Attention Level Measurement During Exoskeleton Rehabilitation Through a BMI System

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Abstract Brain-Machine Interfaces based on wearable robots' control have been proposed in the research field for rehabilitation purposes. The combination of both systems allow the performance of more natural movements and a higher level of involvement of patients on their therapy. Studies focused on this topic should face several issues related to the integration of these systems. The current work is meant to test the accuracy of a real time Brain-Machine Interface based on the detection of gait attention during lower limb exoskeletal rehabilitation. Four users performed the experiment wearing an ankle exoskeleton. The system provides a coefficient between 0 and 1 depending on the level of attention experienced by the subject. These results show good similitude between real and decoded attention level.

1 Introduction

Several studies suggest that rehabilitation results could be improved by taking advantage of the human ability to generate physical changes in the brain structure [1]. This brain plasticity could be enhanced during rehabilitation by increasing the involvement of patients on their therapy. BMIs have been proposed in the literature to introduce

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this involvement in the rehabilitation process [2]. These systems are focussed on the decoding of the brain response of people in different situations. This information could be used to fit the rehabilitation to the mental state of the user.

Current study works on the integration of a BMI to detect the attention level during gait while wearing an ankle exoskeleton. The online BMI presented is based in offline studies previously performed [3]. During systems integration involving the use of BMIs based on electroencephalograpic measurements, the artifact robustness of the system should be evaluated. On the current work, 3 attention levels are going to be measured to provide an attention coefficient. The main goal of this work is to test how accurate is the proposed BMI system during exoskeleton walking. In this case, the BMI system does not provide information to the exoskeleton although this will be the next step of this research. The BMI system is based on the detection of a high gamma band desyncronization produced during a dual task paradigm related to the attention paid to the gait. This selective attention mechanism has been widely applied in other works based on dual tasks paradigms [4, 5].

2 Materials and Methods

2.1 Ankle Exoskeleton

An ankle exoskeleton is attached to the dominant foot of the participants during this experiment. This exoskeleton is being developed in the framework of the BioMot Project (Smart Wearable Robots with Bioinspired Sensory-Motor Skills). This exoskeleton is designed to be a biomimetic mechanical structure with compliant characteristics that allows a natural interface between the patient and the robot.

2.2 EEG Acquisition

The cortical signals are recorded using 21 active channels located on the scalp through an elastic cap (actiCap, Brain Products, GmbH, Germany). Electrodes are placed on the motor and premotor cortex with the following distribution according to the 10/10 International System: FZ, FC3, FC1, FCZ, FC2, FC4, C3, C1, CZ, C2, C4, CP3, CP1, CPZ, CP2, CP4, P3, P1, PZ, P2 and P4 with a reference in the right earlobe and AF4 electrode as ground. Electrical signals are amplified by a wireless commercial amplifier (actiCHamp, Brain Products, GmbH, Germany) and digitalized at 500 Hz. A hardware bandpass filter between 0.5 and 100 Hz is applied to remove unnecessary signal bandwidth and also a 50 Hz Notch filter is used to remove power line interference.

2.3 EEG Real Time Processing and Feature Extraction

The real time acquisition loop records 0.5 s of EEG data on each iteration. Signal is divided in 1 s epochs with a 0.5 s of overlap between them. Each epoch goes to a processing stage. With a previous 30 s offline register, the Segment Maximum Average (SAM) is computed for each channel and used to standardize the data [6]. The power spectral density of the standardized segments is computed using the Maximum Entropy Method (MEM) [7] with a spectral resolution of 1 Hz. An average value of gamma band (from 30 to 45 Hz and from 55 to 90 Hz to avoid the frequencies affected by the 50 Hz Notch filter) is extracted from each channel. Finally these 21 features are concatenated in a single vector and sent to a classification stage. This processing is repeated for each incoming epoch.

2.4 EEG Classification

Features vectors are classified using a Linear Discriminant Analysis (LDA) classifier that fits a multivariate normal density to each group, with a pooled estimate of covariance. The classifier take a decisions every 0.5 s. Each decoded attention level is associated to a coefficient value: 0 for low attention level, 0.5 for standard attention level and 1 for high attention level. After each classification, the value is added to the end of a 10 position buffer (5 s). The final classification is obtained by averaging the values from this buffer. Although the use of this averaged value introduce a small delay in the classification (less than 5 s), it helps reducing the influence of misclassified segments and it is not critical as the attention during rehabilitation do not experience huge variation in a short period of time.

2.5 Experimental Protocol

The users were instrumented with the EEG equipment and the ankle exoskeleton was adjusted to the specific size of each participant. On each run of the experiment the user was asked to perform three tasks during straight walking. During the first task the participant was asked to perform some mathematical operations shown on a tablet carried by an experimenter (low gait attention level). On the second task, the participant was asked to walk without any distractions (standard gait attention level). On the third task the participant was asked to follow some marks placed on the floor with an unsteady gait step (high gait attention level). Each task lasts for 30 s. Each experimental session is composed of eight runs. Four healthy participants performed the experiment, all of them were right handed men with ages between 25 and 37 (31.2 ± 5.3). Runs 1, 2, 3 and 4 of each participants are used to create a classification model and classification results are computed for runs 5, 6, 7 and 8.

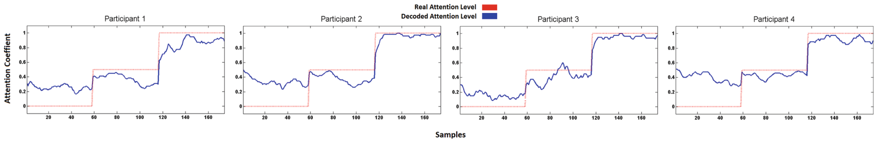

Fig. 1 Averaged value of the attention coefficient provided by the classifier (in *blue*) during runs 5, 6, 7 and 8 and real attentional task performed by each participant (in *red*)

3 Results and Discussion

On Fig. 1 the averaged coefficient obtained for each subject during runs 5, 6, 7 and 8 are shown. The attention coefficient provided by the classifier (in red) is compared to the real attention level (in blue) to appreciate how accurate is the real time system during exoskeleton rehabilitation.

The attention coefficient provided by the system presents appreciable changes related to the attention level experienced by the participant. On this regard, high attention level is easily distinguished from low and standard attention level. However, between low and standard levels there are lower differences but, the use of the average of the 5 s buffer allows to fix a personalized threshold in the attention coefficient depending on the user to approximate the coefficient provided to the real attention level.

4 Conclusions

A real time BMI to decode the attention level during gait has been designed. The system has been validated with four healthy users during the simulation of a lower limb rehabilitation strategy assisted by and ankle exoskeleton that supports dominant leg motion during walking. The exoskeleton provides the assistance to perform a natural gait step. The real time BMI system provides the attention level that the subject experiences during rehabilitation. In future works, this system will be used to modified the exoskeleton assistance.

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References

1. Johnston, M.V.: Plasticity in the developing brain: implications for rehabilitation. Dev. Disabil. Res. Rev. **15**, 94–101 (2009)
2. Ramos-Murguialday, A., Broetz, D., Rea, M., Läer, L., Yilmaz, Ö., Brasil, F.L., Liberati, G., Curado, M.R., Garcia-Cossio, E., Vyziotis, A., et al.: Brain-machine interface in chronic stroke rehabilitation: a controlled study. Ann. Neurol. **74**, 100–108 (2013)
3. Costa, A., Iáñez, E., Úbeda, A., Planelles, D., Hortal, E., Azorín, J.M.: Frequency and number of neighbors study for attention level classification using eeg signals. In: International Workshop on Wearable Robotics (WeRob 2014) (2014)
4. Zhang, D., Maye, A., Gao, X., Hong, B., Engel, A.K., Gao, S.: An independent brain-computer interface using covert non-spatial visual selective attention. J. Neural Eng. **7**, 016010 (2010)
5. Kim, D.W., Hwang, H.J., Lim, J.H., Lee, Y.H., Jung, K.Y., Im, C.H.: Classification of selective attention to auditory stimuli: toward vision-free brain-computer interfacing. J. Neurosci. Methods **197**, 180–185 (2011)
6. Costa, A., Salazar-Varas, R., Úbeda, A., Azorín, J.M.: Characterization of artifacts produced by gel displacement on non-invasive brain-machine interfaces during ambulation. Front. Neurosci. **10**, 60 (2016)
7. Marple Jr, S.L.: Digital Spectral Analysis with Applications, vol. 1. Prentice-Hall, Inc., Englewood Cliffs, NJ, 512 p. (1987)