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Real time control of a CPG-based model of the human trunk in different walking conditions

Jean-Charles Ceccato, Christine Azevedo-Coste, Jean-René Cazalets

***Abstract*—Artificial central pattern generators (CPGs) framework is well adapted to the control of bio-mimetic systems during rhythmic tasks like locomotion. They have the ability to reproduce biological behavior as well as to be used as feedforward controllers for multi-articulated systems. In this paper we present a model of human gait activity based on an oscillator network. The model is especially dedicated to reproduce trunk muscular activities as observed in previous studies, and to fill a lack in trunk modeling in human gait simulation. An offline validation is performed using recorded accelerometer signal that monitors trunk movements during locomotion. We are able to control the model based on this real data and to adapt its pattern to contextual changes (stairs, slope).**

I. Introduction

Central pattern generators (CPGs) are dedicated neuronal networks that generate rhythmic motor behavior such as locomotion [1]. There are evidences that such neural circuits also exist in human [2, 3]. In a previous study, we demonstrated the existence of a metachronal (segment by segment) descending wave of trunk muscles activity during human walking [4]. This pattern of propagation is similar to the one observed in other vertebrates like rats [5], lamprey [6] and salamander [7] and it has been suggested that it relies on the existence of a CPG dedicated to trunk control [8]. Knowing the major contribution of trunk in postural control, it may be therefore interesting to model a human CPG in order to reproduce the trunk metachronal descending wave.

CPGs can be modeled mathematically by coupled non-linear oscillator network [9, 10] allowing generation of traveling waves like we observed in the trunk. The oscillator framework is interesting as it allows changes in frequency and amplitude of the generated output and the switch between locomotors modes in a simple manner.

Some models of CPGs have been developed to simulate human movement, but they mainly focus on limb control [11-14] and not precisely on the trunk control. Bipedal human locomotion results from a complex synergy between limbs but also with the trunk. The trunk has a critical mass and is a highly articulated structure that makes its balance control a challenge. Taking into account trunk activity may be of interest in many cases, such as when dealing with functional rehabilitation involving artificial control of movements like electrical stimulation, orthopedic devices or when designing bipedal robots. In the context of rehabilitation it is relevant to generate commands for artificial control of deficient limbs in order to reproduce movement of valid limb and integrate voluntary control of the rest of the body [15]. The model has to be adaptable to different voluntary controlled modes of locomotion as well as to the influence of external conditions and proprioceptive information. Therefore, such a model must have two levels of control, the "voluntary control" which represents the high decision level like walking, running, going faster, and the "adaptive control" which represents the automatic adaptations to the external conditions like ascending slope, descending slope and terrain texture. For small frequency changes induced by a slope occurrence it may be interesting to adapt the trunk activity by changing CPG frequency or/and shape of output signal without changing the general control.

While the voluntary controlled part of CPGs has already been extensively studied [16-18], the control adaptation to external events is less investigated. Recent papers have addressed this issue by adapting the phase of an oscillator network to the signal of an external sensor [19-21].

As we aimed to model trunk activity, the signal chosen should: 1) represent trunk movement and give information on the walking cycle evolution, 2) be able to be used as reference signal to drive the model. An accelerometer attached to the trunk gives the required information and appears to be interesting as well for further integration in the rehabilitation context. [22]

In the following, we first present the adaptation of the oscillator network of Ispeert and al. [10] to our problematic. Secondly, we detail the controller used to adapt the CPG output to a varying external signal.

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JC Ceccato is with the DEMAR INRIA/ LIRMM 161 rue Ada 34392 Montpellier cedex 5, France and Université de Bordeaux ; CNRS UMR 5227, Université de Bordeaux 2, Zone nord Bat 2, 2e étage, 146, rue Léo Saignat, 33076 Bordeaux cedex, France (phone: +335.57.57.46.26; fax: +335.56.90.14.21; e-mail: jc.ceccato@gmail.com).

C Azevedo Coste is with *DEMAR INRIA/ LIRMM 161 rue Ada 34392 Montpellier cedex 5, France* (e-mail: azevedo@lirmm.fr).

JR Cazalets is with Université de Bordeaux ; CNRS UMR 5227, Université de Bordeaux 2, Zone nord Bat 2, 2e étage, 146, rue Léo Saignat, 33076 Bordeaux cedex, France (e-mail: jean)rene.cazalets@u-bordeaux2.fr).

II. METHOD

A. Modeling trunk and limb rhythmic behaviors

The activity we aim to exhibit through the CPG model is very close to the one proposed in [10] for the salamander, we adapted the corresponding model to our needs. The objective is to mimic the descending metachronal activity we observed during human walking [4] at five spinal levels

(C7, T3, T7, T12 and L3; Fig 1A, B). The proposed architecture is based on a CPG model composed of fourteen coupled nonlinear oscillators, which receive low-level orders to modulate its output (Fig.1). The trunk CPG is composed of ten coupled oscillators, five on each side of the trunk, two at each spinal level. Four additional oscillators are dedicated to each of the limbs.
The oscillator equations are the same as those proposed for the salamander and serpentine robots by [10].
Each oscillator i of the CPG is implemented with the following equations:

$$\begin{cases} \dot{\theta}_i = 2\pi v_i u + \sum_j \omega_{ij} \sin(\theta_j - \theta_i - \Phi_{ij}) \\ \ddot{r}_i = a_i \left(\frac{a_i}{4} (R_i - r_i) - \dot{r}_i \right) \\ x_i = r_i u \,(1 + \cos(\theta_i)) \end{cases}$$

$$\text{if } v_i u_v > 1.6\,Hz,\; v_i u_v = 1.6\,Hz$$
$$\text{if } u_v > 1.45\,Hz,\; \Phi_{ij} = -\Phi_{ij}$$
$$u = u_v \times u_a$$

where: i=1…14
θ_i and r_i variables represent the phase and amplitude of each oscillator. The phase θ_i depends on the intrinsic frequency v_i, modulated by the command u. It also depends on the individual phase of other oscillators j to which it is coupled with the weight ω_{ij} and the phase shift Φ_{ij}. The differential equation for the amplitude r_i allows a smooth convergence to the intrinsic amplitude R_i. The output x_i of the oscillator depends on the phase and amplitude of the oscillator and the control input u. The control input u allows modifying externally the output frequency. The command u is composed of two signals: u_v representing the "voluntary control" and u_a the "adaptive control". u is the combination of voluntary and adaptive controls so that they inhibited each other, making activity impossible without both intention of locomotion and the correct feedback from locomotion observation. It also allows the simulation of behaviors such as running on a slope: in this situation the voluntary control is in charge of the "running part" while the adaptive command is in charge of the "slope part".
This model allows mimicking metachronal descending propagation of the trunk activity as observed during human gait. It also allows exhibiting other patterns like reported in [10]. In humans, the amplitude of muscular activity generally increases with the locomotion velocity while the step frequency increases to a point where running begins (around 7-8 km/h). During running the frequency keeps increasing but much slower. In the model, we added saturation in each oscillator to represent this stagnation of the frequency. We also added a threshold on the frequency that provokes a change of the activity propagation when the voluntary control reaches a given level (to model the switch between walking and running) (Fig 3). Human trunk muscles activity during running is under study in our laboratory and the proposed model could easily be adapted to fit the running behavior.

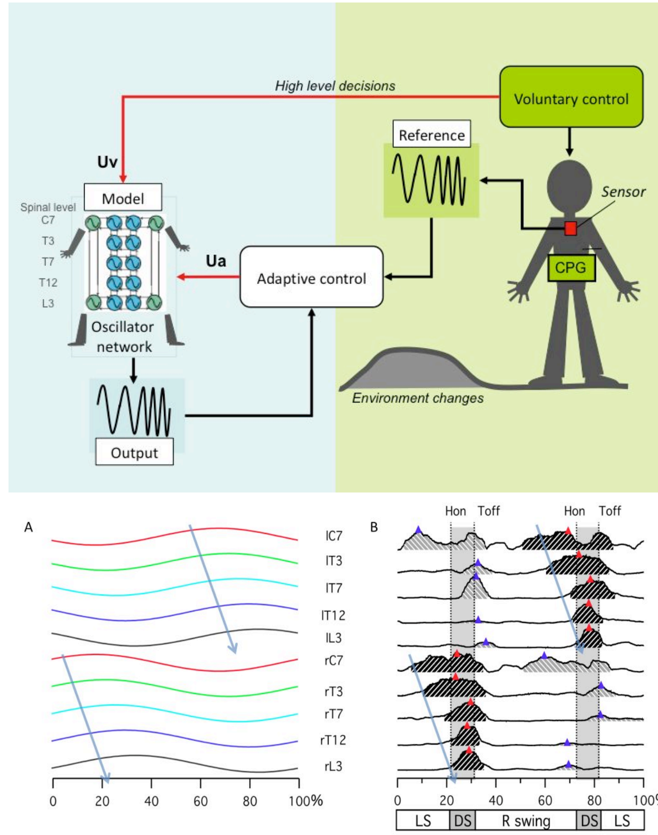

Fig 1. Top: the different components of the locomotion controller. The model reproduces the activity of the CPG under the voluntary controller orders that represents high level decision and the adaptive controller orders that automatically detects external changes to adapt trunk activity pattern. Bottom:
A) Metachronal descendant pattern of the trunk simulated by the model. B) Metachronal descendant pattern of the trunk observed on real datas.

B. Adaptation of the model to gait modifications

As stated in the previous section, the control input u modulates the output of the oscillator network. The input should allow automatic adaptation of the activity pattern changes imposed by external conditions such ascending and descending slopes or stairs. For instance, gait initiation is also seen as a change in external conditions that releases model activity. It is necessary in this context to have reliable information about ongoing movement and associated changes. We present results obtained by evaluating the phase shift between the model and the measured signal. Here, the master signal is an external signal, from a sensor for example, and the slave signal comes from the oscillator network itself. To control the phase of the model with an external signal we adapted a Phase-Locked Loop (PLL) (Fig 2). This closed loop frequency control system uses a phase comparator, which gives a positive or negative output depending on the phase shift between the two input signals. The phase shift between the two signals can then be filtered and integrated with a controller to be used as the input control of the oscillator network (Fig 2).

C. Reference signals

Here, the recorded experimental signal is the acceleration of the thorax. We would like to insist on the fact that the approach is independent from the sensor and the signal chosen. Acquisition was achieved using a wireless inertial sensor (3 axes accelerometers, 3 gyroscopes and 3 magnetometers, Inertia Link, Microstrain, USA) placed on the sternum of a young, healthy individual and sampled at 100 Hz. The recorded sequence corresponds to 17 sec uneven ground walking (fifteen walking cycle, thirty steps), 9 sec stairs up (eighteen step), 22 sec uneven ground walking (nineteen walking cycle, thirty-eight steps) and 20 sec stairs down with 2 sec of uneven ground in the middle (fourteen steps with two walking cycle in the middle) (Fig 3). The signal corresponding to the vertical component of the acceleration was used to control the network and the lateral component was used to check if the left-right swing alternation was respected. We chose the vertical component of the acceleration signal because it carried the more information. It was therefore possible to filter it using a recursive weighted moving average. This approach allowed smoothing the signal with a reduced lag with respect to the real signal.

D. Phase shift measurement

The discrete phase detectors were realized with two flip flops which output is 0 when there is no phase shift and -1 or +1 when the phase shift is negative or positive. The phase shifts were measured between zero crossings events of external and controlled signals. (Fig 2)

E. The controller

The controller was a hand tuned phase lag and phase lead corrector. The controller generated a command based on the phase shift between network and reference signals (Fig 2). As expected, a tradeoff was to be found between efficiency and stability of the controller.
Here after, we present the transfer function of our corrector:

$$H = K \times \frac{1+\tau_i p}{p} \times \frac{1+a\tau_d p}{1+\tau_d p} \times \frac{1}{1+\tau_f p}$$

K is the static gain, τ_i integration time constant, τ_d derivation time constant, $0<a<1$ derivation span and τ_f filter time constant.
The signal used to command the controller presented two oscillations per walking cycle and a ratio that could have been a problem (see Result section). This problem can be overcome by using an intermediary oscillator that oscillates at the reference signal frequency and serves as an output signal for the phase detection. Using this oscillator driven by the adaptive controller, we can divide its output frequency by two to retrieve a whole walking cycle in the oscillator network (Fig 2). The second problem of the asymmetrical oscillations is overcome by adding an offset to the output of the intermediary oscillator making the zero crossing asymmetrical (Fig 2). To compute the offset we integrate and filter a *sign* function (-1 for negative and 1 for positive) on one cycle, which represents the ratio of our reference signal (Fig 3). With the addition of the ratio to the intermediate oscillator output, we are able to properly drive our model with trunk vertical acceleration signal during normal walking and stairs climbing and descending.

F. Simulation parameters

The model was implanted under Matlab/Simulink (Mathworks, USA) to reproduce the conditions of online simulation. The real signals were recorded with provider's dedicated software and imported under Simulink for model simulation.

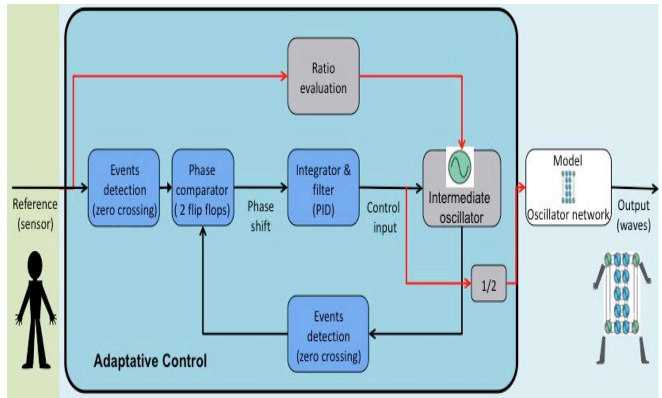

Fig 2. Adaptation of the controller to the real signal phase detection. The addition of an intermediary oscillator and ratio detection allow the use of vertical acceleration to drive the oscillator network.

III. Results

In the following, we will consider that the voluntary control was always the same, i.e. walking at normal speed and it was set to a neutral level (u_v=1). Therefore, the changes in the model output can only be caused by changes in the external signal.

The vertical acceleration of the trunk appears relevant to detect the zero crossing events as is less perturbed by noise than other trunk accelerations. Nevertheless, two problems arise from this choice: first, vertical acceleration oscillates twice per walking cycle, which is twice the frequency we wish to have for our oscillators (one oscillation per walking cycle). Secondly, the signal is not symmetrical around the mean position like a sinusoid, i.e. the zero crossing events are not equally spaced (Fig 3). As seen in the Method section II.E, we dealt with those problems by modifying the controller.
Figure 3 shows that the intermediary oscillator keeps its synchronization with the reference signal during the transition between different conditions and that the duty cycle in the reference signal changes in shape and frequency from normal walking to stairs climbing and descending. However this is handled automatically by the change of the calculated ratio. Finally, the rest of the oscillator network is synchronized with the left/right activity as shown by comparing lateral acceleration of the trunk and the output of one oscillator of the trunk (Fig 3). However, an unexpected drawback will have to be fixed, stairs climbing and descending present analog ratio and frequency. They are hard to differentiate from trunk vertical acceleration based on the considered parameters only (frequency, ratio).

Nevertheless, it might be possible to use amplitude or mean of reference signal to do so. In fact the trunk tends to bend forward during upstairs and backward during downstairs compared to normal walking, and this should be reflected somewhere in the vertical acceleration.

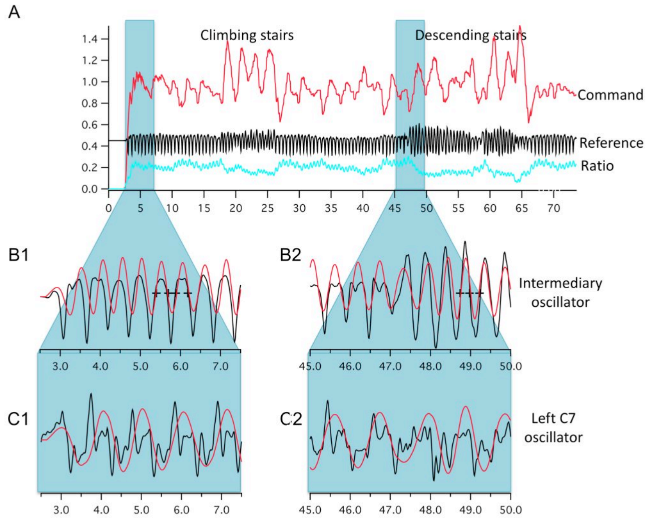

Fig 3. (a) Command signals, (b) upper trunk vertical acceleration and intermediary oscillator output signal, crosses represent zero-crossing events used for phase shift calculation and (c) upper trunk lateral acceleration and oscillator output signal at C7 level.

IV. CONCLUSION AND FUTURE WORK

The control of locomotion requires multi-dimensional coordinated rhythmic patterns that need to be correctly tuned in order to satisfy various constraints. CPG framework allows implementing feedforward type controllers [10]. CPGs combine stereotypy and flexibility in terms of continuous adjustment of speed, direction and types of gait. We adapted an existing system of coupled non-linear oscillator network to mimic human locomotion and exhibit the trunk descending muscular pattern observed during normal gait. Using real recorded informations from a unique sensor placed on the upper body, we validated the approach using signals off-line. The next step will be to perform real-time online observation and control. Then, some improvements would be to use continuous phase detection like developed in [21] and detect intention of gait initiation to develop a specific control of this task.

The CPG model produces traveling waves as limit cycle behavior and allows simple modulation of the frequency, amplitude and phase lag of undulations. This is interesting in terms of functional assistance: one could apply this result to control deficient or prosthetic legs using information from the trunk, using it like a “joystick” [15]. An application to robotics may be to achieve control of biped robots with articulated trunk. In facts, while an articulated trunk is more challenging to maintain balance, it is more versatile, allowing a lager panel of activities in mimicking human movements.

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