Human Walk Modeled by PCPG to Control a Lower Limb Neuroprosthesis by High-Level Commands

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Abstract

Current active leg prostheses do not integrate the most recent advances in Brain-Computer Interfaces (BCI) and bipedal robotics. Moreover, their actuators are seldom driven by the subjects intention.

In this paper, assuming high-level commands reflecting users intention are available (such as accelerate, decelerate or stop), we propose an original and biologically-inspired leg prosthesis control system. A Programmable Central Pattern Generator (PCPG), which is able to model human walk in a perfectly periodic way, generates the output signal to control the prosthesis. One of the main interests of that tool is the possibility to modify the walking pattern learned at a middle speed and to adapt it to different walking speeds in a smooth way.

What is proposed in this paper is to exploit this feature and increase the comfort of the patient thanks to a specific tuning of the PCPG parameters relying on real kinematics of a similar subject. The results of a study for one subject are presented and we show how to modify at best the PCPG parameters. A fourth-order polynomial interpolation between the PCPG parameters and the speeds provides good similarity indices between real walk and generated patterns. The values of these indices are presented for different walking speeds.

Keywords: BNCI, Electrooculography, Eye tracker, Human locomotion, PCPG, Prosthesis.

I. Introduction

Over the years, different kinds of leg prostheses have been developed in order to replace the limb that amputees have lost. The main objective of these prostheses is to allow their user to walk as naturally as possible. In fact, the complexity of human walk is such that most of the leg prostheses available on the market today use passive mechanisms. Although these systems are functional, their performance is really limited compared to a real human leg as they do not have self-propulsion capability. Unfortunately, amputees using this standard technology have to compensate for these limitations. Consequently, they generally develop various strategies which generate reduced locomotion speed, a non-natural gait, considerable fatigue and possibly harmful consequences like recurrent pain and injuries at the interface between their residual limb and the prosthesis. Active prostheses solve these problems partially: powered by a battery-operated motor, they move on their own and therefore reduce the fatigue of the amputees while improving their posture. Two main categories of active prostheses exist to date: firstly, devices controlled according to the motion of other healthy parts of the body and secondly, devices equipped with a myoelectric control system. In the first category, sensors are placed on the healthy leg of the amputee. By analyzing the motion of the leg with a sophisticated algorithm, the control system can identify the phase of the gait cycle and trigger an actuator to appropriately adjust one or more prosthetic or orthotic joints [1], [2], [3]. Instead of exploiting the motion of the healthy leg of the amputee, other systems analyze upper-body motions to trigger and maintain walking patterns [4]. The second type of active prostheses (or orthoses) is controlled by myoelectric signals recorded at the surface of the skin, just above the muscles. These signals are then used to guide the movement of the artificial limb [5], [6], [7].

The improvement brought by the active prosthetic technology with respect to conventional prostheses is indisputable. However, several aspects still need to be improved. For instance, an intuitive interface from which user's intent can be determined is still missing. Additionally, no sensory feedback is provided to the user. Active research is being carried out in these two latter areas, in particular for arm and hand prostheses. Complex nerve surgery techniques are being developed as well as new signal processing algorithms and new electrodes, in order to connect an amputee to an artificial limb that he can control intuitively with his own residual nerves and muscles [8]. Maybe one day amputees will have the opportunity to fully recover human mobility and perception, but paying the price of an important and risky surgery. Thus more simple systems taking into account the user's intent are desirable in the meanwhile.

Recent researches in the field of Brain-Computer Interfaces (BCI) based on EEG signals have considerably increased the performances of such systems [9]. By definition, a BCI is a device that enables communication without movement. For a few years, research has allowed the integration of such BCIs in games, to augment interactivity of healthy users. BCI technology has also offered new communication possibilities to severely disabled people, by enabling them to move their mouse or type an email just by thought. The non-invasiveness of EEG signals represents the major advantage of this technology. However, EEG signals are known to be very noisy implying a very low Signal-to-Noise Ratio (SNR) and, consequently, a low information transfer rate. This low bit-rate leads to the impossibility to send complex commands and the users are rather limited to very high-level commands. Also, the consequence of this low quality signal is the slowness and the lack of reliability of some BCI-based applications [10].
Because of this restriction to high-level commands, systems have to be developed to consider all the low-level problems. This concept is used in robotics and is called shared control [9]. In this case, both an intelligent system and a human operator are in control of a device. The aim of this system is to provide assistance to the user, especially when the user can not do with his abilities or with his command capabilities. Typically, with high-level commands, a lower limb prosthesis can not be entirely controlled. The prosthesis has to generate a kind of standard pattern of walk whose frequency and amplitude will be driven by the user. This prosthesis could also manage obstacles and correct loss of balance. Shared control has been successfully applied in several applications based on EEG signals: an asynchronous wheelchair control [11], a walking robot [12] and a hand grasping system [13].
To control the wheelchair, the patient had to modulate his EEG signals by creating three different mental states (imagination of a left hand movement, word associations and relaxation) leading to three commands (turn left, turn right and move forward). To control the walking robot, a P300 paradigm generated high-level commands and the robot executed all the low-level commands needed to accomplish the actions. Finally, hand grasping was made possible thanks to functional electrical stimulation and detection of foot movement imagery in the EEG signal which activates the correct phase of the process (i.e. grasping and releasing an object).

For decades, neuroscientists have studied the brain activity related to movements. They have shown that precise movements like grasping are directly controlled by the brain [14]. In recent experiments with monkeys, it was demonstrated that a mathematical link exists between reaching and grasping movement characteristics (direction, speed) and the electrical signals recorded by electrodes implanted in the motor cortex [15].
It is now established that locomotion differs from this scheme and is actually governed by a hierarchical system [14]. At the lowest level of this system are found the Central Pattern Generators (CPGs). Studies with cats have revealed that their gait is generated by those CPGs which are located in the spinal cord. A CPG is composed of motoneurons linked together that can generate periodic patterns whose frequencies are controlled by the brain. To prove this concept, scientists have sent impulsive periodic signals in a specific area in the brain stem called Mesencephalic Locomotor Region (MLR) [16]. They found that the frequency of this stimulation signal determined the speed of cat's walk. By increasing the stimulation frequency, they could even make the cat trotting instead of walking.
This mechanism has inspired the field of robotics, particularly in the development of small autonomous walking robots and prostheses [17]. One of the algorithms developed in this framework is called Programmable Central Pattern Generator (PCPG) [18]. A PCPG algorithm is able to generate any periodic pattern after a learning step. The interest of such a system lies in the controllable aspect of the learned parameters. Actually, the pattern magnitude and frequency are easily adjustable. A modification of one of these parameters will lead to a smooth transition of the PCPG output. This is a particularly interesting feature, which is especially important for prosthesis applications and their actuators.

In this framework, this paper presents preliminary results about modeling human walk by a PCPG in order to control a prosthesis by high-level commands. In Section 2, the bases of Programmable Central Pattern Generators to learn a standard pattern and to generate patterns at the wanted speed are presented. In Section 3, results for one subject are exposed.

II. PCPG DESCRIPTION

For the last two decades, models of Central Pattern Generators (CPGs) have been increasingly used to control the locomotion of autonomous robots, from multi-legged insect-like robots to humanoids [16]. Indeed, locomotion is a quasi-periodical phenomenon and it can be modeled by using such systems of coupled nonlinear oscillators. Interestingly, different gaits of animals could be simulated and reproduced with diverse walking robots. Contrary to usual CPG oscillators, the learning of Programmable Central Pattern Generators (PCPGs) is very easy and avoids challenging and heavy parametrization. Furthermore, this oscillating system is able to change the frequency and magnitude of any given periodic walking pattern it has learned in a smooth way and is robust to noise and to perturbations [18].

A PCPG is a kind of Fourier series decomposition and is composed of several adaptive oscillators. This algorithm is governed by the following equation system:

$$\begin{cases} \dot{x}_i = \gamma(\mu - r_i^2)x_i - \omega_i y_i + \epsilon F(t) + \tau sin(R_i - \phi) & (1) \\ \dot{y}_i = \gamma(\mu - r_i^2)y_i + \omega_i y_i & (2) \\ \dot{\omega}_i = -\epsilon F(t)\frac{y_i}{r_i} & (3) \\ \dot{\alpha}_i = \eta x_i F(t) & (4) \\ \dot{\phi}_0 = 0 & (5) \\ \dot{\phi}_i = sin(R_i - sgn(x_i)cos^{-1}(-\frac{y_i}{r_i}) - \phi_i), \forall i \neq 0 & (6) \end{cases}$$

with

$$R_i = \frac{\omega_i}{\omega_0} sgn(x_0) cos^{-1}(-\frac{y_0}{r_0}) \quad (7)$$

and

$$F(t) = P_{teach}(t) - \sum_{i=0}^{N} \alpha_i x_i \quad (8)$$

As depicted in Figure 1, oscillators are coupled between each other compared to an origin phase based on the R_i coupling parameters derived from the phase information ϕ_i. They are composed of adaptive magnitude coefficients α_i and frequency parameters ω_i ($r_i = (x_i^2 + y_i^2)^{\frac{1}{2}}$). μ has a role of normalization of the learned pattern. The other parameters γ, ϵ, τ aim at accelerating the convergence while limiting stability problems. The $Q_{learned}(t)$ signal resulting from the sum of oscillator outputs is compared to the $P_{learned}(t)$ walking pattern target and the error value $F(t)$ is computed. Throughout the learning step, all the parameters of the PCPG are modified in order to minimize $F(t)$. When this learning step is finished, $F(t)$ is close to zero and the system is generating the right pattern at the $Q_{learned}(t)$ output.

Properties of PCPGs make them suitable for trajectory generation in robotics and also for prosthesis applications. In fact, the pattern learned by a PCPG can be easily controlled in magnitude and in frequency thanks to a simple linear change of the $\vec{\omega}$ and $\vec{\alpha}$ vectors representing the $\Re^N$ PCPG states (N is the number of oscillators). This linearity leads to a smooth change of the global system behavior. Figure 3 depicts the various modifications relevant for prosthesis control purposes. For instance, if the $\vec{\omega}$ vector is divided by two, the underlying frequency of the standard temporal pattern is divided by two. The same effect occurs for the $\vec{\alpha}$ vector.

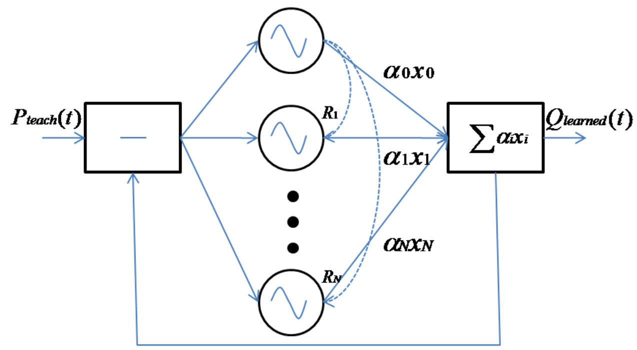

Fig. 1: The PCPG is able to learn the frequency components of a periodic signal as well as the various phases and magnitudes. The main interest of PCPGs is the possibility to modify a learned pattern in amplitude or frequency in a smooth way. This Figure is inspired from [18].

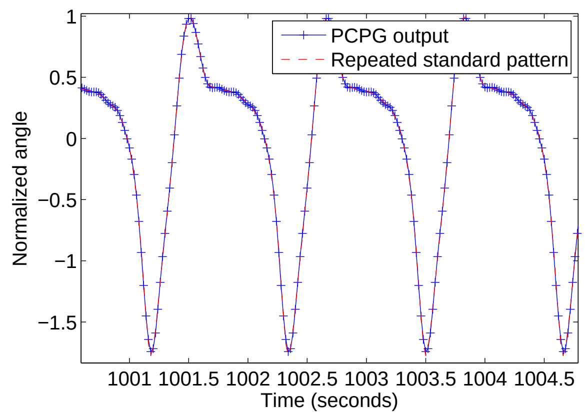

Fig. 2: The PCPG is able to learn perfectly a standard pattern of walk by means of 7 oscillators.

III. Human walk modeled by a PCPG

In this section, we demonstrate that human walk can be learned by a PCPG and subsequently generated at different walking speeds. This aims at controlling a foot elevator orthosis useful for people affected by strokes and who are unable to elevate their feet. This system is shown in Figure 6.

In order to train the PCPG, three standard walking patterns were used. These temporal patterns consist of the angle of elevation of the foot, the thigh and the shank of a healthy subject walking on a treadmill at 3 km/h, a typically medium speed for humans. The elevation angles were computed using the positions of 23 passive markers disposed on the subject, determined thanks to six Infrared Bonita Vicon cameras.
The standard walking patterns were obtained by averaging about 50 walking cycles, determined and synchronized by a peak detection algorithm able to locate all the relevant

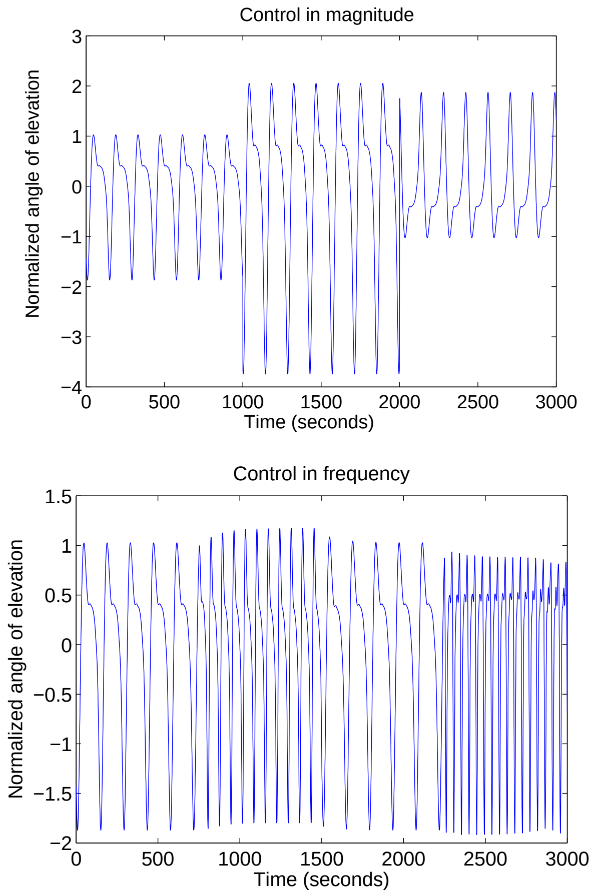

Fig. 3: The output of the PCPG can be controlled in magnitude (top) and/or in frequency (bottom) in a smooth way.

maxima and minima angle values of the kinematics recordings as depicted in Figure 4. Here, the patterns were synchronized by the maxima because of a clearer peak. The kinematics data were recorded for each leg during 60 seconds at 100 Hz. Each standard pattern is thus a kind of average pattern along the 60-second recordings. After determining these standard patterns, the PCPG was trained using the procedure described in [18]. Figure 2 shows how well the PCPG is able to reproduce the standard pattern of the foot elevation angle using 7 oscillators.

What is proposed in this paper is to generate walking patterns with the PCPG in a way differing from the bipedal robots described in the literature which consists in walking so far as possible without taking into account the potential patient itself. Indeed, one of the main goals in prosthetics is to provide the user with the most comfortable walk possible. Therefore, at each step, the pattern should be adapted in terms of frequency and magnitude, i.e. respectively the stepping frequency and stride-related length between two heel strikes whatever the walking

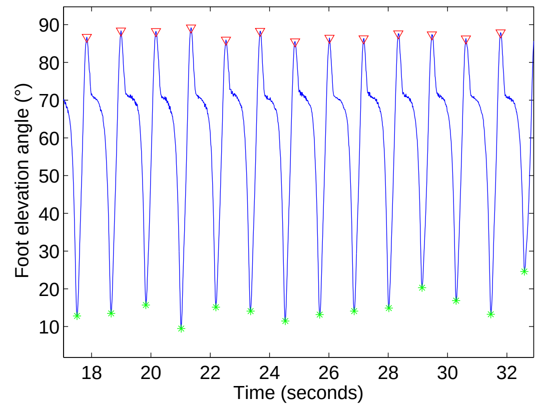

Fig. 4: Local maxima and minima allow synchronization while averaging walking cycle. In this study, the maxima are used.

speed. Kinematics data were thus recorded with the same subject and apparatus for 10 different speeds, from 1.5 to 6 km/h, by step of 0.5 km/h. The normalized and centered pattern learned by the PCPG for the speed of 3 km/h and generated for all the other speeds were manually calibrated (by tuning the magnitude and frequency parameters) in order to fit the standard walking patterns of all speeds. By this procedure, we found a mathematical link between the PCPG amplitude and frequency parameters (the $\vec{\alpha}$ and $\vec{\omega}$ vectors) as a function of the walking speed. This link was established by computing a fourth-order polynomial interpolation function at the least mean square sense. Figure 5 shows results obtained for one subject. One can notice that the subject increases his walking speed at first by extending his stride length, and then by increasing his stepping frequency. This confirms results described in [19]. It has to be emphasized that this interpolation can be computed specifically for any subject, increasing therefore the precision and adequacy of the prosthesis control at each step.
Moreover, as BCI is far from working perfectly, a confidence level of the command could be derived and integrated in the speed parameter change. Considering that an *accelerate* command increases the actual speed of 0.5 km/h by default, if the decision is uncertain, e.g. reliable at 75 %, 75 % of the speed increase can be actually performed thanks to the parameter interpolation.

To prove the relevancy of this approach, a Similarity Index (SI) was assessed between the PCPG output $f_1(t)$ at the right speed with the exact parameters and the standard walking pattern $f_2(t)$ at each speed to show the true potential of this method. This index is defined as:

$$SI = \frac{\int_{-\frac{T}{2}}^{\frac{T}{2}} f_1(t) f_2(t)\,\mathrm{d}t}{\left(\int_{-\frac{T}{2}}^{\frac{T}{2}} f_1(t)^2\,\mathrm{d}t \int_{-\frac{T}{2}}^{\frac{T}{2}} f_2(t)^2\,\mathrm{d}t\right)^{\frac{1}{2}}} \tag{9}$$

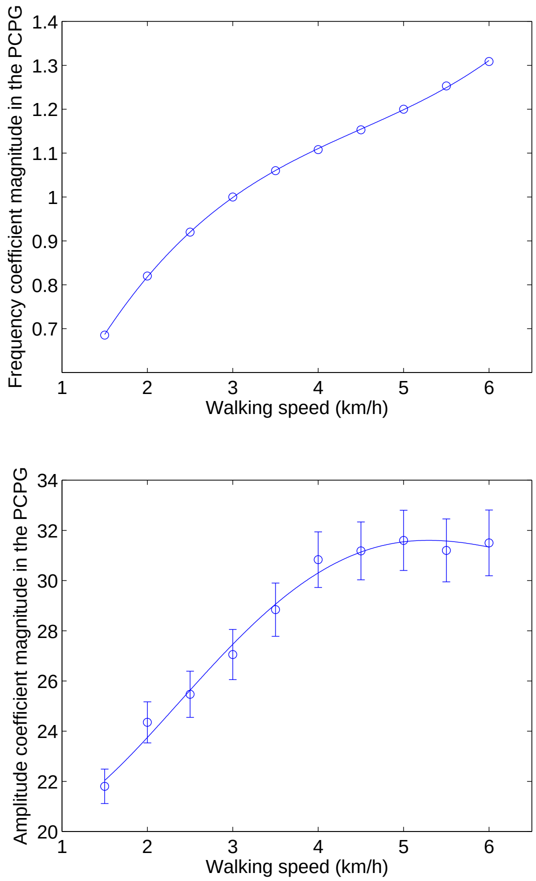

Fig. 5: Evolution of the foot pattern frequency (top) and amplitude (bottom) as a function of the walking speed. The interpolation is performed for 10 walking speeds with a 4th-order polynomial function. Error bars in amplitude show the high magnitude variability of each gait cycle. Similar results are derived from the shank and thigh patterns.

where T is the period of the limit cycle, $f_1(t)$ and $f_2(t)$ being synchronized at the origin. Note that if both functions are identical, $SI = 1$.

Those indices computed over all recorded speeds and depicted in Figure 7 show a logical degradation while keeping away from the PCPG learned speed. However, the dissimilarity is not so important and SI values never drop below 93 %.

An alternative to improve this procedure which relies on a single PCPG could be to manage a multi-PCPG system; each PCPG will model a typical range of speeds, e.g. 0.5-2 km/h where SI are sufficiently high compared to the level of requirements. The merging of those PCPGs would be used to model as perfectly as possible real walk while making the change of PCPG as smoothed as possible.

Fig. 6: Foot elevator orthosis aims at elevating the foot after the toe off.

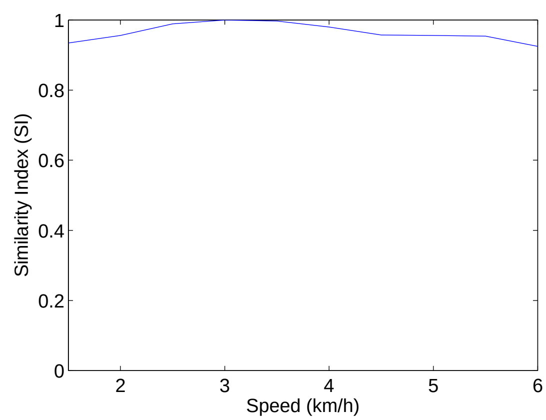

Fig. 7: Similarity indices show that further the generated speed is from the learned speed, the worse is the result although, globally, the results are always good.

IV. Conclusion and Future Work

In this paper, a way to model human walk to drive a lower limb prosthesis given a Brain-Computer Interface output is explained. Considering high-level commands provided by the BCI and after learning average walking patterns (angles of elevation of the different parts of the leg as a function of time), a PCPG provides an adaptive kinematics output to drive the artificial limb, according to the walking speed desired by the user. Unlike current sophisticated active prostheses, the user's intent is fully taken into account in this case.

It is demonstrated that a PCPG is able to learn almost perfectly average human walk patterns. Moreover, it is shown that a four-degree polynomial function can model the evolution of the PCPG parameters as a function of the walking speed. This interpolation enables to drive the prosthesis in a smooth way during accelerations or decelerations, increasing thus the comfort of the patient. This also paves the way to integrate a confidence level of the high-level command. If the command is uncertain, a smaller gap in speed is actually performed than in the certain case.

Future work will be dedicated to extend this study to a larger group of subjects. Another work will be to create a multiple PCPG-based walk modeling. This system could be composed of several PCPGs able to model walk around a central speed. For example, one PCPG will model low speeds, middle speeds, high speeds or running speeds. An important verification will be to ensure the smooh speed change of the PCPG output.

ACKNOWLEDGMENTS

M. Duvinage is a FNRS (Fonds National de la Recherche Scientifique) Research Fellow. The authors thank Rene Jimenez from the MRDV department of the University of Mons for the picture of the orthosis.
This paper presents research results of the Belgian Network DYSCO (Dynamical Systems, Control, and Optimization), funded by the Interuniversity Attraction Poles Programme, initiated by the Belgian State, Science Policy Office. The scientific responsibility rests with its author(s).

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