A Five-State P300-based Foot Lifter Orthosis: Proof of Concept

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***Abstract*—Current lower limb prostheses do not integrate recent developments in robotics and in Brain-Computer Interfaces (BCIs). In fact, active lower limb prostheses seldom consider the user's intent, they often determine the correct movement from those of healthy parts of the body or from the residual limb. Recently, an emerging idea for non-invasive BCIs was proposed to allow such low bitrate systems to control a lower limb prosthesis thanks to a Central Pattern Generator (CPG) widely used in robotics. This CPG allows to automatically generate a periodic gait pattern. Furthermore, the CPG pattern frequency and magnitude can be adapted according to the specific gait behavior of the patient and his desired speed.**

This paper proves the concept of combining a human gait model based on a CPG and a classic but non-natural P300 BCI in order to consider the user's intent. The details of how the entire chain can be practically implemented are given. Finally, preliminary results on four healthy subjects for a four-speed P300-based lower limb orthosis with a non-control state are presented. Globally, results are satisfying and prove the feasibility of such systems.

***Index Terms*—Brain-Computer Interfaces, Human Gait, PCPG, Neuroprosthesis, Rehabilitation.**

I. Introduction

As recently pointed out by [1], although recent developments have considerably enhanced the performance of active lower limb orthoses/prostheses, they still suffer from the non-consideration of a kind of direct user's intent. Most up-to-date non-invasive active prostheses detect gait phases based on healthy leg or upper-body motion by means of sensors to provide the adequate kinematics. An alternative is to use myoelectric signals recorded at the surface of the skin, just above the muscles, to control the prosthesis.

Although promising, invasive prostheses are not considered in this paper. In fact, complex nerve surgery techniques now allow to connect an amputee to an artificial limb that he can control intuitively with his own residual nerves and muscles [2]. However, the recovery is still limited whereas a risky surgery is required. Non-invasive neuroprostheses have the main advantage not to require such heavy surgery and would undoubtedly be more accepted by patients if similar performances are provided.

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To consider the user's intent, current non-invasive Brain-Computer Interfaces (BCIs) based on ElectroEncephalography (EEG) are good candidates. On the one hand, BCIs can be evoked, i.e. 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 [3] or auditory [4], 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) [5], a sound modulated in amplitude (Auditory SSEP) [6], or vibrations provided by a tactor (Somatosensory SSEP) [7].

On the other hand, BCIs can be spontaneous such as motor and sensorimotor rhythms and slow cortical potentials. Those 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 [8], or by performing specific tasks [9]. Increase/Decrease of those magnitudes are Event-Related Synchronization (ERS)/Event-Related Desynchronization (ERD). Slow Cortical Potentials (SCP) are slow modifications of cortical activity, which can last from hundreds of milliseconds to several seconds [10]. By a several-month training, the patient can voluntarily generate either a positive, or a negative variation of this potential.

In this study, the P300 command system was considered. Actually, some advantages of evoked potentials are crucial to develop a non-invasive brain-controlled lower limb prosthesis. Firstly, to our knowledge, no study has been reported about ambulatory SCP- or motor/sensorimotor rhythm-based BCIs. In fact, given that movements activate those potentials, walking while performing such BCIs provoke high interference. Moreover, those spontaneous BCIs are often limited to three or four states (with lower performance than P300 systems) whereas we intend to control gait speeds, which could range from 0.5 km/h to 7 km/h. Finally, as far as the P300 is an evoked potential, no learning step by the user is required to manage the paradigm.

However, as reported in [11], a disadvantage of evoked potentials is that they can only arise with the presence of an external stimulus. Until now, given that most of the BCI experiments were performed without any movement, using an external screen was rationale. But, in ambulatory conditions, another solution has to be considered. Hopefully, a specific emerging and well-designed augmented reality eyewear (Vuzix, Rochester, NY, USA) can circumvent this problem by displaying stimuli on a semi-transparent module containing all the key hardware elements.

Obviously, this P300 command is not natural but it is a first step towards spontaneous non-invasive lower limb prostheses. In fact, as discussed in [12], some ERD and ERS are appearing periodically in the EEG as a function of the gait cycle phase. However, although the authors claim those elements are cortical activities, the conducted experiment is subject to criticisms given the high subjectivity of the used artifact removal technique. On the other hand, in [13], even if some periodical ERD and ERS were found, they do not strictly correspond to those of [12]. On top of that, the artifact-free experiment, which was performed on a chair, moving the feet in-phase or anti-phase on the ground, does not really consider gait but only gait-like movements. Finally, none of those experiments have studied the origins of those periodic activations/deactivations: motor control or sensorimotor feedback. Obviously, if the signal is mainly produced by sensorimotor feedback, it will not be possible to control a prosthesis with this information.

However, given that the bitrate obtained with current BCIs is not sufficient to entirely control complex systems, shared control has been intensively used as reviewed by [14]. This means that the patient will send high-level commands and the system will operate all the low-level problems corresponding to these high-level commands. For instance, to control a wheelchair [11], a P300 system detects the high-level objective such as going to watch TV or to the bed room. Then, the wheelchair is moving to this position considering predefined paths and localization of the current position.

To implement shared control, researchers have developed models of Central Pattern Generators (CPGs), which are able to learn and generate periodic gait patterns. In human locomotion, those CPGs are located in the spinal cord and are controlled by the brain in terms of their produced frequencies. This approach has inspired the field of robotics in the development of autonomous robots from multi-legged insect-like robots to humanoids [15] and active prostheses [16].

Considering results indicating that P300 BCI can be developed for ambulatory applications [4], [17] and that CPGs can model gait quite well [1], this paper presents a proof of concept of a five-state BCI-based foot lifter orthosis. It describes how P300 can be used to control the CPG model and the needed hardware devices. Furthermore, preliminary results for four subjects are presented. The study focuses on the control of a foot lifter orthosis useful for people affected by strokes and who are unable to lift their feet. In Section 2, the P300 pipeline is presented. In Section 3, the CPG model based on a Programmable Central Pattern Generation (PCPG) is exposed. In Section 4, the global strategy and the hardware of the orthosis are detailed. In section 5, preliminary results for four subjects are discussed.

II. P300 System

This section first details the P300 paradigm. Then, the acquisition system, the P300 approach and its pipeline are explained. Finally, the experiment and its purpose are presented.

A. P300 Paradigm

In the space of BCI paradigms, the P300 evoked potential has been widely used to allow disabled people to communicate. This involuntary positive potential arises around 300 ms after the user has perceived a relevant and rare stimulus [3]. Typically, it is generated by the *odd-ball* paradigm, in which the user is requested to attend to a random sequence composed of two kinds of stimuli with one stimulus much less frequent than the other one. In case the infrequent stimulus is relevant to the user and, assuming that the subject was focusing on it by, for example, silently counting it, its actual appearance activates a P300 waveform in the users EEG, which is mainly located in the parietal areas.

The most common application is the P300 speller, which consists in a text editor [18]. In this application, 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. The detection of the target letter/symbol, i.e. a trial, is done after a sequence of intensifications where each row/column is randomly flashed. At the intersection of the detected P300 responses, the computer is able to determine which letter/symbol the subject was looking at.

Because the P300 has a low Signal-to-Noise Ratio mainly due to other brain, muscular and ocular activities, this procedure is repeated several times and the epochs corresponding to each row/column are averaged before classification to obtain better trial classification accuracy.

B. P300-based Command

EEG was recorded using a 32-electrode cap connected to the ANT acquisition system (Advanced Neuro Technology, ANT, Enschede, The Netherlands) digitizing the signals at 512 Hz. Left ear was chosen as reference. Mastoid was not used because of possible pollution from EMG signals of the neck while walking. Electrode impedance was measured and maintained under 20 kΩ for each channel using electrode gel.

In this application, we are interested in a four-speed BCI plus a non-control state, which does not send any instruction to the orthosis control system. The screen was composed of two rows and two columns representing Low-, Medium- and High-speeds and the Stop states as depicted in Figure 1. The different speeds could respectively correspond to 2, 4, 6 km/h whereas the Stop state simulates the standing state. When the user is not looking at the screen, a non-control state is detected leading to no modification of the current speed.

Fig. 1: 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 EEG signals downsampled at 32 Hz, the pipeline is composed of several main components: a temporal high-pass filter, an xDAWN-based spatial filter [19], an epoch averaging and a LDA classifier using a voting rule for the final decision sent to a VRPN server [20].
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 [21].
Afterwards, a spatial filter is designed thanks to an xDawn algorithm [19]. By linearly combining EEG channels, this algorithm defines a P300 subspace. When projecting EEG signals into this 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 [20].

C. Experiment Description

In order 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 a threshold (by a Receiver Operating Characteristic analysis (ROC) [22]) from which the voting rule result is significant. The second one with 25 trials allows to assess the non-control state detection.
Because a practical application should not make mistakes while the subject is not looking at the screen (non-control state), the False Positive Rate (FPR), i.e. the number of non-target elements classified as target ones divided by the total number of non-target, should be as low as possible. In the ROC analysis, the threshold was determined by FPR=1%. 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±4.11). During the experiment, a 20-inch screen in both conditions 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.

III. Modeling Human Gait by PCPG

This section describes the PCPG algorithm equations and principles. A previous study showing the possibility to model human locomotion with this tool is referred.

A PCPG is a kind of Fourier series decomposition and is composed of several adaptive oscillators. As defined in [23], 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

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

As depicted in Figure 2, oscillators are coupled between each other. The instantaneous phase of the fundamental oscillator R_0 is scaled at the frequency ω_i through R_i and the phase difference with the fundamental oscillator is given by ϕ_i. Each oscillator i has an adaptive magnitude coefficient α_i and a frequency parameter ω_i. μ has a role of normalization of the learned pattern through $r_i = (x_i^2 + y_i^2)^{\frac{1}{2}}$. The other parameters γ and ϵ aim at accelerating the convergence while limiting stability problems [23]. The $Q_{learned}(t)$ signal resulting from the sum of oscillator outputs is compared to the $P_{teach}(t)$ gait pattern target and the error value $F(t)$ is computed. Throughout the learning step consisting in integrating the differential equations by a 4th order Runge-Kutta method, all the parameters of the PCPG are modified in order to minimize $F(t)$. When this learning step is finished, the system is generating the right pattern as depicted in Figure 3.

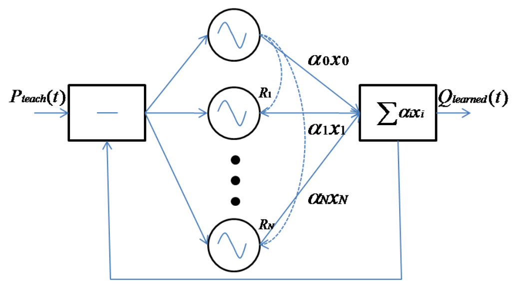

Fig. 2: The PCPG is able to learn the frequency components of a periodic signal as well as the various phases and magnitudes. The main interest of PCPGs is the possibility to modify a learned pattern in amplitude or frequency in a smooth way. This Figure is inspired from [23].

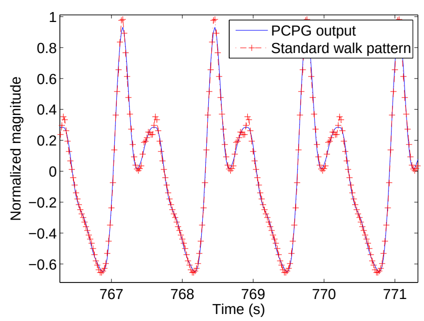

Fig. 3: The PCPG is able to learn quasi-perfectly an average normalized pattern of foot relative angle by means of 5 oscillators determined by the frequency complexity of the signal.

As studied in [1], a simple linear change of the $\vec{\omega}$ and $\vec{\alpha}$ vectors allows to model gait along a large range of speeds. Indeed, people develop a specific strategy in order to minimize the energy consumption during gait. By modifying the $\vec{\omega}$ and $\vec{\alpha}$ vectors to mimic this strategy, the generated pattern should provide more natural gait leading to a reduced patient fatigue.

IV. Global Control Strategy and Orthosis

This section details the global strategy of the foot lifter orthosis aiming at helping people with foot drop problems. Then, it describes its hardware (further details about design and future developments in [16]).

In case of foot drop problem, two specific control modes of the orthosis are needed: active and passive. When the foot is in the air (i.e. during the swing phase), the PCPG algorithm provides the kinematics given the incapabilities of the subject to lift his foot. Otherwise, during the stance phase, the orthosis is completely driven by the patient and the orthosis controller implements a mechanical impedance control mimicking the effect of a spring in the orthosis joint.

As shown in Figure 4, the orthosis under development is made of several components: two custom-fit plastic shells, two commercial 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 [16]. 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 that can be driven by an external analog signal.
The passive and active control algorithms reside in a DsPIC 30F4013 microcontroller running at 120 MHz. Both algorithms are calculated at a sampling frequency of 500 Hz but the actual output is chosen according to the orthosis mode. The differential equations of the PCPG are solved by a simple explicit Euler integration method.
Finally, the link between the VRPN client receiving commands from the P300 system via the VRPN server included in Openvibe and the orthosis control is done by an SBC65EC. This is an embedded (PIC based) Single Board Computer (SBC) with 10 Mbs Ethernet and RS232 interface. This allows to send a byte of information coding the orthosis state through a TCP protocol. In this paper, there are four orthosis states (4 speeds). The SBC generates the sufficient number of interruptions in the DsPIC to obtain the wanted state. The orthosis state is updated the next time the foot is touching the ground. The stop command activates the passive mode.

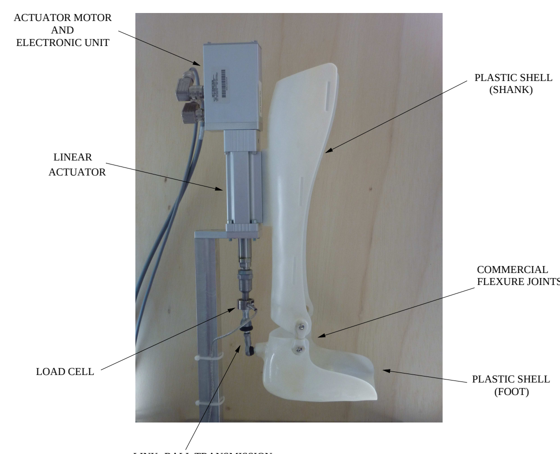

Fig. 4: The most important components are the two force sensors (not represented in the Figure) and the actuators.

V. Results and Discussion

This section presents and analyses the results in sitting and walking conditions. Then, a discussion about limitations of this approach is proposed.

TABLE I: Results for four healthy subjects show that the system is working as designed. There are globally very few errors. When the user is not looking at the screen, the system recognizes it quite perfectly. When the system gives a confidence value below the threshold, it provides an idle state (depicted in parentheses) leading to quasi no error (remaining part of reported values). Furthermore, results in walking and sitting conditions are similar in terms of errors but walking condition results have a higher non-decision rate.

	Test set (sitting)	Non-control set (sitting)	Test set (walking)	Non-control set (walking)
S1	100% (0%)	100%	100% (0%)	96%
S2	100% (0%)	100%	72% (28%)	100%
S3	72% (28%)	100%	68% (28%)	100%
S4	100% (0%)	100%	92% (8%)	100%
Mean±Std	93±14% (7±14%)	100±0%	83±15.45% (16±14.2%)	99±2%

Overall, as depicted in Table I, the system has the desired behavior and, by choosing a very low FPR, it ensures that no decision possibly harmful for the subject is taken. Regarding the non-control state set, only one subject had an error. For this subject, it means that, during a walk of about 12 minutes, if the subject does not want to modify the current speed, he has to re-adjust a misclassification of the system only once, which is obviously not exhausting and conceivable for practical applications.
Regarding the control set, quasi no error, i.e. a bad decision when the subject wants to modify his current speed, occurs at the price of non-decision in grey-areas. It means that when the subject wants to modify the current speed, the system does no error (except once for subject 3 in walking condition). However, when the system is not certain of the subject's volition, it does not take a decision (grey-areas), which could force the subject to concentrate again and in a better way to achieve his goal.
Furthermore, results in walking and sitting conditions are similar. In terms of errors, there is only one additional error for one subject. However, the non-decision rate is much larger in walking conditions. This means that the classification features are less separated and thus, the uncertainty when a decision has to be made is higher.

Although promising, this approach has some limitations. Firstly, the decision time is quite slow for real-time applications. But, it can easily be improved by implementing better and more complex pipelines, which often includes artifact removal techniques 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 [11], 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. Walking condition results can still be improved by applying artifact removal techniques specific to gait-related artifacts [17], [24].
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 [25], [26].
Finally, another limitation is the extension to an autonomous orthosis. Actually, a screen is usable for rehabilitation purposes on a treadmill but not for walking in a street. Therefore, a kind of VUZIX augmented reality eyewear seems to be indispensable. Obviously, the results of such P300 responses have to be validated on this device to assess the decrease (or increase) of performance.

VI. Conclusion and Future Work

A. Conclusion

In this paper, the proof of concept of a BCI-based lower limb orthosis/prosthesis has been demonstrated on four healthy subjects. The present system is composed of three major parts: a P300 BCI sending high-level commands, a human gait model based on a Programmable Central Pattern Generator (PCPG) that could be designed for each subject and an orthosis hardware and control system.
The four-state P300 is inspired from the classic synchronous P300 speller plus a non-control state. This non-control state was determined by a ROC curve analysis allowing to check if the classifier outputs are sufficiently significant for a decision. Results are encouraging although the decision time may be too long for practical applications.
Finally, to help patients with foot drop problems, the control strategy of the orthosis relies on two different modes depending on the gait phase. During the stance phase, when the patient is totally able to control his foot, the orthosis control is passive. On the other side, during the swing phase, when the user is not able to lift his foot, the PCPG gait model, integrated in the orthosis, provides the correct kinematics.

B. Future Work

From this proof of concept, short-term future work will be devoted to study the controllability feedback from a large population of patients and to adapt the available speeds in the P300 interface according to this feedback. Regarding the P300 system itself, some additional components for artifact removal as well as the impact of using the Vuzix augmented reality eyewear should be investigated. In order to enhance the patient's comfort and safety, asynchronous control should also be considered.
Another important aspect will be to study other BCI paradigms and to determine, thanks to patients'feedback, which one is the most suitable for lower limb prosthesis applications.

For middle-term future work, a much more natural command generation system will be studied. Indeed, recent studies showed that EEG signals could detect specific periodical gait activations and deactivations in Event-Related-Potential analyses and Event-Related-Spectral-Perturbation [12], [13]. This would undoubtedly be a great step 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 [16].

For long-term future 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 as already done for cats [15]. Regarding the prosthesis, if the patient has still his limb, Functional Electrical Stimulation can be used. As studied in [27], the PCPG output could be shaped by specific neural network to generate Electro-Myographic signals.

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