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 subject's intention.

This paper aims at showing a summary of our current results in the field of human gait rehabilitation. In a first prototype, the main focus was on people suffering from foot drop problems, i.e. people who are unable to lift their feet. However, current work is focusing on a full active ankle orthosis.

The approach is threefold: a BCI system, a gait model and an orthosis. Thanks to the BCI system, patients are able to generate high-level commands. Typically, a command could represent a speed modification. Then, a gait model based on a programmable central pattern generator is used to generate the adequate kinematics. Finally, the orthosis is tracking this kinematics when the foot is in the air, whereas, the orthosis is mimicking a spring when the foot is on the ground.

Keywords: BCI, Eye Movements, Foot Drop, Human Locomotion, PCPG, Phase-resetting, Prosthesis, Stroke.

I. Introduction

Over the years, different kinds of leg prostheses have been developed in order to replace the limb that amputees have lost [1]. 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 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 [2]–[4]. Instead of exploiting the motion of the healthy leg of the amputee, other systems analyze upper-body motions to trigger and maintain walking patterns [5]. In this category, the Ekso Bionics'powered exoskeleton leads a new class of electromechanical gear that will put paraplegics back on their feet and will be available on the market soon [6]. 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 [7]–[9].

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 [10]. 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 [11]. 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 (in addition to the high temporal resolution and the relative low-cost). However, EEG signals

are known to be noisy implying a low Signal-to-Noise Ratio (SNR) and, consequently, a low Information Transfer Rate (ITR). It has been recently demonstrated that an ITR of more than 50 bits/min can be reached by using an SSVEP-based BCI [12]. Although encouraging, this value is still insufficient to send complex commands limiting the users to high-level commands. Moreover, controlling in a continuous way with this paradigm will result in an exhausting cognitive overload.
To improve the performance of current standard BCIs, Brain-Neuronal Computer Interfaces (BNCIs) interfaces have been proposed. Unlike BCI's, BNCI's rely on indirect measures of brain activity characterized by a better SNR, and thus, a more reliable and faster interaction. Thereby, sensors reflecting activity from the eyes (EOG), heart (ECG) or muscles (EMG) are used as inputs [13]. These concepts have been widely used in rehabilitation/assistive technologies. The most famous application of EMG signals is the control of a hand prosthesis using residual arm muscle activity. This concept is intensively used by the Touch Bionics company (Livingston, Scotland, UK) for hand prostheses. EOG signal has also been widely used for wheelchair control [14] and was recently proposed as a potential way of controlling an orthosis [15]. However, high-level commands are still required.

Because of this restriction, systems have to be developed to consider all the low-level problems. This approach, widely used in robotics, is called shared control, which can be considered as a complementary control of a device from an intelligent system and a human operator [11]. The aim of this system is to provide assistance to users with limited abilities. Typically, with high-level commands only, 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 high-level command. 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 [16], a walking robot [17] and a hand grasping system [18]. 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 needed commands. Finally, hand grasping was made possible thanks to functional electrical stimulation and detection of foot movement imagery in the EEG signal which activate the correct phase of the process (i.e. grasping and releasing an object).

It is now established, at least for animals, that locomotion is governed by a hierarchical system [19]. 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. This mechanism has inspired the field of robotics and could be used for shared control. One of the algorithms developed in this framework is called a Programmable Central Pattern Generator (PCPG) [20]. A PCPG algorithm is able to generate any periodic pattern after an easy learning step compared to the vast majority of other approaches [21]. The interest of such a system lies in the controllable aspect of the learned parameters. Actually, the pattern magnitude and frequency are easily adjustable. Moreover, a modification of one of these parameters will lead to a smooth transition of the PCPG output in real-time. This is a particularly interesting feature for prosthesis applications and their actuators.

In this review of our work, a first prototype is focused on the control of a foot lifter orthosis useful for people affected by strokes and who are unable to elevate their feet (a brief description of our current development for a full active ankle orthosis is also tackled). In Section 2, the bases of BCI/BNCI interfaces and preliminary results are provided. In Section 3, a gait model based on a PCPG, which is properly defined, is proposed and results are summarized. In Section 4, the orthosis design is detailed and some phase resetting methods are given in order to synchronize the orthosis to the actual movement.

II. BCI/BNCI DESCRIPTION

In this section, the standard BCI approach is exposed as well as a brief introduction to the different BCI paradigms. A short introduction to BNCIs is also provided. Then, preliminary results of a P300 interface under ambulatory conditions are given. Finally, future work are mentioned. This section is inspired from [13], [22], [23].

A. BCI/BNCI Interfaces

As depicted in Figure 1, several main steps are considered when using a BCI: mental event/intention, signal acquisition, preprocessing, feature extraction, pattern recognition, post-processing, control of the device and feedback to the user.
First, the subject has to generate the adequate brain activity corresponding to the used BCI paradigm. Secondly, ElectroEncephalography (EEG) signal is acquired using dry or wet electrodes. Wet electrodes are mostly preferred for a precise analysis because of a lower impedance. But, from a user point of view, dry electrodes are obviously more convenient for a daily use. Thirdly, a preprocessing is applied to the data in order to magnify at best the brain activity the system has to detect. Main tools of this step are temporal and spatial filters, independent/principal component analysis and envelope averaging. Fourthly, the feature extraction step tries to summarize at best the relevant information in the preprocessed data. This typically results in a feature vector used for classification in a next step. From the classifier decision, and after some post-processing on the decision, the high-level command is sent to the device. By applying the so-called shared control, the device will operate all the low level commands corresponding to the detected subject's intent, which often provides the feedback to the user.

To consider the user's intent in the mental event/intention step, current non-invasive BCIs based on EEG have two different approaches using either evoked potentials or spontaneous

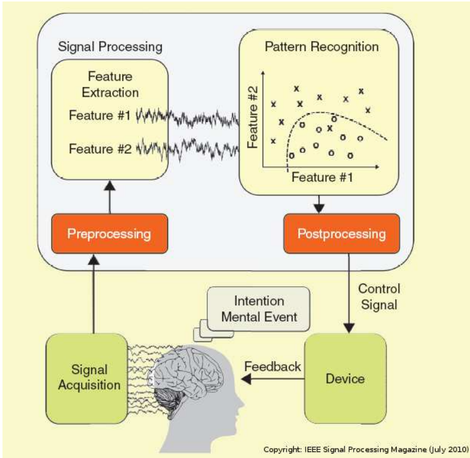

Fig. 1: This Figure shows the main steps of a BCI application: mental event/intention, signal acquisition, preprocessing, feature extraction, pattern recognition, postprocessing, control of the device and feedback to the user [24].

signal. The former one is generated unconsciously by the subject when he perceives a specific external stimulus, such as the P300 and the Steady-State Evoked Potential (SSEP). The P300 evoked potential is a potential elicited 300 ms after a rare and relevant stimulus, visual [25] or auditory [26], which appears, for example, when the traffic lights are turning from the red to the green. The SSEP is a periodic brain potential that occurs when the subject is perceiving a periodic stimulus such as a visual flickering picture (SSVEP) [27], a sound modulated in amplitude (Auditory SSEP) [28], or vibrations provided by a tactor (Somatosensory SSEP) [29].
The spontaneous BCIs can be spontaneously produced. Amongst this type of paradigm, motor and sensorimotor rhythms and slow cortical potentials have been widely used. Typically, μ (8-13 Hz) and β (13-30 Hz) rhythm magnitudes are related to motor actions, such as foot movements or motor imagery and can be controlled voluntarily [30], or by performing specific tasks [31]. Increase/Decrease of those magnitudes are defined as Event-Related Synchronization (ERS)/Event-Related Desynchronization (ERD), which can be easily detected by an envelope detection. On the other hand, Slow Cortical Potentials (SCP) are slow modifications (positive or negative) of cortical activity, which can last from hundreds of milliseconds to several seconds [32]. These potentials can be voluntarily generated after a several-month training.

As an alternative to obtain a fast and reliable interaction, a BNCI interface based on eye movement detection thanks to EOG signals was proposed [13]. Actually, in the case of severely disabled people, eye movements are often one of the last means of communication. This is why researchers have tried to interpret eye movements. Although different methods exist to track the eye movements (special contact lenses, infrared light reflections measured with video cameras), electrooculography (EOG) with simple electrodes around the eyes, as shown in Figure 2, is the most portable and the cheapest technology [33]. Because the electrodes measure the resting potential generated by the positive cornea (front of the eye) and negative retina (back of the eye), it is possible to detect when, how much and in which direction the eye rotates.
Given the huge interest of such EOG-based assistive technologies, some hardware solutions have been proposed. Figure 2 shows the current most close to market hardware system in terms of design and portability, detailed in [33]. This self-contained wearable device consists of goggles with dry electrodes integrated into the frame and a small pocket-worn component with a DSP for real-time EOG signal processing. It has two accelerometers and one light sensor for compensating EOG signal artifacts caused by physical activity and changes in ambient light. It can stream processed EOG signals to a remote device over Bluetooth to command other systems.

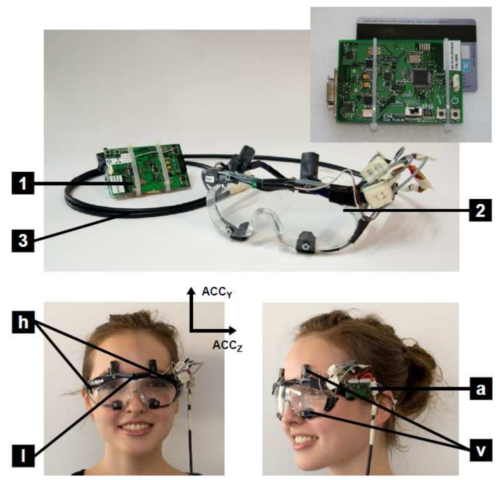

Fig. 2: There are several components in the EOG-based wearable eye tracker: the DSP (1), the Goggles (2) and the shielded core cable (3). The pictures at the bottom show the Goggles worn by a person with the positions of the two horizontal (h) and vertical (v) dry electrodes, the light sensor (l) and the accelerometer (a) with direction of its axes (ACC_Y, ACC_Z). [33]

In order to control an external device, a succession of quick and specific eye movements can activate high-level commands. Actually, the direction of eye movements can be provided in quasi real-time, which can be labeled as left, right, up or down. As advised by [33], the most efficient algorithm to detect eye movement sequences is to use the edit (or Levenshtein) distance. The Levenshtein distance between two given strings is defined as the number of deletions, insertions and substitutions required to transform one of them into the other one. In this case, the string is built by the concatenation of each labeled state of the eyes (e.g. a left-right movement would be a LR string).
To avoid interferences with natural eye movements, the interface can take advantage of the high speed of eye movements and eyeblinks/winks. By winking or blinking, the user could quickly activate or deactivate a high-level command generation environment in which eye movement sequences would be detected. After the patient has completed the speed modification, he closes the command generation environment and eye movements are no more recognized. Moreover, following this approach, emergency stop is easily implementable.

B. P300 Results

Using a P300 paradigm, the most common application is the P300 speller [34]. In this text editor, a 6 x 6 matrix, that includes all the alphabet letters as well as other symbols, is presented to the user on a computer screen. In a trial, the detection of the target letter/symbol is done after several sequences of intensifications where each row/column is randomly flashed in such a way that P300 responses can be used to detect the assumed target.

Based on this approach, it was proposed to control an orthosis using a four-speed BCI plus a non-control state, i.e. which does not modify the orthosis speed [22]. As depicted in Figure 3, the screen was composed of two rows and two columns representing Low- (L), Medium- (M) and High-speeds (H) and the Stop (S) states that could respectively correspond to 1.5, 3, 4.5 km/h and the standing state.
Because this BCI paradigm needs an external screen, it is mostly applied in sitting conditions. This solution is not envisageable under ambulatory conditions. Hopefully, an emerging and well-designed augmented reality eyewear (Vuzix, Rochester, NY, USA) could circumvent this problem by displaying stimuli on a semi-transparent module.

Fig. 3: P300 visualization is divided into four states: Low-speed, Medium-speed, High-speed and Stop. A fifth state is detected by the system when the user is not looking at the screen.

Providing the standard 32-EEG signals downsampled at 32 Hz from an ANT acquisition system (Advanced Neuro Technology, Enschede, The Netherlands) with left ear as reference, the pipeline is composed of several main components: a temporal high-pass filter, an xDAWN-based spatial filter [35], an epoch averaging and an LDA classifier using a voting rule for the final decision sent to a VRPN server [36].
The frequency band of interest was obtained by high-pass filtering the EEG signals at a 1 Hz cutoff frequency through a 4th order Butterworth filter. Thus, after the downsampling, the undesired slow drift in the measurement and high-frequency noise such as power line interference are removed [37].
Afterwards, an xDawn-based spatial filter is designed [35]. By linearly combining EEG channels, this algorithm defines a P300 subspace. When projecting EEG signals into this 3-dimension subspace, P300 detection is enhanced.
Then, the resulting signal is epoched using a time window of 600 ms starting immediately after the stimulus. Groups of two epochs corresponding to a specific row/column were averaged. The flash, no flash and inter-repetition duration are respectively 0.2 s, 0.1 s and 1 s.
Finally, a 12-fold Linear Discriminant Analysis classifier is applied to each two-grouped averaged time windows giving a value which represents the distance to an hyperplane separating at best the target/non-target classes. For a given trial, in a voting classifier, the row/column, which has been activated is determined by summing six consecutive LDA outputs (12 repetitions) and by choosing the maximum value. The decision is sent to a VRPN server to be exploited outside of OpenVibe [36].

To compare the impact on the results due to gait, the experiment was divided into two sessions each corresponding to a specific condition: sitting and walking at 3 km/h, which is a convenient speed for subjects. To train classifiers and assess the entire system for each condition separately, each session was composed of one training set and one test set of 25 trials each (around 12 minutes each).
To allow the detection of the non-control state, two additional databases were recorded. During these recordings, the subject did not look at the screen. The first one with 10 trials combined with the training set aims at determining the threshold (by a Receiver Operating Characteristic analysis (ROC) [38]) from which the voting rule result is significant. The second one with 25 trials allows to assess the non-control state detection.
Actually, the non-control state is very important for the patient's comfort and needs a specific design. When the patient is not looking at the screen because he does not want to modify the speed, the system should detect this non-control state quite precisely to avoid continuous re-adjustments of the BCI system. Therefore, a threshold on the classifier confidence indicator was determined by a ROC analysis with a very low False Positive Rate (FPR=1%), i.e. the number of non-target elements classified as target ones divided by the total number of non-target. Then, the system was assessed on the test set and on the second non-control set.

Four male subjects participated in this experiment with age between 24 and 33 years old (27.7$\pm$4.11). During the experiment, a 20-inch screen was placed at about 1.5 meter in front of the subject. Subjects were healthy and did not have any known locomotion-related or P300 disturbing diseases or handicap. Moreover, for this proof of concept, the orthosis was not attached to the subject but the entire chain was successfully tested by playing offline the experiment thanks to the OpenVibe software.

As exposed in [22], preliminary results show that the system is working as desired. It was shown that the system is actually performing a very low number of errors, i.e. when the user wants to modify the speed, the system does not provide a bad speed decision, and recognizes quite perfectly the non-control state. However, the price to pay is sometimes a relatively high non-decision rate, i.e. when the decision is not enough reliable, the system does not make a decision to avoid potential errors and laborious re-adjustments. Obviously, this leads to some perturbations when the speed has to be changed and the patient has to focus again on the BCI interface.

Although interesting, this approach has some limitations. Firstly, the decision time is quite slow for real-time applications even if it can be improved by implementing better and more complex pipelines as well as a better management of flash, no-flash and inter-repetition duration, of the number of trials and of the classifier choice. As reported in [39], a P300 system with a dozen of items can reach an accuracy of 95 % for a time of decision between 10-20 seconds in sitting condition. Under ambulatory conditions, although *a priori*, it is assumed that results can be improved by applying specific gait-related artifact removal techniques, artifacts seem to be non-problematic in a low-speed and/or low complexity embedded framework [23], [40].
Secondly, the current implementation of the pipeline does not allow to work in an asynchronous way, which is an important feature for the patient's comfort and safety and should be investigated for future work [41], [42].
Finally, the impact of a kind of VUZIX augmented reality eyewear has to be assessed for a real application.

C. Future Work

The feedback will be the main point of BCI/BNCI future work. Actually, we are currently able to control the speed of the treadmill according to the detected high-level command. What we intend to do is to study the subjective feedback of the user using this commendable treadmill thanks to questionnaires. Usability and cognitive workload can be assessed by the System Usability Scale and NASA Task Load questionnaires [43].
Another future work will be to assess other BCI/BNCI pipelines. Typically, SSVEP and EOG based systems will be compared to the P300 approach using the subjectivity of subjects/patients to determine the most suitable option.

III. Shared Control By A PCPG

This section describes the PCPG itself and its abilities. A special focus is on the coupling between several PCPGs, e.g. between foot, shank and thigh angles of elevation. Then, results of gait modeling on seven healthy subjects are depicted. Finally, some future works are pointed out.

A. PCPG Definition and Properties

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:

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

with

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

and

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

As depicted in Figure 4, 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 $P_{teach}(t)$ 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.

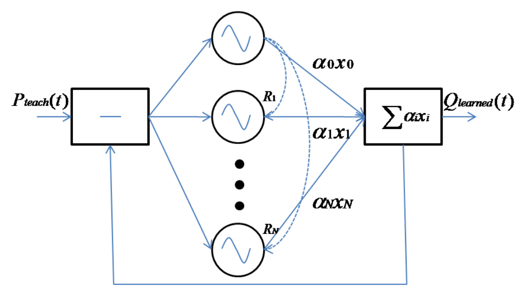

Fig. 4: The PCPG is able to learn the frequency components of a periodic signal as well as the various phases and magnitudes. The main interest of PCPGs is the possibility to modify a learned pattern in amplitude or frequency in a smooth way. This Figure is inspired from [20].

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. 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.

Finally, as proposed in [44], it is possible to couple several PCPGs to model different angles of elevation. This is performed thanks to equations of coupling between the fundamental oscillators of each PCPG and by learning the phase difference:

$$\begin{cases} \dot{x}_{0,k} = \gamma(\mu - r_{0,k}^2)x_{0,k} - \omega_{0,k}y_{0,k} \\ \qquad + \tau sin(R_{0,k-1} - \phi_{0,k}) & (9) \\ \dot{\phi}_{0,k} = sin(R_{0,k-1} - R_{0,k} - \phi_{0,k}) & (10) \end{cases}$$

where $(0, k)$ denotes the first oscillator of the kth PCPG (frequencies of different angles are the same).

B. ***Human gait modeled by a PCPG***

In order to train the PCPG, one standard (average) walking pattern over a gait cycle was used. This temporal pattern consists of the angle of elevation of the foot of seven healthy subjects walking on a treadmill at 3 km/h, a typically medium speed for humans. Actually, this angle was studied for two reasons: this is the most complicated angle variation of human gait and the focus in this paper is on the development of an active foot lifter. The elevation angles were computed using the positions of 23 passive markers disposed on the subject, determined thanks to six Infrared Bonita Vicon cameras.

This standard walking pattern was obtained by averaging about 50 walking cycles, determined and synchronized by a peak detection algorithm able to locate all the relevant maxima and minima angle values of the kinematics recordings as depicted in Figure 6. Here, the gait cycle patterns were synchronized with the maxima due to clearer peaks and to their proximity with the heel strike, when the heel is touching the ground (which is often considered as the gait cycle beginning). The kinematics data were recorded for each leg during 60 seconds at 100 Hz. This standard pattern is thus a kind of average pattern along the 60-second recordings. Then, the PCPG was trained using the procedure described in [20]. Figure 5 shows how well the PCPG is able to reproduce the standard pattern of the foot elevation angle using 7 oscillators.

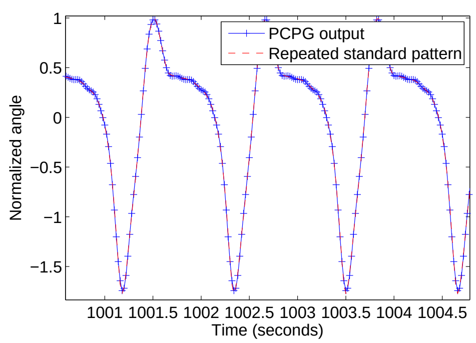

Fig. 5: The PCPG is able to learn perfectly a standard pattern of walk by means of 7 oscillators.

What is proposed is to generate walking patterns with the PCPG in a way differing from the bipedal robots described in the literature which consists in walking as 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 speed. Kinematics data were thus recorded with seven healthy subjects for 10 different speeds, from 1.5 to 6 km/h, by step of 0.5 km/h. The normalized and centered patterns 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.

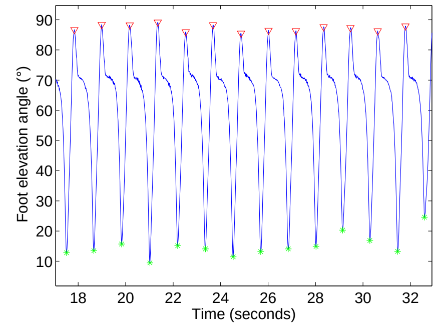

Fig. 6: Local maxima and minima allow synchronization while averaging walking cycle. In this study, the maxima are used because of a clearer peak and due to its proximity with the heel strike.

Obviously, this procedure cannot be directly used with amputees or a paraplegics. As mentioned in [45], a series of standard patterns ranked by age, weight, height, etc. can be used for the amputee depending on these parameters. Another simple approach is to record as soon as possible kinematics data for population at risk such as soldiers.

By doing this, we found a simple mathematical link between the PCPG amplitude and frequency parameters (respectively, the $\vec{\alpha}$ and $\vec{\omega}$ vectors) as a function of the walking speed. This link was established by computing a relatively low-order polynomial interpolation function at the least mean square sense as indicated in Table I. Figure 7 shows results obtained for one specific 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. Globally, this confirms results described in [46]. 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. In fact, this interpolation can be considered as reliable given the relatively low-order polynomials and the smoothed transitions between parameters of successive speeds.

TABLE I: The orders of the polynomial interpolation are quite low except for subject 2. For this subject, a strange behavior in frequency was observed, i.e. the frequency first decreases and then increases while speed is increasing.

Order	Magnitude	Frequency
Subject 1	4	3
Subject 2	4	8
Subject 3	4	5
Subject 4	5	3
Subject 5	4	3
Subject 6	4	4
Subject 7	3	3

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.

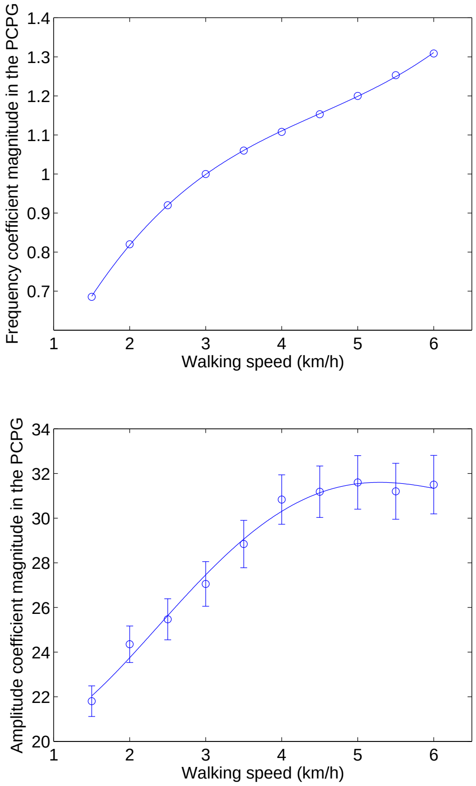

Fig. 7: Evolution of the foot pattern frequency (top) and amplitude (bottom) as a function of the walking speed for a specific subject. The interpolation is performed for 10 walking speeds with a 4th-order polynomial function. Error bars in amplitude show the high magnitude variability of each gait cycle. Similar results are derived from the other subjects.

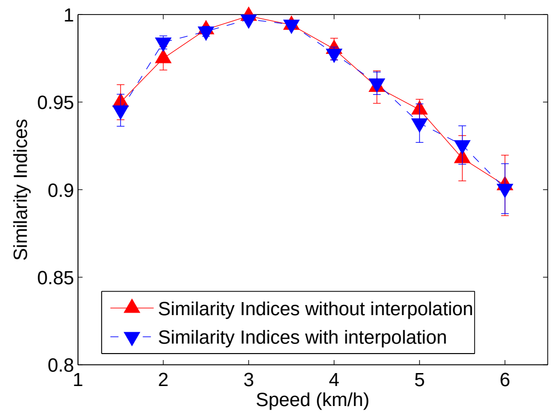

Fig. 8: The difference between SI values obtained with and without the interpolation is not significant. Error bars are standard errors.

To prove the relevancy of this approach in an objective way, 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:

$$SI = \frac{\int_{-\frac{T}{2}}^{\frac{T}{2}} f_1(t) f_2(t)\, \mathrm{d}t}{(\int_{-\frac{T}{2}}^{\frac{T}{2}} f_1(t)^2\, \mathrm{d}t \int_{-\frac{T}{2}}^{\frac{T}{2}} f_2(t)^2\, \mathrm{d}t)^{\frac{1}{2}}} \tag{11}$$

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, $SI = 1$.

For the seven subjects, similarity indices were computed with and without interpolation. Globally, SI values without interpolation are very good but show a logical degradation for speeds differing more and more from the PCPG learned speed as shown in Figure 8. Regarding the interpolation, the impact of the dissimilarity increase is clearly negligible.
An alternative to improve this procedure which relies on a single PCPG could be to manage a multi-PCPG system at a multi-interpolation level; each PCPG will model a typical range of speeds with its own interpolation, e.g. 0.5-2 km/h where SI are

C. Future work

The main future work about the gait modeling will be to refine it while considering relative angle, i.e. the angle needed to control the orthosis. Although the proposed scheme seems to be efficient on a large range of speeds, it is not possible to achieve the best comfort as possible without changing the standard pattern from low speeds to high speeds. Indeed, as shown in [47], across speeds, relative angle patterns are slightly modified, which is consistent with the exposed results in this study. If this phenomenon is not considered, this could result in some inconvenience.
To enhance this model, a non-linear filter could be used at the output of the PCPG. This filter would allow to modify the PCPG output waveform to fit at best standard patterns at each speed. This filter would also be required to allow smooth transitions.
Another aspect is the use of feedback. Given that this work aims at improving the patients' comfort, it is needed to get their opinion to compare different solutions.

IV. Orthosis

In this section, the specific case of a foot lifter orthosis is exposed. Firstly, some considerations about the orthosis control strategy and design in our framework are given. Then, some encountered practical problems and some contributions to resolve them are detailed. For further details, see [48].

A. Orthosis control strategy

In gait, there are mainly two events: the Heel Strike (HS) and the Toe Off (TO) for each foot. The heel strike is the time when the heel is touching the ground for the first time in the gait cycle and the toe off is the time when the foot is leaving the ground. These events divide gait into two gait phases: the stance phase, i.e. when the foot is on the ground, and the swing phase, i.e. when the foot is in the air.

Actually, people have two highly different control schemes depending on the gait phase. In the stance phase, the foot is force-controlled while during the swing phase, the foot is controlled in position. For people suffering from foot drop problems, the control in position is deficient. Therefore, the orthosis also comprises two different control modes, one for the stance phase when the subject entirely drives the orthosis and another one for the swing phase when the PCPG output governs the system.

The first passive mode, during the stance phase, allows the free motion of the foot around an equilibrium point while, at the same time, it provides a certain level of stability through a virtual stiffness element by mimicking a spring.
The second active mode is associated to the swing phase and is intended to help the patient to achieve enough foot clearance to initiate the next gait cycle. This mode can basically be considered as a trajectory tracking scheme to follow the PCPG position pattern similar to that developed by a healthy foot during the swing phase.

B. Orthosis design

In a first prototype described in [48], the orthosis is made of several components: two custom-fit plastic shells, two flexure joints, a linear actuator, a ball-link transmission, a load cell to measure the actuator force, and two force sensors installed in the orthosis sole, under the heel and the toes (not depicted in the Figure). The plastic shells were designed using a 3D scan of the right foot and leg of a healthy subject, adding mounting surfaces for the actuator, the flexure joints, and the mechanical transmission. The actuator includes a position control unit based on a PID controller that can be driven by an external analog signal in the range of 0 to 10 V.
One of the main challenges that is encountered in the development of active orthoses is the commercial actuator weight. To satisfy the mechanical requirements for developing a complete gait cycle, this weight was above 3.5 kg. For the particular case of a foot lifter orthosis, the weight is about 1.6 kg and its maximum power is around 117 W, which corresponds to a third of the peak power developed by a healthy ankle [49]. In a second prototype shown in Figure 9, a lightweight custom-fit actuator with passive energy-storage elements was developed, powerful enough for the stance phase as well. Control strategies specific to an active stance phase are explored in parallel implied by the torque-angle law of a healthy ankle during the heel strike, the flat foot and the toe off. This mainly consists in three different but similar controls mimicking a spring with different parameters.

The control and the PCPG algorithms reside in a DsPIC 30F4013 microcontroller running at 120 MHz. Both algorithms are calculated at each time step at a sampling frequency of 500 Hz but the output of one or the other is chosen according to the orthosis state, as detailed in the next section. The differential equations of the PCPG are solved by a simple explicit Euler integration method. The microcontroller manages three analog (two sole force sensors and one load cell) inputs for the signals coming from the force sensors.

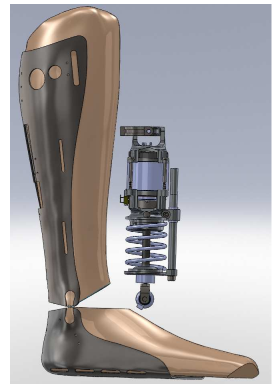

Fig. 9: The orthosis prototype is composed of several main components. The spring is used to stock energy during specific gait phases. A homemade ultra-compact actuator of around 3 kg is controlling the orthosis in a way depending on the current gait phase. Moreover, this system is suitable for an active stance phase as well.

C. Phase-resetting

As mentioned in [50] and reported in [48], at a given speed, gait cycles are not perfectly identical due to intrinsic properties of human gait and potential external perturbations. Those problems result in phase mismatch between the perfectly periodic PCPG output and the real gait pattern in addition to change in frequency. If this mismatch is too important, the subject has to compensate for it leading to a non-natural gait. Therefore, phase-resetting techniques aim at making the orthosis to adapt to the patient as quickly and smoothly as possible for the subject comfort.

Technically, as reported in [48], the phase-resetting consists in resynchronizing the PCPG state according to special events such as heel strikes.
As proposed in [48], two approaches are available: a *hard* and a *soft* phase-resetting. The hard phase-resetting relies on a direct modification of the integrated values: in each oscillator i, x_i and y_i are put to standard values corresponding to the heel strike event. The main advantage of this approach is the quick phase-locking whereas the disadvantages are (1) a more sensitive reaction to noise in the frequency estimation due to small variations in gait cycles at constant speeds or in the measurement itself and (2) important modification of the actuator state, although mitigated by the low-pass filter. In the case of a foot lifter orthosis, during the stance phase, the actuator is not commanding the system and thus, the latter disadvantage vanishes. However, it could be a real problem when a full position control, which is not advised in prosthesis/orthosis, is envisaged.
In the soft phase-resetting, in order to control the phase recovery, the first oscillator of the PCPG is coupled to an external oscillator. This oscillator is used as a reference oscillator at instantaneous phase $R_{0,r}$. This allows to modify the phase difference $\phi_{0,r}$ between the reference oscillator and the first oscillator of the PCPG.
Formally, the reference oscillator is as follows:

$$\dot{x}_{0,r} = \gamma(\mu - r_{0,r}^2)x_{0,r} - \omega_{0,r}y_{0,r} + \tau sin(R_{0,r}) \qquad (12)$$

whereas the coupling with the PCPG (subscripted by p) is shown in:

$$\dot{x}_{0,p} = \gamma(\mu - r_{0,p}^2)x_{0,p} - \omega_{0,p}y_{0,p} + \tau sin(R_{0,r}k - \phi_{0,r}) \quad (13)$$

where $k = \frac{\omega_{0,p}}{\omega_{0,r}}$. The coupling with the other oscillators of the PCPG is identical to the previous description. Because the phase of higher order oscillators had more difficulties to follow a phase change in experiments, coupling constant was defined as $\tau_i = \tau\frac{\omega_{i,p}}{\omega_{0,p}}$. In our experiments, we chose $k = 1$. Figure 10 shows how this modification can produce a smooth and robust kinematics output when a phase reset is applied.

The main advantage is the possibility to recover the phase in a smooth and thus more comfortable way if a fully-position control system is used. On the other hand, the main drawback is the difficult control of the phase recovery speed, which could potentially create some uncomfort for the patient.

D. Future Work

Future work will be dedicated to control the speed of phase recovery in the soft phase resetting in a better way while keeping the smooth aspect. A better phase resetting procedure could be to use other gait events or sensors or by combining the two types of phase-resetting. Indeed, although a force control during the stance phase allows a hard phase resetting to be used without any problems (the PCPG output is not used), this feature could be interesting for smoothly resynchronize the system in prevision of the next heel strike, just after the toe off.

From experimental data, the evaluation of metrics such as the settling time, i.e. the time the system needs to recover the phase given a certain error band, could be interesting to precisely characterize the recovery speed of soft phase-resetting. When combining both phase-resettings, the determination of the hard phase reset step distribution with and without soft phase-resetting in realistic application will make it possible to judge the relevancy of this combination to reduce the magnitude of the hard phase-resetting step.

Finally, the feedback from the patients will drive our trials to enhance the orthosis design.

V. Conclusion and Future Work

A. Conclusion

Given the huge development of Brain-Computer Interfaces, a lot of different applications devoted to handicapped people have popped up. From communication to motor substitution through wheelchair control, brain control capabilities have been enhanced for a certain type of disabled people. However, until now, lower limb prostheses have not been equipped with this technology yet due to the relatively low bitrate of such interfaces.

In this paper, a global review of our current research on how to control an orthosis based on a Brain-Computer Interface (BCI) or on a Brain-Neuronal Computer Interface (BNCI) is proposed. Contrary to most current active prostheses, a kind of direct user's intent is here considered. This paper explains the three main parts of this biologically-inspired approach: the BCI/BNCI definition, the gait modeling and the orthosis design.

The BCI/BNCI is detecting some high-level commands that the patient wants such as modifying the current speed. It has been shown on four healthy subjects that a P300 interface is feasible using four different speed states and a non-control state, i.e. a state which represents that the subject does not want to modify the current speed. Although this approach is working as desired, some limitations are still strong. Firstly, the duration to modify the speed is too long (around 20 seconds). Secondly, the system has to be used considering augmented reality eyewear for real applications. Thirdly, this approach is synchronous and the subject can not decide when to change the speed.

Then, by shared control, all the low-level operations are done by the orthosis design using a kinematics-based model. It was demonstrated that a Programmable Central Pattern Generator is able to learn quite well average human walk patterns at a given speed using angle of elevations. Then, it was shown that a low-order polynomial function can model the evolution of the PCPG parameters as a function of the walking speed in order to adapt the orthosis to the patient's kinematics in a large range of speeds. Given that this interpolation was quite smooth, this enables the integration of 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.

Finally, by integrating a spring, a more compact orthosis design has been proposed. People suffering from foot drop problems are completely able to control the foot when it is on the ground (stance phase), but they are unable to lift it when the foot is in the air (swing phase). Therefore, the orthosis control is mimicking a spring during the stance phase and is tracking the PCPG model during the swing phase. This approach can be easily extended to a complete active prosthesis given that it is force-controlled during the stance phase. On top of that, because gait is not totally periodic and that some external perturbations can occur, two phase resetting techniques were proposed to resynchronize the PCPG output and the actual movements. The soft-phase resetting is able to phase reset in a smooth way but with a difficult control of the recovery speed, whereas the hard-phase resetting is able to recover immediately the correct phase at the price of uncomfortabilities for the patient that vanish in our dual-control approach.

B. Future Work

Short-term future work will be devoted to study the system usability with an online application from a large population of patients with a series of different BCI and BNCI pipelines. Typically, SSVEP- and EOG-based interfaces will be studied from a user point of view. System Usability Scale questionnaires will be used to compare user's feedback amongst the different BCI/BNCI approaches. In order to increase the comfort of the patients, a refinement of the PCPG gait model will be proposed to fit at best slight modifications of gait patterns across speeds. For middle-term future work, to increase the comfort of the patients, we will search for a much more natural command generation system. Indeed, as reviewed in [51], recent studies showed that EEG signals could detect specific periodical gait activations and deactivations in Event-Related-Potential analyses and Event-Related-Spectral-Perturbation, although a lot of suspicions about the potential spurious conclusions due to a lack of artifact cleaning. This would undoubtedly be a

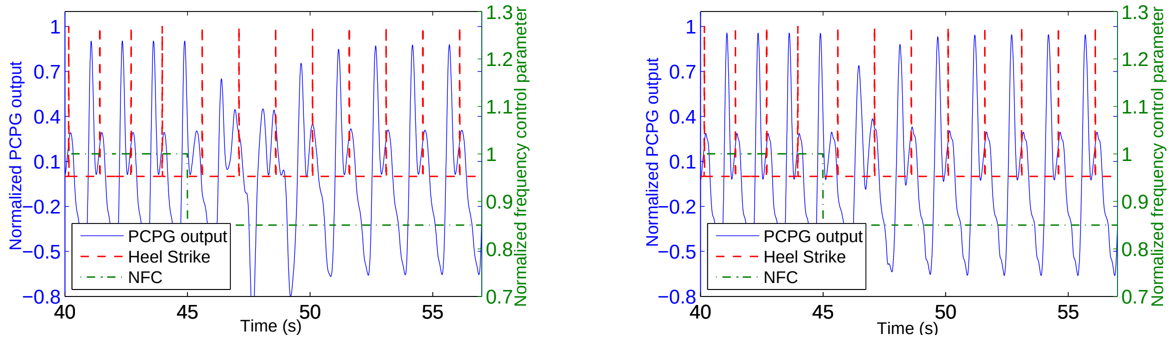

Fig. 10: On the left: without enhancements, the soft phase-resetting leads to an important and long transient. On the right: this problem is strongly mitigated.

great step in non-invasive neuroprostheses if such a frequency information or, even more important, a phase information could be extracted to directly command the PCPG either in frequency, or in phase [48].

For long-term work, two main achievements could be realized. First, the frequency/phase information could be derived from invasive technique to increase responsiveness and Signal-to-Noise Ratio. Regarding the prosthesis, if the patient has still his limb, functional electrical stimulation could be used. As studied in [52], the PCPG output could be shaped by specific neural network to generate Electro-Myographic signals.

In any case, balance control by the system for tetraplegia is highly challenging. Robotics research has not provided a complete solution yet. To reach the market, the product has to consider this aspect. Shared control has also to be increased for gait pattern adaptation when specific situations arise such as climbing stairs, slope, etc.

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