Locomotion Control of a Biped Robot through a Feedback CPG Network

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Abstract. This paper proposes a locomotion control system for biped robots by using a network of Central Pattern Generators (CPGs) implemented with Matsuoka's oscillators. The proposed control system is able to control the system behaviour with a few parameters by using simple rhythmical signals. A network topology is proposed in order to control the generation of trajectories for a biped robot in the joint-space both in the sagittal and coronal planes. The feedback signals are directly fed into the network for controlling the robot's posture and resetting the phase of the locomotion pattern in order to prevent the robot from falling down whenever a risk situation arises. A Genetic Algorithm is used to find optimal parameters for the system in open-loop. The system behaviour in closed-loop has been studied and analysed through extensive simulations. Finally, a real NAO humanoid robot has been used in order to validate the proposed control scheme.

Keywords: Biped locomotion, CPGs, Humanoid robots.

1 Introduction

Biped locomotion is a complex problem that requires a robust control system that deals with several unexpected situations that can arise during the robot's motion. Thus, the locomotion system should allow a natural integration of three fundamental aspects: the robot's body, the environment and the control system. This control system basically consists of two stages. The first stage is responsible for the generation of the locomotion pattern, whereas the second stage is responsible for introducing feedback into the system in order to modulate the current locomotion pattern such that stability may be recovered whenever unexpected situations appear while the robot walks.

The generation and control of locomotion patterns have been addressed in several ways for humanoid robots that use electric motors for controlling the motion of their joints. Basically, the main objective is the generation of reference signals for the robot's joints, either as an angular displacement or as a torque in

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order to describe a stable motion. These signals are mainly generated through either pre-computed trajectories or trajectories computed in real-time through diverse control schemes. For example, the most common methodology to generate biped locomotion is by using simplified dynamic models of the humanoid robot's body in order to describe the trajectories for the robot's arms and legs in the task-space. These approaches are mainly based on a controller of the position of the Zero Moment Point (ZMP), which is used to ensure the robot's stability [1].

Alternatively, biological studies have shown that neural networks control the locomotion of vertebrate and invertebrate animals. These networks are called Central Pattern Generators. They are constituted by a set of neurons that can generate complex multi-dimensional rhythmic signals with simple input signals for controlling coordinated periodic movements. Currently, there is a growing interest in CPGs for controlling different types of robots [2]. Thus, some approaches recently used to solve the biped locomotion problem have been inspired by CPGs. The first studies about biped locomotion with CPGs were conducted by Taga, who investigated the use of CPGs for controlling the walking of a simulated humanoid robot on a 2D plane [3], [4].

The control systems for biped locomotion based on CPGs can be classified into CPG-joint control methods (e.g. [5]) and CPG-task-space control methods (e.g. [6], [7]). The first one aims at the appropriate generation and control of the multidimensional control signals in the joint-space through a CPG network that generates the coordinated locomotion. In the second approach, CPGs are used in the task-space to describe the Cartesian-space trajectories for the robot's joints. In that case, it is necessary to solve the inverse kinematics to determine the joint signals in order to control the biped locomotion.

In this work, a control system based on CPG-joint control methods is proposed in order to generate simple rhythmical signals for locomotion control of biped robots. The system behaviour is characterized by a reduced number of parameters. In an off-line stage, the parameters that characterize the walking pattern are determined by means of dynamics simulations. Afterwards, in an on-line stage, those parameters are directly tested on the humanoid robot in order to validate the obtained locomotion pattern. This paper is organized as follows. Section 2 describes the proposed controller based on a CPG network for generation of biped locomotion patterns. Section 3 presents some automatic feedback strategies implemented in the proposed CPG network. Section 4 discussed the obtained experimental results. Finally, conclusions and future work are given in Section 5.

2 Generation of Biped Locomotion Patterns

The proposed biped motion controller is based on a CPG network. The goal is to generate the signals for the angular displacement of each of the robot's joints in order to describe a valid locomotion pattern. The combination of parameters of the proposed network is found by evaluating the locomotion performance through dynamics simulations by applying a genetic algorithm.

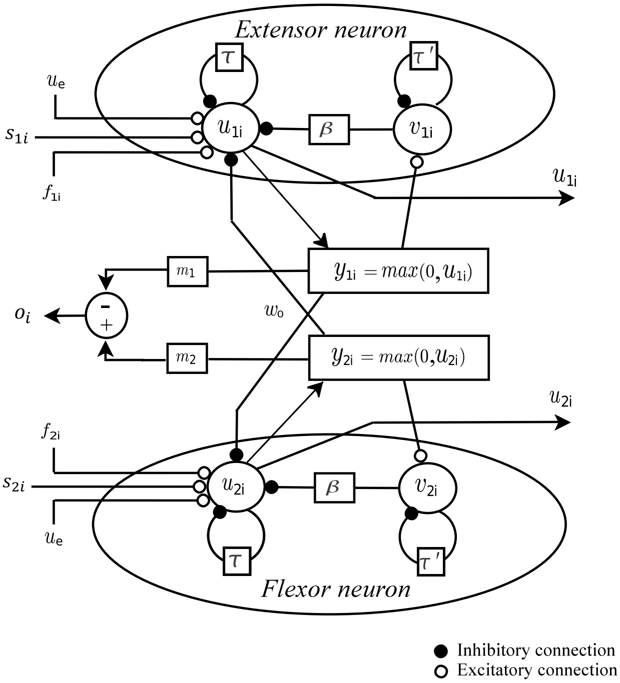

Fig. 1. Matsuoka's non-linear oscillator generalized to be applicable to a system with multiple degrees of freedom, as proposed in [10]

2.1 Basic Oscillator

The proposed CPG network is modelled by means of a set of interconnected non-linear oscillators previously proposed by Matsuoka in [8], [9]. The formulation of the Matsuoka's oscillator has been generalized to be applicable to a system with multiple degrees of freedom, as proposed in [10]. In the present work, the connections between oscillators are established in a single direction in order to control the desired output phases corresponding to the outputs of the CPG network. Each non-linear oscillator consists of two tonically excited neurons with a self-inhibition effect, which are reciprocally linked via inhibitory connections, as shown in Fig. 1. Each oscillator has four state variables $(u_{1i}, v_{1i}, u_{2i}, v_{2i})$. Its behaviour is described by (1) and (2). In this mathematical model, subscript 1 corresponds to the extensor neuron and subscript 2 to the flexor neuron, with num representing the number of oscillators.

$$\begin{cases} \tau \dot{u}_{1i} = -u_{1i} - w_0 y_{2i} - \beta v_{1i} + u_e + f_{1i} + a s_{1i} \\ \tau' \dot{v}_{1i} = -v_{1i} + y_{1i} \end{cases}$$

$$y_{1i} = max(0, u_{1i}), \qquad i = 1, ..., num \tag{1}$$

$$\begin{cases} \tau \dot{u}_{2i} = -u_{2i} - w_0 y_{1i} - \beta v_{2i} + u_e + f_{2i} + a s_{2i} \\ \tau' \dot{v}_{2i} = -v_{2i} + y_{2i} \end{cases}$$

$$y_{2i} = max(0, u_{2i}), \qquad i = 1, ..., num \tag{2}$$

The external input u_e affects the amplitude of the oscillator output, whereas its frequency is determined by the time constants τ and τ' [11]. The set of parameters must satisfy some requirements in order to yield stable oscillations [12]. The terms f_{1i} and f_{2i} are feedback variables. They can be used to control the output amplitude and phase. Parameters s_1 and s_2 represent the interaction between neighbouring oscillators within the CPGs. They are defined as (3), where w_{ij} represents the unidirectional connection weight between a master oscillator, O_j, and a slave oscillator, O_i. Only two types of connections between oscillators are possible:

1) Excitatory connection: The weight w_{ij} is set to 1 in this case.
2) Inhibitory connection: In this case, the weight w_{ij} is set to -1.

$$\begin{aligned} s_{1i} &= w_{ij} u_{1j} \\ s_{2i} &= w_{ij} u_{2j} \end{aligned} \tag{3}$$

The output signals of the oscillators are calculated using (4). They are used to directly control the joints of the humanoid robot.

$$o_i = -m_1 y_{1i} + m_2 y_{2i} \tag{4}$$

In order to modulate the frequency of the oscillator, an additional parameter, k_f, is introduced as proposed in [13]. The time constants in (1) and (2) are thus reformulated as:

$$\begin{aligned} \tau &= \tau_o k_f \\ \tau' &= \tau'_o k_f, \end{aligned} \tag{5}$$

where τ_o and τ'_o are the original time constants of the Matsuoka's oscillator. For certain values of its parameters, an oscillator will generate a periodic oscillation by itself. However, when a network of oscillators is set, they all oscillate together according to the network connections, converging to a specific pattern and limit cycle. Table 1 shows the internal values used for each non-linear oscillator. Figure 2 shows the output signals for the aforementioned parameters. Basically, the objective is to generate a periodic output signal with a stable limit cycle.

2.2 Proposed CPG Network

The main goal of the proposed CPG network is to generate stable patterns for controlling the motion of the humanoid robot. This network generates the motion of the robot arms and synchronizes them with the motion of its legs in order to yield a more stable walking pattern. The proposed CPG network follows a master-slave topology, in which a central non-linear oscillator is used to drive

Table 1. Oscillator parameters

Parameter	Value	Parameter	Value
τ_o	0.2800	u_e	0.4111
τ'_o	0.4977	$m1, m2$	1
β	2.5000	a	1
w_0	2.2829	k_f	0.2193

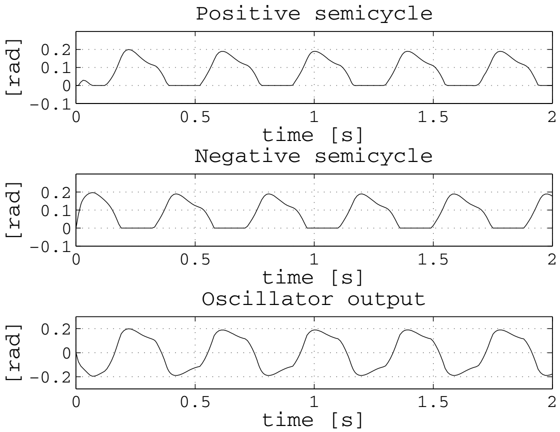

Fig. 2. Oscillator outputs for the fixed internal oscillator parameters defined in Table 1

the different joints of the robot through slave oscillators associated with each of those joints.

The central oscillator is referred to as a pacemaker oscillator, since it generates the first electrical impulse or master signal that is propagated across the other oscillators in the different chains of the robot (left arm in the sagittal plane, right arm in the sagittal plane, left leg in the sagittal and coronal planes and right leg in the sagittal and coronal planes). The concept of pacemaker oscillator was introduced in [14]. However, they did not utilize it to directly control the angular displacement of joints with the CPG outputs. If the pacemaker oscillator does not have any input or feedback signal, it exclusively oscillates according to its internal parameters.

The proposed CPG network has been designed in order to imitate the human gait, which has the following features:

1. The arms' motion in the sagittal plane is in anti-phase.
2. The legs' motion in the sagittal plane is in anti-phase.
3. The two motions mentioned above are in anti-phase, that is, the motion of the right arm is synchronized with the motion of the left leg, whereas the motion of the left arm is synchronized with the motion of the right leg.

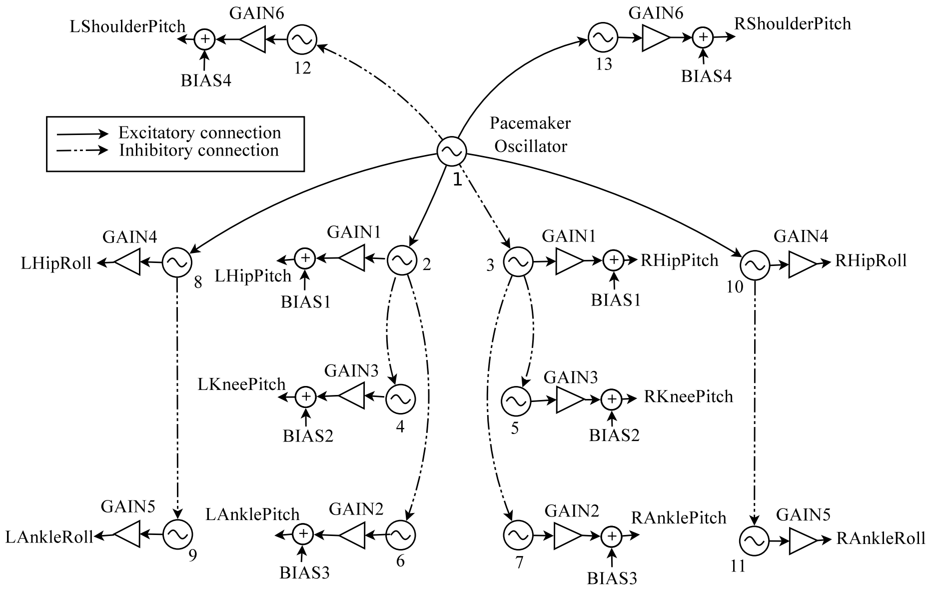

Fig. 3. Proposed topology for the CPG network

4. The coronal motion of legs is synchronized with the sagittal motion of legs in order to generate the periodic motion by changing the location of the center of masses.

The large number of parameters is one of the main drawbacks when dealing with CPG networks. In order to minimize this problem, all oscillators have been configured with the same parameters presented in Table 1. The parameters of the CPG network shown in Fig. 3, which characterize the locomotion pattern of a biped robot are: seven gains (k_f, GAIN1 ,GAIN2, GAIN3, GAIN4, GAIN5, GAIN6) and four offsets (BIAS1, BIAS2, BIAS3, BIAS4). Parameter k_f can be utilized for changing the walking speed, since it controls the locomotion pattern's frequency, achieving an extra control on the robot's velocity. This is an important feature, since it is possible to modulate the locomotion pattern's frequency with a single parameter.

2.3 Automatic Estimation of CPG Network Parameters through Genetic Algorithms

Evolutionary algorithms are typically used to solve high-dimensional optimization problems. These algorithms have proven to be a good approach for finding the parameters associated with CPG networks. A genetic algorithm has been applied off-line in order to calculate the CPG network parameters with the objective of describing an optimal locomotion pattern in straight line. Each individual of the genetic algorithm represents a different combination of parameters for the

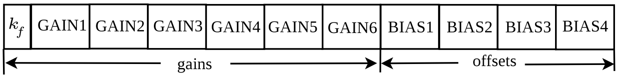

Fig. 4. Chromosome structure

proposed CPG network. In particular, each individual is modelled by a chromosome with 11 traits that represent the combination of parameters of the CPG network, as shown in Fig. 4. The genetic algorithm has been initialized in this work with a randomly selected initial population of 200 individuals. This number was heuristically set after a large amount of simulations. The locomotion pattern associated with every individual has been evaluated during 16 seconds using a dynamics simulator and a 3D synthetic model of the robot in order to allow the robot to walk a significant distance for calculating its fitness value. If the robot falls down or strongly oscillates during that evaluation period, the fitness value is set to zero for the current individual. Otherwise, its fitness value is calculated as follows. The individual with the best fitness score proceeds to the next generation. The other individuals are chosen based on the roulette wheel selection rule. In particular, each individual is given a probability of being selected that is proportional to its fitness value. This rule makes it possible to select individuals with a low score, thus preventing a fast convergence of the genetic algorithm to a local maximum. The individual with the best fitness score and the selected individuals from the current generation constitute a mating pool. Crossover and mutation procedures are then applied in order to obtain the individuals of the next generation. The simulation stops when a maximum number of generations is reached or the variation of the fitness function is lower than a given threshold ϵ ($\epsilon = 0.01$ in this work). The fitness function used for sorting the individuals in each generation has been formulated as (6), where vel represents the average straight line velocity, dev is the lateral deviation distance with respect to the straight line, α and γ are weighting coefficients.

$$f = \alpha(vel) - \gamma(dev) \tag{6}$$

3 Introduction of Feedback Strategies into the System

This section presents some automatic feedback strategies implemented in the proposed CPG network in order to modulate the locomotion patterns obtained with the methodology explained above. This modulation is performed according to the analysis of the available feedback signals in order to compensate for internal mismatches or external perturbations. It takes advantage of the ability of the CPGs for adapting their behaviour through external feedback variables introduced in the CPG model. The feedback strategies are introduced into the system as explained below.

3.1 Phase Resetting Controller

Whenever a humanoid robot walks on flat terrain, it interacts with the floor through its feet soles. If the robot is walking at a constant speed on flat terrain, the elapsed times between the transition from the left to the right foot and from the right to the left foot should be approximately equal. This indicates that the walking pattern is symmetric and the robot is correctly interacting with the floor.

However, if the robot is walking on irregular terrain, the interaction times with the floor can be modified. For instance, if the robot steps on an obstacle or if it is experimenting an external perturbation, the interaction time could be smaller or higher for one or both interaction times. The information extracted from these time measures is used to synchronize the interaction between the feet and the floor by means of phase resetting. It aims to synchronize the pattern generation with the current interaction between the robot and the environment.

As explained above, the model proposed by Matsuoka for the non-linear oscillator is used in this work. To our knowledge, the phase resetting of the oscillator's output has not been implemented in Matsuoka's oscillator to control the biped locomotion. In the study presented in [15] by the same author, some initial studies about the phase resetting behaviour in the oscillator are presented. In that work, two phase response curves of the oscillator for slow and fast dynamics are presented. These curves show that the phase shift introduced in the oscillator output depends of the oscillator internal parameters and also on the current phase of the output signal. These phase response curves have a non-linear behaviour. In order to adequately control the phase resetting through the current interaction times between the robot and the floor, it is necessary to exactly impose the needed phase difference. By using the phase response curves, the phase resetting cannot be easily controlled since it can happen in whatever instant of the gait due to irregularities in the walking terrain or perturbations that can be applied to the robot.

Therefore, an alternative strategy for controlling the phase resetting is proposed in this work by using the feedback signals of the original Matsuoka's oscillator model in order to adequately control the phase of the oscillator's output signal. This is done by controlling the current state of the oscillator variables through the feedback signals in order to reset the phase of the output signal. The introduction of this feedback in the oscillator model is presented below.

The mathematical model of each oscillator has two feedback variables, referred to as f_1 and f_2. If these variables have a positive value, they can be used to control the oscillator's output amplitude in real-time. Otherwise, if they are negative and with specific values, it is possible to control the time during which the output signal is disabled and then turn it on again in order to impose the required phase for the output signal. If these variables are set to zero, there is no effect on the oscillator output.

In this work, the phase resetting mechanism is implemented in the pacemaker oscillator. The output signal imposed by the central oscillator is propagated along the slave oscillators in order to synchronize the interaction between the

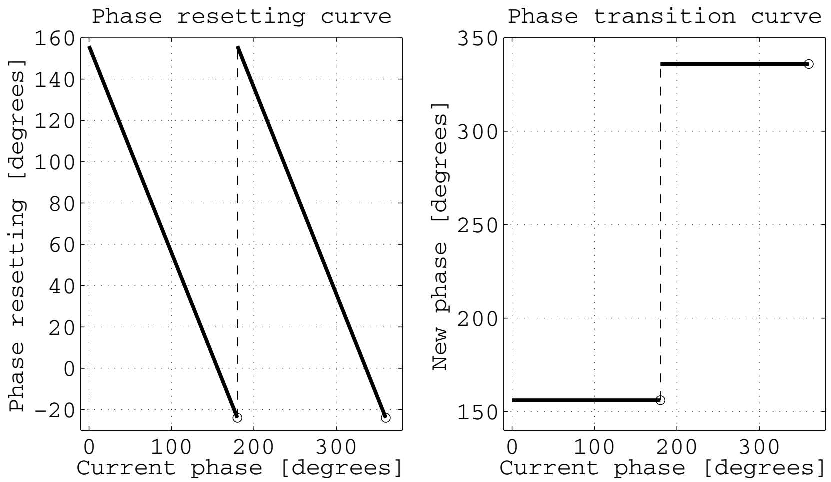

Fig. 5. Phase resetting

robot and the floor in real-time, aiming to prevent the robot from falling down due to an unstable situation.

The exact moment of impact between each robot's foot sole and the floor is detected through the analysis of the signals provided by the force sensors located in the feet soles. These force measures are used to calculate the elapsed time between the change in the robot's support leg. If this time is smaller or higher than some fixed limits determined by the current walking frequency, the phase resetting mechanism is activated in order to synchronize the interaction between the robot feet and the floor. The phase resetting mechanism implemented for the pacemaker oscillator is described in Fig 5. The zero phase for the pacemaker oscillator signal is defined as the point of transition of the pacemaker oscillator amplitude from a negative value to a positive value.

3.2 Pose Controller

In a bipedal gait, the robot's trunk pose during motion must be controlled since it has a higher concentration of mass and, therefore, it plays an important role in the robot's stability. A feedback strategy to control the robot's pose through the control of the pose in the sagittal plane is implemented. In order to maintain the robot's trunk in a correct pose, parameter BIAS1 is modified for controlling the pitch angle of the trunk according to:

$$BIAS1_{new} = BIAS1 + K_1(\theta_{trunk} - \hat{\theta}_{trunk}), \tag{7}$$

where $BIAS1_{new}$ is the new value for the parameter BIAS1, $\hat{\theta}_{trunk}$ is the reference value for the trunk inclination in the sagittal plane and θ_{trunk} is the current inclination in the sagittal plane for the trunk provided by the robot sensors.

Table 2. Fixed angles for other joints

Joint name	Angle [radians]	Joint name	Angle [radians]
HeadPitch	0	LShoulderRoll	0.23
HeadYaw	0	LElbowYaw	-1.51
RShoulderRoll	-0.23	LElbowRoll	-0.5
RElbowYaw	1.51	HipYawPitch	0
RElbowRoll	0.5		

4 Experimental Results

In order to validate the proposed controller, a NAO humanoid robot has been used [16]. The proposed CPG network, shown in Fig. 3, aims at imitating the main features of the human gait in order to describe a biped motion by specifying the phase differences for 12 joints of the sagittal and coronal planes. This network is able to generate a 3D motion in both simulated and real environments. The motion control of the arms is performed through position control of the shoulders in the sagittal plane. The other joints in the arms, hip and head have constant angles that aim to mimic an upright walking pose. These angles are shown in Table 2.

The robot simulations have been performed with Webots [17], a commercial dynamics simulator that includes the physical models of different real robots and is able to simulate the dynamic interaction between the robots and the simulated environment.

The genetic algorithm works in coordination with the CPG network and the robot simulator in order to estimate the best combination of CPG parameters within the predefined search space. The aim is to control the signals of the robot joints through the CPG network in order to generate an optimal locomotion pattern. The genetic algorithm was initialized in this work with an initial population of 200 chromosomes. The crossover probability was set to 80 percent and the probability of mutation to 10 percent. Those values were heuristically set after a large number of simulations.

When the frequency of the locomotion pattern is higher than 2.28 Hz, the simulator is unable to reproduce the real interaction between the feet soles and the floor, leading to a noticeable deviation between the simulated motion pattern and the real one. Therefore, the maximum frequency allowed for the simulated locomotion pattern has been set to 2.28 Hz, which is reached with $k_f = 0.2$.

Table 3 shows the different limits that have heuristically been defined for the gains and offsets. Those limits define the search space of the genetic algorithm. Figure 6 shows the results obtained with the simulator in order to find out the optimal locomotion pattern in straight line. The weighting coefficients α and γ have heuristically been set to in 80 and 100 respectively. The CPG parameters shown in Table 4 were finally obtained through the proposed methodology. The total simulation time was 132 minutes on an Intel Core 2 Quad Q9400 processor at 2.66 GHz with 8GB of RAM.

Table 3. Genetic algorithm search space

CPG network parameters	Parameter range	CPG network parameters	Parameter range
GAIN1	0.01 - 1.00	BIAS1	-0.90 - 0.00
GAIN2	0.01 - 1.00	BIAS2	0.5 - 1.2
GAIN3	0.01 - 0.50	BIAS3	-0.70 - 0.00
GAIN4	0.01 - 0.50	BIAS4	1 - 2
GAIN5	0.01 - 0.50	k_f	0.2 - 0.5
GAIN6	0.01 - 1.00		

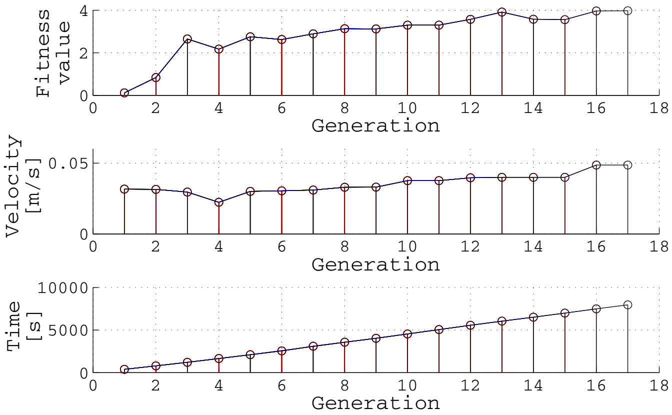

Fig. 6. Simulation results obtained with the genetic algorithm

Table 4. CPG network parameters found by the GA

CPG network parameters	Value	CPG network parameters	Value
GAIN1	0.24555	BIAS1	-0.60598
GAIN2	0.18665	BIAS2	0.70700
GAIN3	0.11685	BIAS3	-0.30590
GAIN4	0.40850	BIAS4	1.4797
GAIN5	0.43000	k_f	0.462
GAIN6	1.00000		

In order to feedback the system, the phase resetting mechanism described above was implemented in the pacemaker oscillator. One example of the phase resetting mechanism is shown in Fig. 7. The value for the parameter K1 in (7) was experimental set to 10 in order to control the robot's vertical pose.

For testing the robustness of the proposed closed-loop system, an environment with diverse classes of obstacles on the walking terrain was designed. Those

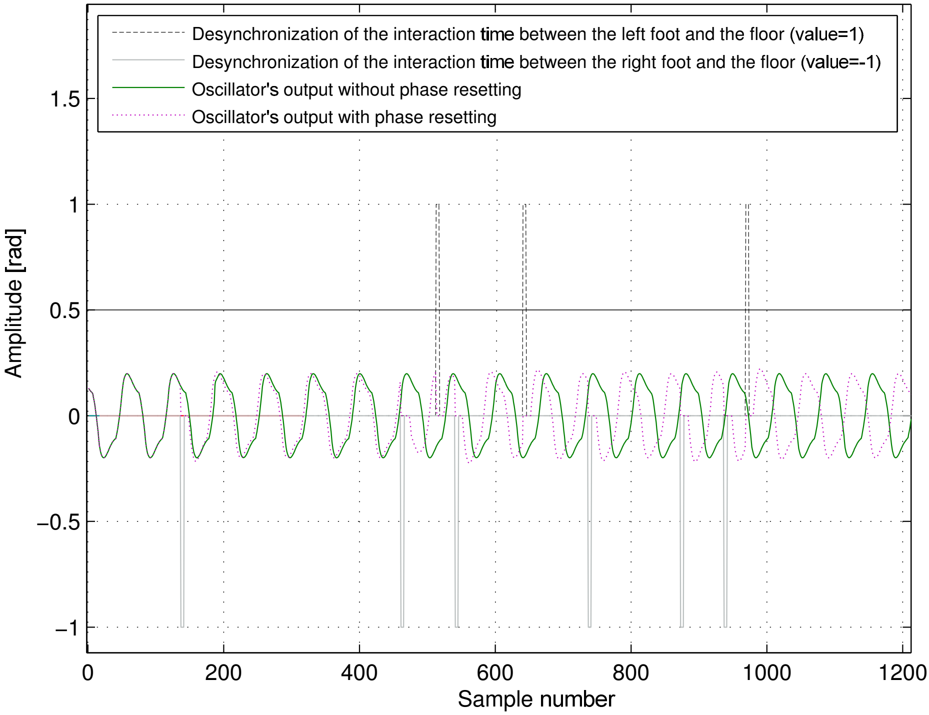

Fig. 7. Phase resetting example for the pacemaker oscillator

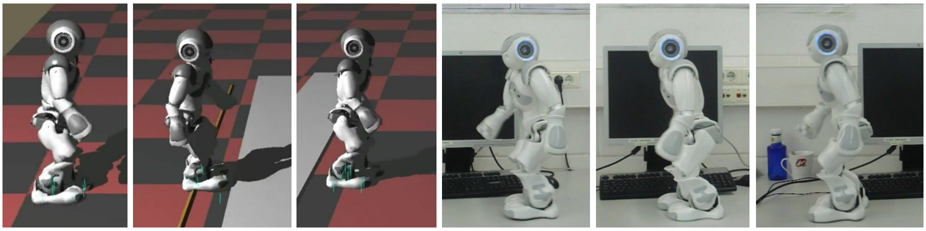

Fig. 8. Snapshots of the simulation and real experiments

obstacles have round, triangular and rectangular shapes such as is shown in the simulation experiments. Due to their shape, those obstacles produce forces in different directions in the robot's feet soles while it is walking on those obstacles and as a consequence, different types of perturbations are presented. These perturbations are used to test the robustness of the feedback system in order to mainly prevent the robot from falling down while it is exposed to unexpected situations. The system provides feedback to the locomotion pattern that is being generated on-line in order to modify the joint signals for preventing the robot from falling down. The proposed methodology has been validated on a real NAO humanoid robot. Comparative videos between the results obtained in simulation and the real environments have been included in the companion website[1]. Some snapshots with simulated and real experiments are shown in Fig. 8.

5 Conclusions

A control architecture has been proposed to control the locomotion of a biped robot by using a CPG network based on Matsuoka's oscillators. A new CPG network has been proposed whose parameters are determined through evolutionary computation in order to generate optimal biped locomotion patterns. These patterns are generated in the joint-space by controlling the angular displacement of the robot's joints both in the sagittal and coronal planes. A feedback mechanism is introduced in the network to modulate the locomotion patterns according to the current sensory feedback in order to compensate for internal mismatches and external perturbations. The feedback is performed by controlling the robot's pose and the interaction between the robot and the floor through phase resetting of the pacemaker oscillator. The system behaviour is characterized with a few parameters using simple rhythmical signals.

Experimental results have validated the proposed methodology on a NAO humanoid robot. It can be easily adapted to other biped robots with a similar structure of joints after performing the corresponding changes (robot model, limits for the genetic algorithm search space, etc.).

Future work will include the study of the parameters that characterize the CPG network in order to find out a mathematical description that automatically finds the optimal values for the variables of the model.

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References

1. Vukobratović, M., Borovac, B.: Zero-moment point - thirty five years of its life. International Journal of Humanoid Robots 1(1), 157–173 (2004)
2. Ijspeert, A.: Central pattern generators for locomotion control in animals and robots: A review. Neural Netw. 21(4), 642–653 (2008)
3. Taga, G., Yamaguchi, Y., Shimizu, H.: Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment. Biol. Cybern. 65(3), 147–159 (1991)
4. Taga, G.: A model of the neuro-musculo-skeletal system for human locomotion. Biol. Cybern. 73, 113–121 (1995)
5. Righetti, L., Ijspeert, A.: Programmable central pattern generators: an application to biped locomotion control. In: Proc. IEEE Int. Conf. Robot. Autom., pp. 1585–1590 (May 2006)

[1] Companion website: `http://deim.urv.cat/%7Erivi/NAO%5FROBOT2013.html`

6. Park, C.-S., Hong, Y.-D., Kim, J.-H.: Full-body joint trajectory generation using an evolutionary central pattern generator for stable bipedal walking. In: Proc. IEEE Int. Conf. Intell. Robot. Syst., pp. 160–165 (October 2010)
7. Liu, C., Chen, Q.: Walking control strategy for biped robots based on central pattern generator. In: Proc. IEEE Int. Conf. Robot. Autom., pp. 57–62 (May 2012)
8. Matsuoka, K.: Sustained oscillations generated by mutually inhibiting neurons with adaptation. Biol. Cybern. 52(6), 367–376 (1985)
9. Matsuoka, K.: Mechanisms of frequency and pattern control in the neural rhythm generators. Biol. Cybern. 56(5), 345–353 (1987)
10. Kamimura, A., Kurokawa, H., Yoshida, E., Murata, S., Tomita, K., Kokaji, S.: Automatic locomotion design and experiments for a modular robotic system. IEEE/ASME Trans. Mechatronics 10(3), 314–325 (2005)
11. Williamson, M.: Robot arm control exploiting natural dynamics. Ph.D. Thesis, Massachusetts Institute of Technology (1999)
12. Matsuoka, K.: Analysis of a neural oscillator. Biol. Cybern. 104(4-5), 297–304 (2011)
13. Zhang, D., Poignet, P., Widjaja, F., Ang, W.T.: Neural oscillator based control for pathological tremor suppression via functional electrical stimulation. Control Eng. Pract. 19(1), 74–88 (2011)
14. Aoi, S., Tsuchiya, K.: Locomotion control of a biped robot using nonlinear oscillators. Auton. Robots 19, 219–232 (2005)
15. Nakada, K., Sato, Y.D., Matsuoka, K.: Tuning time scale parameter of piecewise linear oscillators for phase resetting control. In: The 21st Anual Conference of the Japanese Neural Network Society (December 2011)
16. Gouaillier, D., Hugel, V., Blazevic, P., Kilner, C., Monceaux, J., Lafourcade, P., Mariner, B., Serre, J., Maisonnier, B.: The NAO humanoid: a combination of performance and affordability. In: IEEE - International Conference on Robotics and Automation (2009)
17. Michel, O.: Cyberbotics ltd. webots tm: Professional mobile robot simulation. Int. J. Adv. Rob. Syst. 1, 39–42 (2004)