

# Minimal decentralized control in a *Drosophila*-inspired walking robot

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**Abstract**—In bio-inspired robotics, rhythmic coordination of limbs can be obtained either by using Central Pattern Generators (CPGs) without the involvement of sensory signals, or with a massive feedback that, mainly through proprioceptive sensors, allows the emergence of walking gaits. The aim of this paper is to propose a minimal approach to develop a decentralized locomotion controller for a *Drosophila*-inspired simulated robot, based on spiking neurons, with the addition of an attitude controller to improve locomotion stability. Walking gaits can be successively learned to create a CPG that can be used in absence of external stimuli or in order to build an internal locomotor estimator.

## I. INTRODUCTION

In literature the problem of locomotion control in multi-legged structures, inspired by insects, follows two distinct approaches: a centralized control able to generate in feed-forward the joint signals needed to obtain a coordinated locomotion gait [1], [2] and a decentralized solution that relies on proprioceptive sensors to adapt the joint movements for a stable walking [3], [4], [5]. A comparison between the main elements of the two approaches is synthesized in Table I. Several intermediate solutions can be adopted between these two extreme cases: for instance the inclusion of high level sensors in a CPG to adapt the walking gaits to the environment [6] or the inhibition of the sensory-driven control when the robot speed is high (e.g. escaping reactions). Our aim is to develop a minimal decentralized controller inspired by the Walknet control scheme [7], able to generate the joint position signals for a stable walking in a 18 DoF hexapod robot inspired by the *Drosophila melanogaster*. The control system is therefore distributed among the legs and was developed using a spiking neural network based on an agonist-antagonist structure: each joint is controlled by two neurons that modulate the clockwise and anticlockwise movement (e.g. Elevator/Flexor). We included a limited number of sensors, in particular stretch sensors and ground contact sensors, that guide each neuron activity. A relevant aspect consists in considering the interaction between the network and the input signals (i.e. sensors) based on events. When an event occurs, it determines a change in the network dynamics (e.g. modifying the input current in some neurons) and gives rise to a certain locomotion phase. In this way the network dynamics is subject to specific sensor signals only for a limited time window, reducing the data acquisition and processing to generate a stable walking gait. The neural controller was designed considering a simulated, but realistic

TABLE I  
COMPARISON BETWEEN CENTRALIZED AND DECENTRALIZED APPROACHES.

Characteristics	Centralized	Decentralized
Central Oscillators	✓	x
Flexible	x	✓
Sensory feedback	x	✓
Escape reactions	✓	x
Predictions	✓	x
Independent control of legs	x	✓

biomimetic model of the *Drosophila melanogaster*, characterised by a highly asymmetric leg structure as shown in Fig. 1. The simulations were performed in a dynamic environment where all the relevant data were acquired and processed to evaluate the performance of the proposed locomotion control strategy. The Izhikevich's spiking neuron, for its very low-cost computational burden, was recently employed as a basic block to model high level capabilities of the insect brain [8], like motor-skill learning [9] and sequence learning [10], [11]. This paper extends the range of applications of the Izhikevich's neural model [12] also to the decentralised locomotion control, addressing from reflex based locomotion to perceptual behaviors as demonstrated in other works using spatio-temporal patterns of activity [13], [14].

## II. DYNAMICAL STRUCTURE AND NEURAL MODEL

The dynamic simulation environment taken into account is the V-REP from Coppelia Robotics [15]. This environment can be easily interfaced with other programming tools using the available API. In our case the neural controller was designed in Matlab to allow a fast development facilitating the data post-processing. The use of a dynamic simulator allowed to design, based on the insect leg motion, a stereotyped periodic trajectory for the tip of each leg to be used as a reference motion signal for the robot legs. In this way, the time evolution of the angular position of the leg joints (see Fig. 1) was obtained through an inverse kinematics approach. The realization of a minimal spiking neural network controller was then performed, based on mechanosensory feedback, with the aim to emulate the behaviour of motor neurons characterised by a non-endogenous periodic dynamics. The periodic motion should emerge from the interplay among the spiking activity and the sensor triggering, enabling the

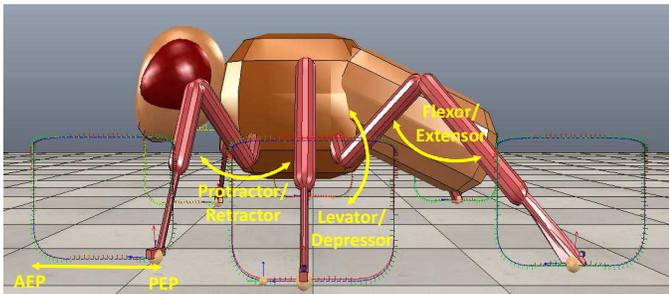


Fig. 1. Fly-inspired dynamical model developed in V-REP. The reference trajectory for each leg is outlined together with the main phases of the leg motion: protraction/retraction (via the thoraco-coxa joint), levation/depression (via the coxa-trochanter joint), and flexion/extension (using the femur-tibia joint). AEP (PEP) indicates the Anterior (Posterior) Extreme Position.

generation of a walking gait which can be adapted to different situations identified by the sensors. We considered, as network inputs, a series of proprioceptive and exteroceptive sensors, namely the stretch of the leg muscle and the ground contact (GC) on each leg tip. The whole spiking network used to model the locomotion controller is based on the Izhikevich's spiking neuron, proposed in [12]. This model offers many advantages from the computational point of view. Due to its simplicity, several circuits implementation, including VLSI, were recently proposed. The adopted parameters elicit the behaviour of a Class 2 neuron which, for a given input current shows a constant spiking frequency after a very short transient. Coordination among all leg joints is necessary for a proper walking. It is known that in stick insects, at least at low speed, there is no central coupling between the activities of motorneurons controlling different leg joints. For a proper walking control system, two key aspects should be considered: the control of movement of individual legs and the spatio-temporal coordination among different legs. Insect leg motion, apart from the particular leg kinematics peculiar for each species, consists in a series of basic motions, outlined in Fig. 1, whose suitable combination guides the leg through either the stance phase (where the leg supports the body weight) or the swing phase (with the leg lifted off the ground). A decentralised approach requires a proper chaining among these phases, triggered by sensory stimuli. Mechanosensors found in insect legs can functionally be separated into position sensors and load sensors. Position sensors monitor joint angle position and eventually speed. The main receptors that detect forces in insect legs are the *campaniform sensillas* that monitor forces as strains in the exoskeleton [5]. To obtain the desired synchronization between the three leg signals, based on the reference motion trajectories, we designed three networks, one for each joint, consisting of two antagonistic neurons. The inputs to the networks, analogously to the biological case discussed in [16] for the stick insect, are only the stretching sensors of coxa and tibia, and the GC. Their role, in our implementation, is to trigger a given event, modulating the injected neural current, in order to onset locomotion in relation to the feedback from the environment.

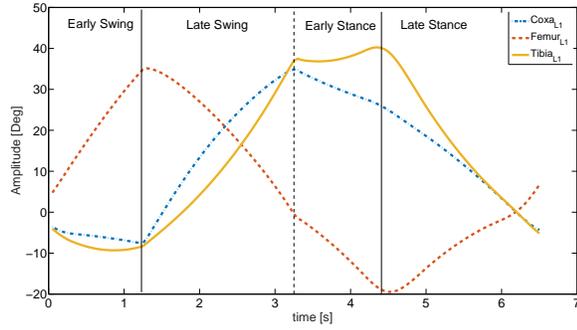
TABLE II  
STRETCHING SENSORS OF ANTERIOR LEG

Stretching sensors	Joint	Value [deg]	Involved motorneurons
$S_1$	Coxa	$\geq 35$	Retractor
$S_{1,1}$	Coxa	$\approx 25$	Retractor, Levator, Flexor
$S_{1,2}$	Coxa	$\approx -3$	Retractor
$S_2$	Coxa	$\leq -7$	Protractor, Depressor, Extensor, Flexor
$S_3$	Tibia	$\geq 35$	Extensor
$S_4$	Tibia	$\leq -9$	Extensor, Flexor

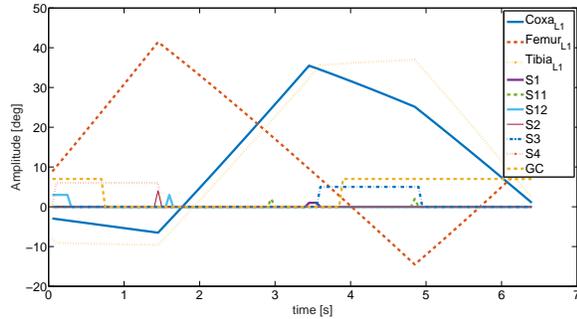
The biological walking model of the stick insect [7], was simplified considering less stretching sensors for the different joints and including GC sensors instead of load sensors. This is also convenient in order to avoid oscillations in the load signals caused by the natural undulations appearing in the legged robot attitude while walking. All the three joint signals are referred to the stretching sensors monitoring the coxa joint that is considered as a driver.

In table II, the sensors (reported only for the anterior leg) are used as inputs for the motor neurons involved during a stepping cycle. It can be noticed that we are using only position sensors related to the coxa joint to guide the motorneurons of each leg. This minimal solution further simplifies the design process of the network and is also supported by target trajectories acquired in the simulation environment. Finally, the outputs of the neural network are the incremental angular positions of the coxa, femur and tibia joints, generated through the integration of the neuron spiking rate normalized with a constant  $K$  set in order to have the desired angular variation per second.

The time evolution of the joint position of one anterior leg, obtained using the inverse kinematics, is shown in Fig. 2 (a). The stepping cycle can be sub-divided into four phases: early and late stance and early and late swing, as results from the change in the coxa joint signal slope (Fig. 2 (a)). To reproduce this behaviour a network of motorneurons was designed: for each leg there are six motorneurons that are either excited (+) or inhibited (-) by the sensory inputs. The interactions with the sensors during the four phases of the stepping cycle for the anterior leg are reported in Fig. 3. In Fig. 3 (a) and (b) the two parts of the swing phase are indicated. The sensor  $S_{1,2}$  triggers the start of the early swing phase: the coxal retractor motorneuron is excited with a reduced current that produces a slow starting of coxa retraction. The femur, in this phase, is still in rising phase being activated in the previous late stance phase (Fig. 3 (d)). Moreover, during this phase, the two antagonist tibial motorneurons (flexor/extensor) are spiking, triggered by the stretching sensor  $S_4$  (see Fig. 3). This freezes the tibia joint, approximating the inverse kinematic signal. Subsequently, in the Late swing phase,  $S_2$  the coxal stretching sensor, acts on the protractor coxal motorneuron, on the femural depressor and on the tibia joint. In details,  $S_2$  becomes active when coxa reaches its minimum angular value ( $\approx -7^\circ$ ), hence, the coxal protractor motorneuron starts



(a)



(b)

Fig. 2. (a) Swing and stance phases of anterior leg (L1) acquired through the inverse kinematics approach applied to the simulated robot. (b) Stepping cycle of an anterior leg obtained using the neural controller. The sensor activities that generate the state transitions are also reported.

to fire and the retractor motorneuron is inhibited, allowing coxa to move forward. Furthermore,  $S_2$  triggers the action of femur depressor motorneuron, and contemporarily inhibits the flexor motorneuron and excites its antagonist, allowing the tibial extension. Fig. 3 (c) and (d) are related to the stance phase. Initially, sensor  $S_1$  triggers the start of stance, causing the excitation of the retractor. Simultaneously,  $S_3$  produces the activation of both tibial motorneurons, to approximate the plateau region indicated by the inverse kinematics. During early stance, femur depressor continues to be active, since this action was triggered in the previous state. The leg in this phase reaches its Anterior Extreme Position (AEP), causing the triggering of the GC. In the last state, the GC, together with sensor  $S_{1,1}$  increases the current of the coxal retractor motorneuron, which is still in the firing state, enhancing its spiking rate. Contemporarily, they excite the femoral levator, inhibit the tibial extensor and excite the flexor, allowing the tibial flexion. For the other legs a similar procedure was adopted. The dynamics produced by the network is reported in Fig. 2 (b) to be compared with Fig. 2 (a). It can be noticed that the time evolutions of all the joints fairly approximate the target signals, taking also into account the simplifications caused by the minimal amount of slope changes triggered by the leg sensors. Moreover the sharp changes in position will be filtered by the actuators improving the matching with the

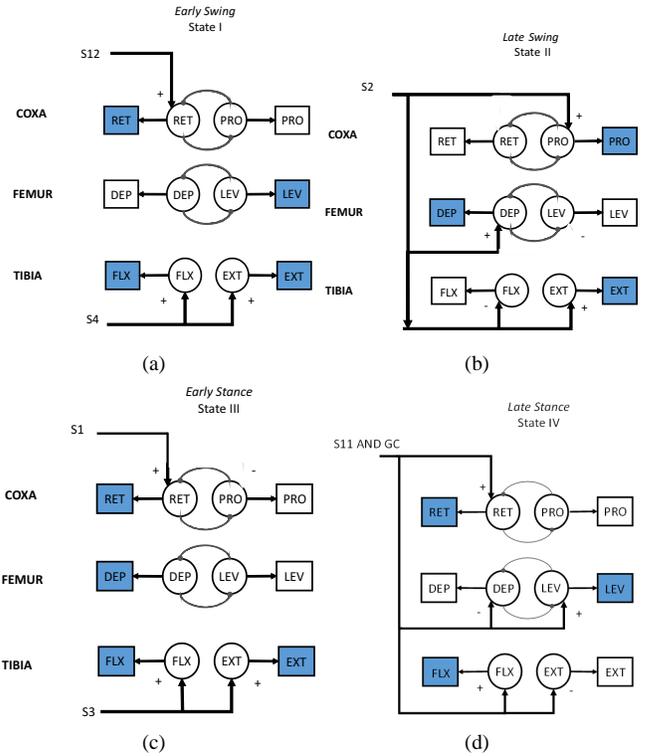


Fig. 3. Active stimuli for the Anterior leg Network at the beginning of the swing phase (a) and at the end (b). The Signals triggering the early (c) and late (d) stance phase are also reported.

targets.

### III. COORDINATION RULES AND ATTITUDE CONTROL

Basic leg motions need to be coordinated to generate and maintain the robot walking stability. Therefore in addition to sensory information, we need to implement a minimal number of coordination rules: each leg has to receive information about the state of its ipsilateral and contralateral neighbouring legs. We found that two inhibitory coordination rules, one for the leg in swing condition and the other for the stance condition can be adopted: when a leg arrives at the posterior extreme position (PEP), i.e. before starting the swing phase, if its ipsilateral or contralateral neighbours have not yet reached the AEP, i.e. they are not in stance, its swing phase is temporarily inhibited. Similarly, if a leg arrives to the AEP, if its ipsilateral and contralateral neighbours have not yet reached the PEP, it will have to wait before starting the stance phase. This last rule prevents more than three legs to be in stance phase, encouraging a steady state alternating tripod. Relaxing this rule, a number of different gaits are possible. The stepping diagrams acquired from the GC sensors reported in Fig. 4, demonstrate how, even if the legs start from a tripod gait configuration, the absence of coordination rules (in Fig. 4 (a)) produces a phase shift (due to environmental disturbances) that can affect the robot stability. Instead, the afore mentioned coordination rules allow a maintenance of a stable walking gait (see Fig. 4 (b)). Due to the system asymmetries in the

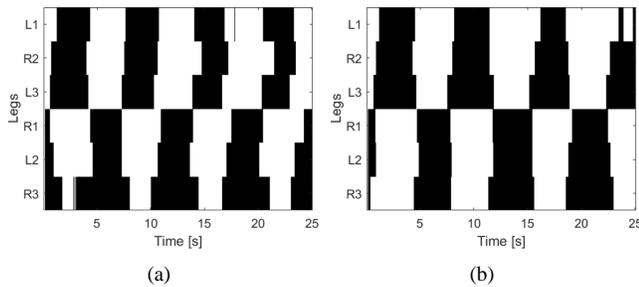


Fig. 4. Stepping diagrams starting from an alternating tripod initial conditions when the coordination rules are turned off (a) or applied (b). The stance phase is shown in white whereas the swing phase in black.

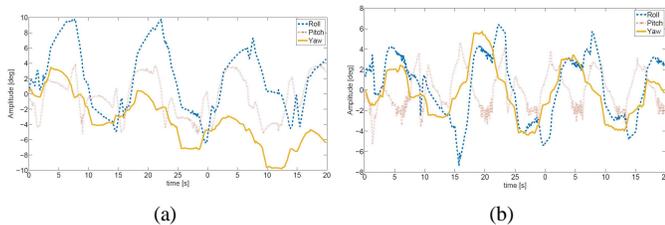


Fig. 5. Time evolution of the roll, pitch and yaw angle when the robot moves forward without (a) and with (b) an attitude controller.

leg design as well as to the approximation of the inverse kinematics, the interaction with the environment during walking produces oscillations of the robot body as reported in Fig. 5 (a) in terms of roll, pitch and yaw. To reduce this problem, we included an attitude controller that, acting on the femur leg joint, reduces the pitch and roll oscillation during walking. The controller introduces a Proportional Integral action on the the robot absolute position, modifying the offset of the femur joint of the front and hind legs to control the pitch angle and the offset of the femur joint in the left and right side of the robot to control the roll angle. Since the target is to maintain the posture during walking, the controller is active when the roll and pitch error exceed a given threshold (see Fig. 5 (b)). Starting from the decentralized approach, a CPG controller can be developed through a simple learning of the activation delays among the neurons in each leg. In this way sensory information can be ignored maintaining the learned stable coordination. This mechanisms is useful both to further simplify the control mechanism and to evaluate if the environmental conditions are changing. If, for instance, the robot encounters a different terrain, the predicted sensory signals and the real ones have a discrepancy. When this type of change is detected the decentralized controller can take the lead again to adapt the robot locomotion to the new external condition waiting for a new steady state condition to be learned again.

#### IV. CONCLUSION

The minimal decentralized control network here proposed is constituted by three pairs of spiking neurons for each leg and it is able to generate the needed oscillatory motion integrating

the local sensory information. To coordinate the phase relations among legs, simple coordination rules were developed guaranteeing the robot stability during the stance/swing transition of the different legs. Moreover, due to the asymmetric design of the legs, inspired by the *Drosophila melanogaster*, robot posture needs to be controlled to improve the stability of the locomotion gait. Centralized and decentralized approaches to locomotion have to be seen as complementary, therefore we tried to develop a minimal decentralized control scheme that can be reduced to a simple CPG creating virtual sensors that reproduce the timing of the real ones.

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