

A P300-BASED QUANTITATIVE COMPARISON BETWEEN THE EMOTIV EPOC HEADSET AND A MEDICAL EEG DEVICE

Matthieu Duvinage and Thierry Castermans and Thierry Dutoit

TCTS Lab

University of Mons

20, Place du parc

7000 Mons, Belgium

email: Matthieu.Duvinage@umons.ac.be

M. Petieau and T. Hoellinger and C. De Saedeleer and K. Seetharaman and G. Cheron

LNMB Lab

Université Libre de Bruxelles

50 Av F Roosevelt

CP 168, Brussels, Belgium

ABSTRACT

EEG-based systems have been the most widely used in the field of Brain-Computer Interfaces (BCI) for two decades. Plenty of applications have been proposed from games to rehabilitation systems. Until recently, EEG recording devices were too expensive for an end-user. Today, several low-cost alternatives have appeared on the market.

The most sophisticated of these low-cost devices is the Emotiv EPOC headset. Some studies reported that this device is suitable for customers in terms of performance. However, none of the previous studies reported to what extent the Emotiv headset is working well compared to a medical system.

The aim of this paper is thus to scientifically compare a medical system and the Emotiv EPOC headset by determining their respective performances in the context of a P300 BCI paradigm. In this study, seven healthy subjects performed P300 experiments and two different conditions were studied: sitting on a chair and walking on a treadmill at constant speed. Results show that the Emotiv headset, although able to record EEG data and not only artifacts, is sometimes significantly worse than a medical system. Those results suggest that the design of a specific low-cost EEG recording systems for rehabilitation purposes at a low price is still required.

KEY WORDS

Brain-Computer Interfaces, Emotiv EPOC Headset, Hardware Comparative Study, P300.

1 Introduction

Non-invasive Brain-Computer Interfaces (BCI) have known a huge development for less than two decades in terms of performance and varieties of applications. Actually, a non-invasive BCI can be defined as a device that enables communication without movement, namely a direct communication pathway between a human (or

an animal) and an external device. Given its portability, its relative low-cost and its high temporal resolution compared to other non-invasive methods such as MEG, fMRI, fNIRS, Electroencephalography (EEG) is widely used for BCI purposes [1].

As reviewed by [2], since its beginning, lots of BCI applications have emerged. They have been used for communication and control, notably by allowing to control a mouse or to use a web browser just by thought. Another main focus was the study of motor substitution or motor recovery whose main applications were hand grasping [3] and wheelchair control [4]. Finally, BCIs have also been used to augment interactivity in games by using multimodality from the EEG signals and the standard control [5, 6].

Indubitably, one of the most important fields for BCIs is rehabilitation-related applications. Hand grasping systems were one of the first rehabilitation devices. In 2006, a BCI commanded the activation or deactivation of grasping [3]. This approach enables the patient to grasp objects thanks to Functional Electro Stimulation (FES). Since this first experiment, this system has been improved for a better grasping position based on a Steady-State Evoked Potential (SSVEP) [7].

Simultaneously, a large focus was devoted to wheelchair control. As described in [4], several strategies have been proposed: predefined locations or direct control. In a predefined location strategy, the patient is choosing the place he wants to go by a BCI. Then, thanks to sensors and shared control [2], all the low-level commands are executed by the wheelchair control system in order to reach the desired position. On the other hand, in a direct control, the orientation of the wheelchair and the choice of going forward is directly and quite continuously controlled by the patient. Obviously, the latter approach leads to more overhead problems whereas it is more flexible.

Recently, an original approach has been proposed regarding BCI-based gait rehabilitation [8]. Given that non-invasive BCIs are only able to produce high-level commands, the shared control is performed by a Central Pattern Generator (CPG), which generates a perfectly periodic gait pattern whose gait-equivalent speed is controllable. In this proof of concept, a P300 paradigm including a non-control state detection, i.e. when the subject does not want to modify his state by avoiding looking at the screen, was used on a treadmill and results on four subjects showed the feasibility of such an application. In [8], it was proposed a possible extension to lower limb prostheses/orthoses by using a specific emerging and well-designed VUZIX augmented reality eyewear (Vuzix, Rochester, NY, USA). This can circumvent the practical problems resulting from the use of the P300 paradigm in terms of screen portability by displaying stimuli on a semi-transparent module containing all the key hardware elements.

Although all these aspects look promising, one of the main drawbacks of EEG system is its high cost for customers. This is why plenty of commercial EEG devices are now available such as Neurosky, Mindflex, Emotiv EPOC, etc [9]. Based on usability [9], the best low-cost EEG device is the Emotiv EPOC headset. However, a scientific study of their performance is seldom available. To our knowledge, no scientific comparison of this headset with a medical system has been done. In the NeuroPhone project [10], an Emotiv EPOC P300 system is used on a PDA without showing comparative results. In [11], based on mental tasks (relaxation and imaging of two types of pictures), it was reported that an ActiCap medical system was much better than the Emotiv EPOC. However, the authors did not compare the performance of both systems in the same experimental conditions. For instance, the electrode number and their location were significantly different. Consequently, the conclusion of this study is possibly spurious. In a qualitative study [12], the authors suggested that data provided by both systems are alike in general, but the signal is cleaner and stronger in the medical system (G-TEC device). Moreover, none of those studies has analyzed the impact of gait-related movement artifacts.

Given our purpose to develop a low-cost and non-invasive BCI-based active lower limb orthosis [8], this study is focusing on the quantitative comparison of a four-state P300 BCI relying on a medical device and the low-cost Emotiv EPOC headset. This aims at answering questions of researchers about the relevancy of the Emotiv headset [13]. Section 2 details both recording systems. Section 3 is devoted to describe the P300 paradigm, the used pipeline, the experiment conditions and the performance measure for comparison. Section 4 discusses the results.

2 Acquisition Systems

In this section, both acquisition systems are detailed. Their main features as well as the electrodes used in this study (identical for both systems) are given.

2.1 ANT

The ANT acquisition system (Advanced Neuro Technology, ANT, Enschede, The Netherlands) is composed of a high-density WaveGuard cap system and the corresponding full-band DC amplifier. The WaveGuard cap has 128 Ag/AgCl electrodes (based on the International 10-20 locations) with shielded wires in order to be less influenced by exterior noise. Moreover, three different sizes are available to adapt as well as possible to the subject's head specificities. Regarding the full-band DC amplifier, it can reach a sampling rate of 2048 Hz.

In our experiment, left ear was chosen as reference instead of mastoid because of possible pollution from EMG signals from the neck under walking conditions. Electrode impedance was measured and maintained under 20 k Ω for each channel using electrode gel.

2.2 Emotiv EPOC

The Emotiv Software Development Kit for research mainly includes a 14 channel (plus CMS/DRL references, P3/P4 locations) each based on saline sensors. Available channels (also based on the International 10-20 locations) are depicted in Figure 1. The headset is completely wireless and has a large autonomy of 12 hours as announced by the company. The sampling rate can reach 128 Hz.

In our experiment, all the standard available electrodes of the Emotiv EPOC headset were used. Electrode impedance was decreased by using saline liquid until the level required by the software was reached.

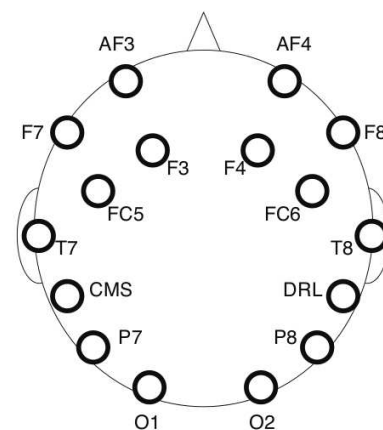


Figure 1. The Emotiv EPOC headset is using 14 different electrodes in addition to two references.

3 P300 System

This section first details the standard P300 paradigm. Then, the P300 approach and its pipeline are explained. Afterwards, the experiment and its purpose are presented. Finally, the performance evaluation method is explained.

3.1 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 [14]. Typically, it is generated by the *odd-ball* paradigm, in which the user is requested to attend to a random sequence composed of two kind 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 [15]. 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 epoch corresponding to each row/column is averaged before classification to obtain better trial classification accuracy.

3.2 P300-based Command

In this application, following [8], a four-state BCI was studied to allow comparison during sitting and walking conditions (in such applications, a 6 x 6 P300-speller is not easily conceivable due to the quite high distance to the screen. Additionally, considering Vuzix eyewear for lower limb orthoses/prostheses, it is not implementable in practice). Because lower limb rehabilitation was proposed in [8], the screen was composed of two rows and two columns representing Low-, Medium- and High-speeds and the Stop states as depicted in Figure 2.

Providing the EEG signals downsampled at 32 Hz from a sampling rate of 512 Hz (ANT) or 128 Hz (Emotiv Epoc), the pipeline is composed of several main components: a temporal high-pass filter, an xDAWN-based spatial filter used on the very same electrodes in both systems [16],



Figure 2. P300 visualization is divided into four states.

an epoch averaging and an Linear Discriminant Analysis (LDA) classifier using a voting rule for the final decision. 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 (high cutoff frequency of 16 Hz by Shannon theorem), the undesired slow drift in the measurement and high-frequency noise such as power line interference are removed [17].

Afterwards, a spatial filter is designed thanks to an xDAWN algorithm [16]. 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 (LDA) is used. The k -fold approach relies on the division of the training set into k uniform segments. Then, $k - 1$ segments are used for training the LDA classifier and the test is performed on the remaining segment. After k different training steps, the classifier obtaining the best results is applied to each two-grouped averaged time window 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.

3.3 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 on a treadmill, which is a convenient speed for subjects. To train classifiers and to 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 for each session).

Seven healthy male subjects participated in this experiment with age between 24 and 33 years old. 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.

3.4 Performance Evaluation

For each condition, both systems were assessed based on their recognition rate on the test set. Additionally, standard t -tests were performed using Matlab. As a reminder, assuming normality, two different populations X_1 and X_2 with their mean $\mu_{1,2}$ and their standard deviations $\sigma_{1,2}$, their respective number of observations N_1 and N_2 , the unilateral t -test of mean values is defined as:

$$t = \frac{\mu_1 - \mu_2}{\sigma_{\mu_1 - \mu_2}} \quad (1)$$

where

$$\sigma_{\mu_1 - \mu_2} = \sqrt{\frac{\sigma_1^2}{N_1} + \frac{\sigma_2^2}{N_2}} \quad (2)$$

This t -value is following a Student's t distribution with a degree of freedom df :

$$df = \frac{(\frac{\sigma_1^2}{N_1} + \frac{\sigma_2^2}{N_2})^2}{(\frac{\sigma_1^2}{N_1})^2 + (\frac{\sigma_2^2}{N_2})^2} \quad (3)$$

Because the medical system should have better performance than the low-cost headset, the hypothesis H_0 is defined as: "The ANT EEG device is inferior or equal to the Emotiv headset". H_1 is thus defined as: "The ANT EEG device is superior to the Emotiv headset".

Attention idem assis debout

4 Results

In this section, results on seven subjects, obtained in two different conditions and for two different hardware recording systems are given in terms of the k -fold learning, training and testing results. Then, the significance of those results is provided and discussed.

Globally, as shown in Table 1, the Emotiv Epoc results are not bad at all for such a low-cost system. In fact, the performance is far above the chance level of 25 %, which is consistent with previous studies and responds to criticisms that this system mainly records muscular and ocular artifacts.

However, as depicted in Figure 3, the Emotiv headset seems to be worse than the ANT system. On a k -fold based comparison, p -values under sitting and walking conditions are respectively 4.77 % and 6.12 % indicating relatively strong results. This induces that the signal-to-noise ratio seems to be worse in the Emotiv headset than in the ANT system. Strictly speaking, only the comparison under sitting conditions is significant worse at the 5 % level. On test sets, results are less strong. This could be due to the averaging included in the P300 pipeline.

While comparing sitting and walking conditions, p -values are quite similar whatever the hardware EEG device. In a k -fold learning, although not significant at the 5 % level, the p -value is relatively small (around 15 %) indicating that there could be an unfavorable effect of the gait-related artifacts on P300 results that needs to be confirmed on a larger number of subjects. On the testing set, the averaging procedure makes this effect totally insignificant (p -value is around 50 %).

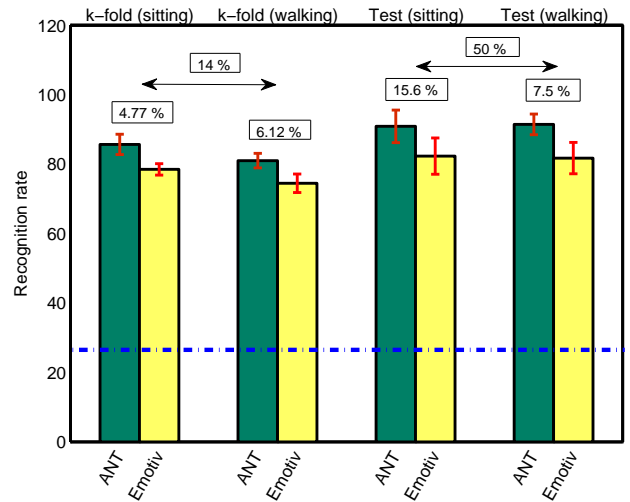


Figure 3. This Figure reports average and standard error values of classification rates under sitting/walking conditions for both EEG recording devices as well as p -values. Tests between sitting and walking conditions were similar with both systems and results are depicted above the double arrows. The chance level of 25 % is shown by the horizontal line. This concludes that some results are strong.

Finally, although the Emotiv Epoc performance is quite creditable especially regarding games, this lower-than-the-benchmark performance could be problematic in rehabilitation and prosthesis control. For instance, for Subject 1 in walking conditions, the decrease of performance could imply that the overall system is not working as desired anymore [8]. This suggests that the design of a new low-cost EEG headset device dedicated to applications needing a highly reliable interface, such as rehabilitation systems, is somehow indispensable.

5 Conclusion and Future Work

5.1 Conclusion

In conclusion, in this paper, a scientifically quantitative comparison of a low-cost Emotiv Epoc headset and an ANT medical/research EEG device is performed. This

Table 1. A comparative study of the Emotiv Epoc headset and the ANT medical EEG device is reported for seven healthy subjects based on a P300 application under both sitting and walking conditions. Classification rates of the k -fold learning, the training and the testing sets are detailed. Globally, results provided by the Emotiv Epoc headset seem to be less good than those provided by the ANT medical system.

Hardware	ANT (sitting/walking)			EMOTIV (sitting/walking)		
	k -fold	Training set	Testing set	k -fold	Training set	Testing set
Subject 1	90 %/85.5 %	100 %/100 %	100 %/100 %	78.16 %/72.5 %	100 %/92 %	84 %/56 %
Subject 2	94.66 %/88 %	100 %/100 %	100 %/88 %	76.5 %/76.2 %	100 %/96 %	92 %/80 %
Subject 3	94.66 %/86.7 %	100 %/100 %	100 %/96 %	81.3 %/83.3 %	100 %/100 %	84 %/96 %
Subject 4	89 %/80.2 %	100 %/100 %	100 %/100 %	82.63 %/75.3 %	100 %/100 %	92 %/92 %
Subject 5	79.9 %/77.83 %	100 %/100 %	96 %/96 %	85.4 %/81.5 %	100 %/100 %	100 %/88 %
Subject 6	70.3 %/69.7 %	88 %/100 %	72 %/76 %	70.8 %/74.2 %	96 %/100 %	72 %/88 %
Subject 7	81.16 %/79 %	96 %/100 %	68 %/84 %	74.5 %/58.3 %	96 %/92 %	52 %/72 %
Mean	85.7 %/81 %	97.7 %/100 %	90.9 %/91.4 %	78.5 %/74.5 %	98.9 %/97.1 %	82.3 %/81.7 %
Std	7.7 %/5.5 %	4.5 %/0 %	12.4 %/7.86 %	4.4 %/7 %	2 %/3.8 %	13.8 %/12 %

aims to answer the questions of a lot of BCI researchers about the relevancy of the Emotiv Epoc [13]. This study focuses on a standard P300 Brain-Computer Interface for rehabilitation purposes and possibly for prosthesis control, as proposed in [8].

Globally, results provided by the Emotiv Epoc headset are consistent with previous applications using it: it records EEG data and not only muscular or ocular artifacts as criticized by some BCI leaders. This was supported by far above chance classification rates, although less good than the ANT system in average. This indicates that it can be used in non-critical applications such as games.

Some of the comparative results are strong. On a k -fold based comparison, p -values under sitting and walking conditions are respectively 4.77 % and 6.12 %, which is probably due to a higher signal-to-noise ratio of the medical system. On the test sets, p -values are less strong, which is probably due to the averaging effect in the P300 pipeline. Regarding the comparison between sitting and walking conditions, although none of the results are significant, some trends emerge but need to be confirmed. On the k -fold learning, a p -value of 14 % was found indicating that gait-related artifacts could impact P300 results. However, due to the averaging effect in the testing sets, this effect seems to disappear (p -value of 50%).

5.2 Future Work

For future work, three main axes can be explored: a larger number of subjects, other BCI paradigms and the design of a new low-cost EEG headset. Firstly, some results are not enough strong to settle the question about the Emotiv performance. Therefore, a much larger number of subjects could be used to obtain even clearer results.

Secondly, this study focuses on the P300 speller-like sys-

tem, i.e. inspired from the so-called P300 speller. However, other standard BCI paradigms exist and could be studied to confirm the results presented in this paper. More specifically, a SSVEP-based comparison is ongoing.

Thirdly, given the needs for a higher reliability in critical applications such as rehabilitation or even orthosis/prosthesis control, the design of a new low-cost EEG headset is required. Ideally, this headset should be light, have a large autonomy, have performance closer to a medical system and be relatively cheap.

Acknowledgments

M. Duvinage is a FNRS (Fonds National de la Recherche Scientifique) Research Fellow. The authors want to express their gratitude for the financial support provided by Fonds Européen de Développement Régional (FEDER) and the Région Wallonne and by the European Commission through the MINDWALKER project (FP7 - 2007-2013). 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 authors.

References

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767 – 791, 2002.
- [2] J. del R. Millán, R. Rupp, G. Mueller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann,

- C. Vidaurre, F. Cincotti, A. Kubler, R. Leeb, C. Neuper, K. R. Mueller, and D. Mattia, "Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges," *Frontiers in Neuroscience*, vol. 4, no. 0, p. 12, 2010.
- [3] G. Pfurtscheller, G. R. Müller, J. Pfurtscheller, H. J. Gerner, and R. Rupp, "'Thought' - control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia," *Neuroscience Letters*, vol. 351, no. 1, pp. 33 – 36, 2003.
- [4] B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, M. Ang, and E. Burdet, "A brain controlled wheelchair to navigate in familiar environments," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 18, no. 6, pp. 590–598, 2010.
- [5] A. Nijholt, D. P.-O. Bos, and B. Reuderink, "Turning shortcomings into challenges: Brain-computer interfaces for games," *Entertainment Computing*, vol. 1, no. 2, pp. 85 – 94, 2009.
- [6] C. Mühl, H. Gürkök, D. Plass-Oude Bos, M. Thurlings, L. Scherffig, M. Duvinage, A. Elbakyan, S. Kang, M. Poel, and D. Heylen, "Bacteria hunt," *Journal on Multimodal User Interfaces*, vol. 4, pp. 11–25, 2010.
- [7] R. Ortner, B. Z. Allison, G. Korisek, H. Gaggl, and G. Pfurtscheller, "An SSVEP BCI to control a hand orthosis for persons with tetraplegia," *IEEE Trans Neural Syst Rehabil Eng*, vol. 19, no. 1, pp. 1–5, 2011.
- [8] M. Duvinage, T. Castermans, R. Jimnez-Fabian, T. Hoellinger, C. De Saedeleer, M. Petieau, K. Seetharaman, T. Dutoit, and G. Cheron, "A five-state P300-based foot lifter orthosis: Proof of concept [accepted for publication]," in *5rd ISSNIP Biosignals and Biorobotics IEEE Conference*, 2012.
- [9] K. Stamps and Y. Hamam, "Towards inexpensive BCI control for wheelchair navigation in the enabled environment - a hardware survey," in *Proceedings of the 2010 international conference on Brain informatics*, ser. BI'10. Berlin, Heidelberg: Springer-Verlag, 2010, pp. 336–345.
- [10] A. Campbell, T. Choudhury, S. Hu, H. Lu, M. K. Mukerjee, M. Rabbi, and R. D. Raizada, "Neurophone: brain-mobile phone interface using a wireless EEG headset," in *Proceedings of the second ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds*, ser. MobiHeld '10. New York, NY, USA: ACM, 2010, pp. 3–8.
- [11] P. Bobrov, A. Frolov, C. Cantor, I. Fedulova, M. Bakhnyan, and A. Zhavoronkov, "Brain-computer interface based on generation of visual images," *PLoS ONE*, vol. 6, no. 6, p. e20674, 06 2011.
- [12] K. Stytsenko, E. Jablonskis, and C. Prahm, "Evaluation of consumer EEG device emotiv epec," in *MEi:CogSci Conference*, 2011.
- [13] IEEE review, "IEEE Spectrum." IEEE Press Piscataway, NJ, USA, January 2009.
- [14] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and Clinical Neurophysiology*, vol. 70, no. 6, pp. 510 – 523, 1988.
- [15] B. Z. Allison, E. W. W. Wolpaw, and J. R. Wolpaw, "Brain-computer interface systems: progress and prospects." *Expert review of medical devices*, vol. 4, no. 4, pp. 463–474, Jul. 2007.
- [16] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert, "xDawn Algorithm to Enhance Evoked Potentials: Application to Brain Computer Interface," *Biomedical Engineering, IEEE Transactions on*, vol. 56, no. 8, pp. 2035 –2043, 2009.
- [17] U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens, "An Efficient P300-based BrainComputer Interface for Disabled Subjects," *Journal of neuroscience methods*, vol. 167, no. 1, pp. 115–125, Jan. 2008.