

EEG-Based Attention Assessment in Motor-Rehabilitation

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Abstract – A wireless and wearable device with a low number of channels and dry electrodes is proposed for EEG-based attention assessment during motor-rehabilitation tasks. The system is a part of an instrument for real-time engagement assessment in rehabilitation 4.0. An experimental campaign on nine volunteers was realized for metrologically characterizing the system. Common Spatial Pattern (CSP) algorithm was used for features selection from the brain signal. The performance of three different supervised classifiers for distracted and non-distracted conditions were compared. The higher accuracy, 71.63 ± 3.43 %, was obtained by the *k*-Nearest Neighbors classifier.

Index Terms - Attention, Engagement, motor-rehabilitation task, wearable system, few-channels

I. INTRODUCTION

The concepts of interest, motivation and effort in achieving a goal were used for a concise and effective definition of engagement [1]. According to Fredricks and colleagues [2] [3], the engagement is characterized by three dimensions: cognitive, emotional and behavioral. It reflects the allocation of brain processing resources, including the cognitive mechanisms associated with decision making, such as information gathering, visual scanning, auditory processing and selective attention focused on one aspect of the environment while ignoring other sources of distraction [4]. Engagement is therefore, a complex construct heavily dependent on the context. In the medical field, engagement concept has become essential. For example, the concept of *patient engagement* has become fundamental in the health sector and especially in the rehabilitation one. In rehabilitation programs, the engaged patient is also called *ideal patient*, as rehabilitation improvements occur in reduced times. The increase of patient engagement using, e.g., serious games, collaborative tele-rehabilitation, or virtual reality allows to improve therapy effectiveness. The success

of a therapy is therefore related to the ability to perform the rehabilitation-exercise focusing on it [5]. The most common methods for measuring engagement are based on self-assessment questionnaires to be completed by the patient [6][7]. In recent years the neurophysiological signals like heart rate, galvanic skin response, body temperature and brain waves have begun to be used. Currently, new wearable and low cost solutions for electroencephalography (EEG), allow for a more widespread application of this approach [8].

According to Posner and Petersen, the ability to maintain a brain state of vigilant or alert (engaged) is one of the main functions of the human attention system [9]. There are different dimensions of attention:

- Arousal: indicates the activation level and defines the psychophysiological activation allowing the afference of the different stimulations;
 - Selective attention: refers to the ability to focus attention on a specific source or sensory channel;
 - Distributed attention: refers to the ability to simultaneously process information from multiple sources;
 - Sustained attention: refers to the ability to direct and maintain cognitive prolonged activity on specific stimuli.
- Attention is one of the most important aspects of cognitive performance. Numerous studies showed that EEG frequency bands (rhythms) can be specifically related to certain brain functions [10] [11]. Current electroencephalography techniques allow to explore various electrical brain activities including attention and the distracted process [12] [13] [14]. Monitoring brain activity through EEG systems can be used to analyze the attention. The aim of this paper is the EEG-based evaluation of attention during the execution of a motor task in presence of distracted sources [15]. A wireless and wearable device with a low number of channels and dry electrodes is proposed for EEG-based attention assessment during motor-rehabilitation tasks.

II. BASIC IDEAS

The concept design of the real-time attention monitoring tool is based on the following basic ideas.

- *Real time EEG-Based attention assessment during robot-assisted rehabilitation:* Attention levels affect the effectiveness of therapy even in the case of passive movement execution [16]. Robots supporting the patient in rehabilitative tasks can synchronize with the output of an EEG-based attention monitoring system.

- *Accurate components:* An EEG system Class IIA certified (according to Medical Device Regulation (UE) 2017/745) with accurate components is used to monitor brain signal. The system incorporates a Texas Instruments analog front-end, the ADS1298 [17] with a 24-bit, ($\Delta\Sigma$) analog-to-digital converter (ADCs) with built-in programmable gain amplifiers (PGAs), internal reference, and an onboard oscillator. The device presents:

- Eight Low-Noise PGAs and Eight High-Resolution ADCs (ADS1298, ADS1298R);
- CMRR: -115 dB;
- Input-Referred Noise: $4 \mu\text{VPP}$ (150 Hz BW, $G = 6$);
- Input Bias Current: 200 pA;
- Data Rate: 250 SPS to 32 kSPS;
- Low Power: 0.75 mW/channel;
- Supports systems meeting AAMI EC11, EC13, IEC60601-1, IEC60601-2-27, and IEC60601-2-51 Standards;
- Unipolar or Bipolar Supplies: $\text{AVDD} = 2.7 \text{ V}$ to 5.25 V , $\text{DVDD} = 1.65 \text{ V}$ to 3.6 V ;
- Built-In Oscillator and Reference.

- *High Wearability:* The Helmate system is realized in ultra-light foam and EEG signal detection is allowed by dry electrodes (Fig.1). The device is ergonomic and comfortable, has an internal μSD used to save data automatically, transmits the acquired data via Bluetooth and is equipped with a rechargeable battery. Dry electrodes are used to avoid the inconvenient of electrolytic gel. These are made of conductive rubber with an Ag/AgCl coating at their endings. Three different types of electrodes, with different shapes, are used to pass hair and reach the scalp. The ultra-light foam, the onboard rechargeable battery and the dry electrodes, take the system ergonomic, comfortable and easy-to-use.

Low number of channels: The system guarantees 8 acquisition channels (in unipolar configuration) through 10 dry electrodes [18] [19]. According to the international 10-20



Fig. 1. Type of dry electrodes.

EEG system [20] they are located in: Fp1, Fp2, Fz, Cz, C3, C4, O1, and O2. Reference and ground electrodes are placed in frontal region at AFz and Fpz respectively (Fig.2).

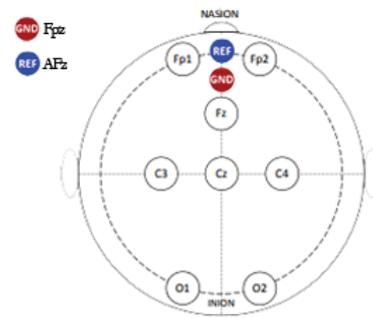


Fig. 2. Dry electrodes position in the EEG Helmate acquisition system. Fpz is the Ground and AFz is the reference.

III. PROPOSAL

III.1 Hardware

The EEG acquisition system employed in this study is the *AB-Medica Helmate* [21] (Fig.3). The system guarantees 8 acquisition channels through 10 dry electrodes [18] [19]. Each of the 8 resulting signals are recorded as the difference between the single electrode and the ground electrode (Fpz). The difference is after referenced with respect to the electrode (AFz).



Fig. 3. abmedica Helmate.

A dedicated *Helm8 Software Manager* checked the contact impedance between the electrodes and the scalp. A sampling rate of 512 Sa/s is used to acquire EEG signal. The software allows to choose a large variety of filters. In

this study, only a notch filter at 50 Hz is applied to preserve all EEG signal information.

III.1.1 Signal processing

A 4 order Butterworth-Band Pass Filter with 0.5-45 Hz cut-off frequencies is applied to EEG signals.

Epochs of 3 s with an overlap of 1.5 s are given as input to the Common Spatial Pattern (CSP) algorithm for the feature selection step [22]. CSP extracts the spatial components common to the two tasks and the data projected on these components have therefore, a different variance between the classes. Hence, the projection related to the n smallest and largest eigenvalues are selected. Then, a supervised classifier distinguishes between attention or non-attention condition (Fig 4).



Fig. 4. Step of the brain signal processing: (i) Common Spatial Pattern and (ii) machine learning classifier.

IV. EXPERIMENTAL RESULT

In this section the experimental campaign and results are reported and discussed.

IV.1 Experimental Set-up

Nine volunteers subjects (five males and four females, with an average age of 29.2 ± 5.4) participated in the session. All of them had a normal clinical history with normal vision and normal hearing, and no neurological disease. The participants were seated in a comfortable chair with armrests in a very quiet room, about one meter away from a PC screen. The protocol consisted in realizing a rehabilitation motor-execution during two different tasks: *ball-squeeze exercise* in *attention task* and *distracted task*. A squeeze ball for rehabilitation was used. The ball-squeeze is one of the most common rehabilitation exercise. Following a period of immobilization in plaster, after a surgical intervention or in the presence of inflammatory or degenerative pathologies (arthrosis, rheumatoid arthritis ..) hand-ball rehabilitation showed to be important in maintaining or restoring the hand functionality [23]. The *distracted tasks* were of three different types: (i) Audio task played with a conventional headphone, (ii) Visual task displayed on a PC screen, and (iii) an Audio-Visual task as a mixture of the previous ones. The *distracted tasks* were based on the *Oddball paradigm* [24][25], an experimental design used within psychology research, consisting in the presentations of sequences of repetitive stimuli infrequently interrupted by a deviant stimulus. The volunteer was asked to count the number of deviant stimuli [26] [27]. During *attention task* the subjects were instructed to perform the

movement paying attention to this one; in the *distracted tasks* they were instructed to perform the same movement during oddball task. Each participant completed a protocol composed of 30 trials: 15 *attention task* and 15 *distracted tasks* (5 Audio, 5 Video and 5 AudioVideo tasks). The trial sequences were randomly chosen for minimizing the influence of task learning. Each trial was organized as exposed below: 2 s of task identification (a screen view on PC identify the following task), 9.5 s of Task execution and 5 s of Relax. Furthermore, 15 s of baseline were acquired at the beginning of each of session execution (composed of 30 trials) (Fig.5).

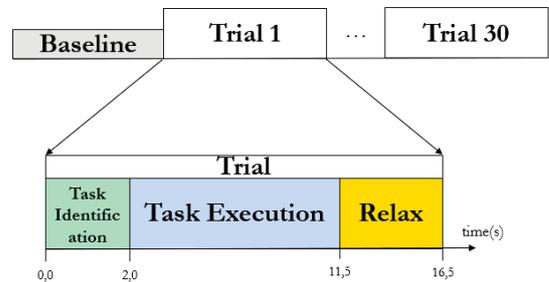


Fig. 5. Experimental protocol

IV.2 Experimental Results

Three different supervised classifier were tested for distinguish between distracted or not distracted condition: *Support Vector Machine* (SVM) [28, 29, 30, 31, 32]), *k-Nearest Neighbors* (k-NN)[31, 32, 33, 34], and *Linear Discriminant Analysis* (LDA) [35, 36].

A SVM is a supervised machine learning method which generates a possible model of the best separation hyper-plane capable of discriminating a set of data belonging to one of two possible classes. SVM is one of the most used machine learning classification technique due to its robust mathematical foundation in statistical learning theory [29] and its strong results obtained respect to other classifiers commonly used in the machine learning literature [37]. The k-NN is a classification method which exploits the k nearest neighbors of each point to make predictions. Specifically, at each observation the most frequent class among its k nearest points (in terms of euclidean distance) is assigned [31, 32].

The k-NN is a simple method utilized in many real application and also in attention levels classification [33]. The choice of k is essential: high value of k leads to reduce the variance but increase the bias, while a low value of k -neighbors provide high variance but low bias.

The LDA is a method to separate data belonging to different classes searching for a linear decision boundary. [36, 35]. The LDA method tries to project the data in a new space with high variance between the data and high sepa-

rability between classes. For each class, the LDA models the data as sampled from a Gaussian distribution, assuming that all classes share the same covariance matrix.

A stratified 5-fold cross validation repeated 10 times was used as cross validation method for the gridsearch technique to obtain the best model. A Grid Search cross validation approach is adopted to perform both the classifiers and the CSP hyperparameters optimization. For each classifier accuracy, precision, recall and F1-score were computed [38]. The best model and the specific hyperparameters for each classifier are reported in Tab.1; the accuracy in Tab.2, and precision, recall, and F1-score in Tab.3.

Table 1. Best Models: SVM, k-NN, and LDA.

Classifier	SVM
Kernel	RBF
C	100.0
Gamma	0.1
CSP components	7

Classifier	k-NN
Algorithm	Ball Three
Metric	Minkowski
Nearest Neighbors	6
Weights	Distance
Power parameter	Euclidean Distance
CSP components	7

Classifier	LDA
Solver	Singular Value Decomposition
N components	6
CSP components	6

V. CONCLUSIONS

In this paper an analysis of attention assessment during motor-rehabilitation-task was presented. A wearable, comfortable and non-invasive system was used to acquire the EEG signal during task execution. An experimental campaign was realized with nine volunteers. Furthermore, a combination of a Common Spatial Pattern algorithm and a supervised classifier was proposed for signal processing. Three different classifiers (SVM, k-NN, LDA) were evaluated and their performance were presented in terms of accuracy, precision, recall and F1-score for each class. The preliminary results showed that the k-NN achieved the higher accuracy of 71.63 ± 3.43 % in distinguishing between two different classes (attention and non attention condition). Further experimental campaigns will be realized for increasing the sample size. Other features extraction and selection methods will be tested for identifying

Table 2. Accuracy of each classifier

Classifier	Accuracy %
SVM	70.21±3.70
k-NN	71.63±3.43
LDA	55.90±3.77

Table 3. Precision, Recall and F1-score% for each classes

	Precision %	Recall %	F1-score %
SVM			
Attention	68.50±3.94	75.33±4.71	71.65±3.40
distracted	72.60±4.17	65.09 ±6.10	68.50±4.46
k-NN			
attention	71.17±3.75	72.99±5.22	71.97±3.57
distracted	72.38±3.98	70.27±5.16	71.19±3.68
LDA			
attention	55.82±3.68	56.79±5.04	56.24±3.99
distracted	56.04±3.98	55.01±4.91	55.46±4.07

the attention levels and emotional conditions during rehabilitation task. The final aim is to assess the engagement of children affected by complex neurological diseases, during their rehabilitation sessions.

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