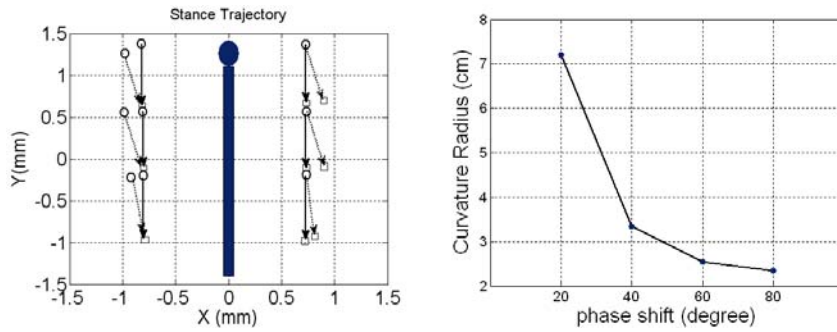Fig 2. a) Stance Phase Trajectory of the legs during forward slow gait (solid line) and during left turning (left side φ$_{FT}$= 60°; right side φ$_{FT}$= -60°); b): XY curvature radius for different value of φ$_{FT}$.

Fig.3c)-3f) show how large can be the effect in the orientation of the stance phase for a given leg, as a function of $\phi_{steering}$ and of $\Delta\phi_{C,F}$. By selecting different values for each of these two parameters for each leg we can accurately control the orientation and the step length for each leg of the robot, making it similar to any desired trajectory experimentally found in insects, considering the reduced number of DoF used. However, as outlined above, our main aim is to start from the biological observation, retaining the issue of phase stability and also applying a minimal control strategy. According to this, an efficient steering control can be obtained, as in Fig.2a) using only one parameter ($\Delta\phi_{F,T}$), equal for all the legs belonging to one side of the robot.

Finally, observe that the gait (Fig.4b) is subjected to the effect of the robot steering, since additional opposite shift phases are imposed on the two sides through $\Delta\phi_{F,T}$: the new gait is fairly similar to the caterpillar gait. However, this impact on the stepping diagram can be evaluated, and compensated for, a priori because directly determined by the chosen rotational matrices which define the imposed gait. Then, selecting the $\Delta\phi$ values exhibiting a steering effect while maintaining the original gait can be easily implemented by subtracting the imposed $\Delta\phi_{F,T}$ from the connection between the Backbone and the Coxa joint in the same leg: the results is equal to Fig.4a. This in fact corresponds to impose a new flow invariant subspace which is still a stability subspace, thanks to the invariant properties of the Laplacian operator on the considered tree graph and the sufficient conditions proven.
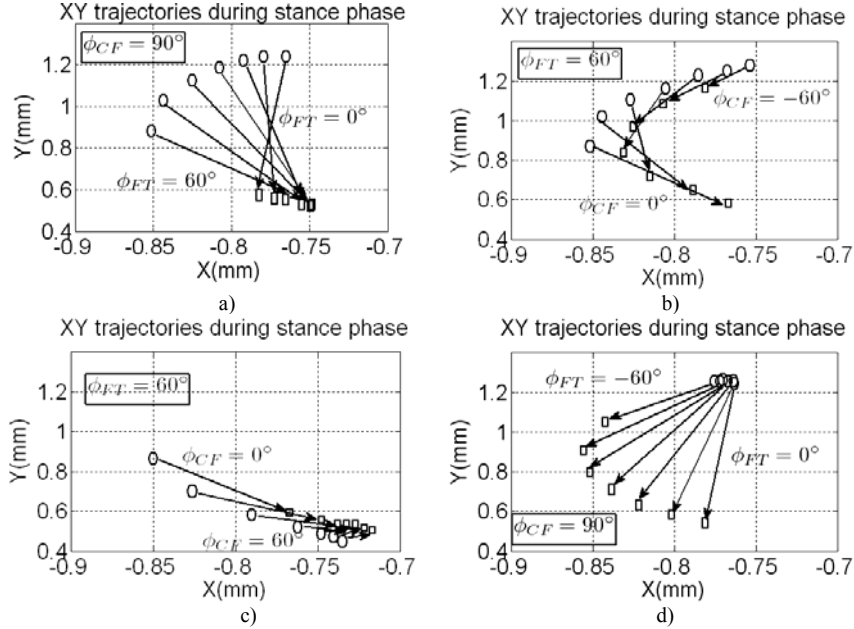
Fig 3: a) step length and amplitude modulation for the leg $L_1$ as a function of $\varphi_{FT}$ [0:60°], maintaining $\varphi_{CF}$ =90°; b) step length and amplitude modulation for the leg $L_1$ as a function of $\varphi_{CF}$ =90°+[0°:-60°], maintaining $\varphi_{FT}$= 60°; c) step length and amplitude modulation for the leg $L_1$ as a function of $\varphi_{CF}$ =90°+ [0: 60°], maintaining $\varphi_{FT}$ 60°; d) step length and amplitude modulation for the leg $L_1$ as a function of $\varphi_{FT}$ =[0: -60°], maintaining $\varphi_{CF}$= 90°. All variations are reported at steps of 10°.

The experimental results have been tested in a dynamic simulation environment to prove their validity. The simulated robot legs were built with strictly resembling approximation the real anatomy of Drosophila leg, and Open Dynamic Engine libraries [10] were used to simulate motion in an environment whereas contact and friction forces act on the robot.
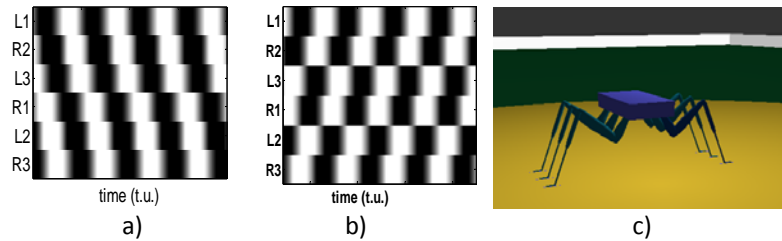


Fig 4. a):Stepping diagram when the forward slow gait is imposed; b): Stepping steering diagram when slow gait with ($\varphi_{FT} = 60°$) is applied. c) robot in the ODE dynamic simulator environment.

In Fig.5a, the XY-trajectories of the simulated robot are plotted when a steering control towards left ($\varphi_{steering} = 60°$ on the left-side legs, the opposite on the right) is firstly applied and then toward right ($\varphi_{steering} = -60°$ on the left, the opposite on the right). The black solid line indicates the trajectory of the body while the blue and red line show the stance phase, respectively, of the $L_1$ and $R_1$ leg. The length of the protraction (stance) phase is shorter in the inner side of the curvature than the outer one, as also results by Neurobiological evidence. The curvature of the trajectories is strictly dependent on the phase shifts imposed during the steering control. In Fig.5b, the temporal positions of

the body for different values of $\phi_{steering}$ are reported. Videos on these results are available in [11].
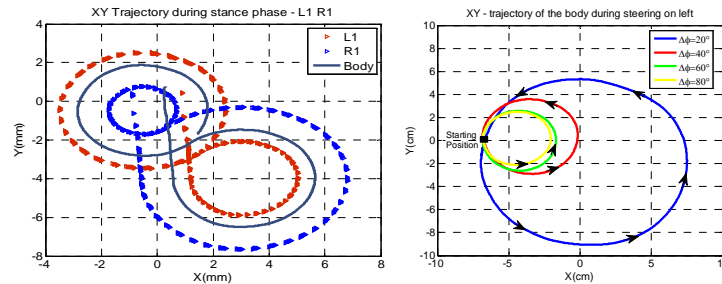


Fig 5. a): Trajectory on the XY plane when a steering on left and then on right is performed; b): body position in the XY plane for different value of $\phi_{steering}$

## Conclusion

In this paper a steering control strategy for hexapod robots is implemented. In particular, using a 3DoF leg structure, it has been experimentally shown that, modulating the synaptic values among the neurons controlling the leg joints, a wide variety of leg orientations and step lengths can be achieved. At the aim to use a minimal number of control parameters, is was demonstrated that modulating only the Femur-Tibia neuron connections for the left and right legs, an efficient steering control can be obtained. The whole procedure is supported by a rigorous stability result which gives sufficient conditions on the stability of arbitrary phases imposed on the neural structure.

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