Brain-computer Interfaces for Daily-life Applications: a Five-year Experience Report

Brain-computer Interfaces for Daily-life Applications: a Five-year Experience Report

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***Abstract*—This work reports the research on brain-computer interfaces (BCI) carried out in the last five years at the Augmented Reality for Health Monitoring Laboratory (ARHeMLab), at the University of Naples Federico II (Italy). In the research, particular attention has been dedicated to wearability, portability, and other key features for obtaining user-friendly BCI systems. Indeed, the interest in the adoption of BCI systems is becoming particularly relevant for cyber-physical human systems (CPHSs), where possible applications relate to industry, healthcare, and daily-life activities in general. In such a context, materials and explored methods are reviewed, and results are presented with reference to reactive, active, and passive paradigms.**

***Index Terms*—BCI, brain-computer interface, CPS, Cyber-physical systems, EEG, electroencephalography, wearable sensors, machine learning.**

I. Introduction

Cyber-physical human systems (CPHSs) integrate the physical and human components into a synthetic hybrid system [1]. In the context of Industry 4.0, humans do not just exercise a defined role in an organization; on the contrary, they are part of a highly-composite automated system [2], [3]. In industry or in health care, smart machines (i.e., the non-human components of a CPHS) are increasingly connected to the physical environment through a multitude of sensors. Thanks to a distributed intelligence, the non-human actors can elaborate information and make decision, resulting highly empowered by technology innovation. Also humans can benefit from new technological opportunities: by interacting with new-generation user interfaces, they can enhance their cognitive, sensory, and motor skills [4]. Among biosignal-based interfaces, brain-computer interfaces (BCIs) allow both monitoring and control [5]. Through BCI, humans can send commands or decisions to the CPHS through intentional modulation of brain waves. Moreover, through the same signal, the system acquires information on the status of the user.

Electroencephalography (EEG)-based BCIs are characterized by numerous paradigms according to the different contents transmitted. A useful BCI taxonomy is proposed in [6]:

- *passive BCI*, where the user does not directly and consciously control his electrical brainwaves. This paradigm is generally used for monitoring the user's mental state;
- *active BCI*, where the subject voluntarily produces an appropriate modulation of the brain waves for controlling an application, independently of external events;
- *reactive BCI*, where brainwaves are produced in response to external stimuli; the subject can consciously or unconsciously expose himself to external stimuli. In the first case, once again, he can control an application; otherwise, monitoring is carried out.

For five years, research has been in progress at the Augmented Reality for Health Monitoring Laboratory (ARHeMLab) of the University of Naples Federico II (Italy), on all the three BCI paradigms: (i) reactive BCI, by focusing on steady-state visual evoked potential (SSVEP); (ii) active BCI, by focusing on the signal produced by the motor imagination and brain signals related to the voluntary closing of the eyes; and (iii) passive BCI, by studying the brain wave pattern of a distracted subject while performing a rehabilitative motor task. Both off-the-shelf instrumentation and CE-marked devices for medical use were exploited for acquiring brain signals. In particular, the focus of the research has been on the design and prototyping of wearable devices for daily-life applications. Databases available online were consulted and experimental campaigns were carried out involving a total of more than 200 subjects. In this manuscript, the research experience is reviewed according to the aforementioned BCI paradigms.

In particular, the present paper is organized as follows. Section II reports the methods explored in terms of brain signals detection and classification. Section III discusses the results obtained for the different paradigms that were considered during this five-year research. Conclusions follows in Section IV, and the future work is outlined.

II. Materials and Methods

A BCI architecture generally includes (i) a signal acquisition block; (ii) signal processing block, typically consisting of features extraction and features classification; and (iii) an application. The latter concerns the control or the communication with an external device, usually providing a feedback to the user. The following sections present the solutions that have been investigated for the implementation of the major system blocks. The common thread is the possibility to adopt such systems in daily life, and the focus is on EEG-based BCIs.

A. Signal acquisition

The key strength of the proposed methods lies in the high wearability and portability of the implemented BCI systems.

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EEG non-invasiveness is essential for employability in everyday activities; moreover, ease-of-use is guaranteed by the adoption of dry electrodes and by keeping their number as low as possible.
In the research, the firs instrument that was adopted is the Olimex EEG-SMT [7], which allows EEG acquisition through active electrodes, with up to two differential channels. Analog pre-processing is implemented on this low-cost board: it consists of pass-band filtering (0.16-59 Hz nominal bandwidth), amplification (nominal gain about 6500 V/V), and analog-to-digital conversion with a 10-bits ADC.

In some applications, however, more EEG channels are required. Therefore, another commercial system was employed, namely the Helmate by ab-Medica [8]. This wireless device exploits ten dry electrodes, providing up to eight single-ended channels. The dry electrodes are made of conductive rubber with an Ag/AgCl coating [9]. Three different shapes are used to reach the scalp by passing the air or by joining hairless areas.

Finally, in the case of reactive BCIs, an external stimuli generator is also needed. In the case currently under investigation at ARHeMLab, augmented reality (AR) glasses were considered in order to provide visual stimulation. The proximity of the icons appearing on the display allowed both wearability and setup optimization, which resulted in higher signal-to-noise ratio for the measured EEGs.

B. Features extraction

The techniques explored to extract signal features can be divided into two broad categories: band power-based and time points-based [10]. In preliminary studies, FFT-based algorithms were compared [11], [12], eventually leading to the adoption of power spectral density (PSD) as a signal feature. The band to consider does depend on the specific BCI paradigm. As an example, the typical spectrum of an EEG measured in presence of a flickering light at 10 Hz is represented in Fig. 1. The PSD in the frequency range close to 10 Hz (and 20 Hz) determines if the user is staring at an icon flickering at 10 Hz, rather than at another icon. This is the basic concept of a BCI paradigm relying on SSVEPs.

In multi-channel acquisitions, also the relation between different channels can be exploited. To this aim, a widely adopted approach is the "common spatial pattern" (CSP) [13], which re-maps the spatial information to increase the separability between different EEG patterns. Ultimately, CSP considers log-power of re-mapped EEG signals, thus falling within band power-based features extraction.

Among the time points-based techniques "canonical correlation analysis" (CCA) was used in SSVEP detection for minimizing the latency of the measurement method. The CCA made it possible to reduce the duration of the time window used by the approaches in the frequency domain for the necessary resolution. The direct use of temporal samples was proposed for the recognition of voluntary eye blinking through comparison with an amplitude threshold. Also in the case of the stress measurement each feature corresponded

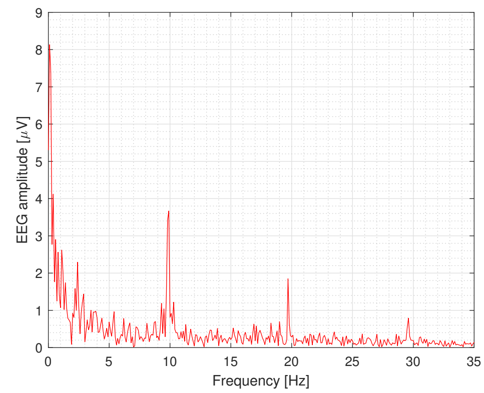

Fig. 1. Spectrum of an SSVEP component of the EEG corresponding to a 10 Hz flickering stimulus.

to just one time sample and feature selection was carried out by a standard machine learning technique, the "principal component analysis" (PCA). The latter allows to compress data [14] and to approximate signals as a linear combination of a restricted number of orthogonal components.

C. Classification

Classification methods were chosen among well known supervised machine learning algorithms. In a binary classification problem, a "support vector machine" (SVM) [15] finds the best separation hyperplane for the input data. *BoxConstraint, KernelFunction, KernelScale, PolynomialOrder* were the SVM hyperparameter optimized in the different studies reported below. Meanwhile, "random forest" (RF) [16] is made up of a large number of small decision trees (estimators) and their autonomous predictions. The random forest model combines the predictions of the estimators to produce a more accurate prediction. The number of estimators was the hyperparameter subjected to optimizatione. Then, the "k-nearest neighbor" classifier (k-NN) was also considered. Compared to other supervised machine learning methods, k-NN [17] is non-parametric (i.e. without a-priori assumption on the data) and it uses the labelled data themselves for the classification without training. The behavior of a k-NN in its simplest version can be described as follows: given a set D of labelled points, a distance measure (e.g, euclidean, Minkowski), and a positive integer k, when a new unlabelled point p is provided, the k-NN algorithm searches in D for the k nearest points from p and assigns to p the most present class label along its k neighbors found. Thus, the only hyperparameters required to k-NN are (i) a positive integer k and (ii) the type of distance measure to use together with any parameters related to the distance measure if required. Next, "linear discriminant analysis" (LDA) [18] involves developing a probabilistic model per class based on the specific distribution of observations for each input variable. A new sample is then classified by calculating the conditional probability of it belonging to each class and selecting the class with the highest probability. *Gamma Delta, and Discriminant Type* hyperparameters were optimized. Finally, an "artificial neural networks“ (ANN) [15] was adopted in the *shallow* version with one hidden layer. The optimized hyperparameter were the *activation function* (relu, sigmoid, or tanh) and the *hidden layer number of neurons*.

III. Results

In this section, the results achieved in experimenting different BCI paradigms are reported. The discussion is conducted by dividing the BCI systems into reactive, active, and passive. Moreover, an hybrid BCI is reported, which integrates a reactive paradigm with voluntarily generated artifacts. Classification accuracy is mainly adopted as a performance metric. The overall aim is to give some indications about the current state of wearable BCI technologies, and to evaluate the possibility of their daily-usage.

A. Reactive BCI

Among reactive BCI paradigms, SSVEPs have relatively high signal-to-noise ratio and great inter-subject reproducibility [19], [20]. SSVEP occurs in EEG as a response to a visual stimulus and it exhibits the same main harmonic component. In general, extensive user and/or algorithm training is not required, eventually leading to a training-free system [11], [12], [21]. SSVEP-related activity is measured in the occipital area of the scalp. Therefore, the system was implemented by measuring brain activity between occipital and frontal lobe through a single differential channel.

In the considered case study, the user could carry out an inspection task within the Industry 4.0 framework. Flickering icons on the display of AR glasses were exploited to communicate hands-free with a wireless sensor network. In particular, icons were activated by simply staring at them [22]. Two flickering icons were chosen, at nominal frequencies equal to 10.0 Hz and 12.0 Hz, respectively. The AR glasses application was developed with Android Studio. The architecture of the proposed system is reported in Fig. 2.

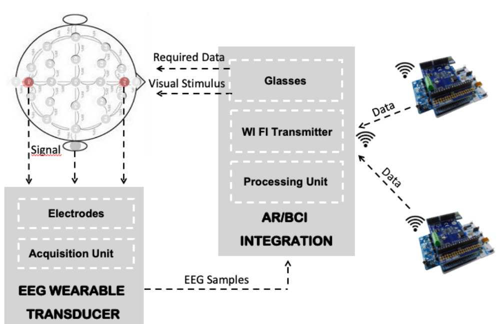

Fig. 2. BCI architecture for the Industry 4.0 case study [23].

Twenty subjects (13 males), between 22 and 47 years old, took part to the experiments. For each subject, 24 trials with two flickering icons were conducted. In each trial, the brain signal acquisition lasted up to 10.0 s, with few seconds between consecutive trials. Nonetheless, smaller time windows were also analyzed. An average accuracy of 98.9% was achieved with a latency of 10.0 s, dropping to 81.1% at 2.0 s (Table I).

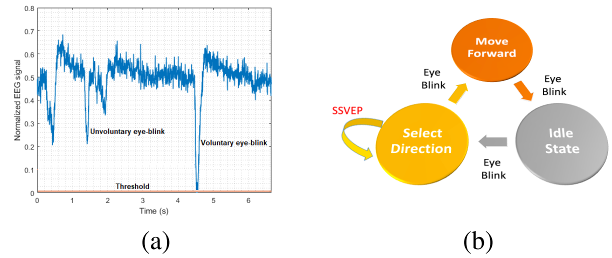

Fig. 3. SSVEP-BCI with eye blink detection: (a) voluntary and involuntary blinks, (b) state machine associated to the system operation [23]

TABLE I
SSVEP classification accuracies obtained as a mean among 20 subjects and at varying time window. The standard deviation is also reported

	10.0 s	**8.0 s**	**6.0 s**	**5.0 s**	**4.0 s**	**3.0 s**	**2.0 s**
MEAN	98.9%	98.1%	97.5%	96.0%	94.8%	88%	81%
STD	2.3%	3.2%	4.1%	6.0%	6.1%	12%	17%

B. An hybrid BCI

The next step of the research at ARHeMLab was to enhance the performance of reactive BCI by exploiting voluntary eye-blink as an additional command. Eye-blink artifacts are characterized by negative peaks along the EEG track. Voluntary blinks are generally emphasized with respect to involuntarily ones, as shown in Fig. 3. Therefore, a proper threshold must be fixed in eye-blinking detection. Moreover, SSVEP signals were processed in the time domain by calculating correlation with respect to two reference sine waves, at 10 Hz and 12 Hz, respectively. This allowed to study also time windows shorter than 2 s.

This hybrid BCI was tested in a rehabilitation protocol for children with attention deficit hyperactivity disorder (ADHD) and/or autism. The children were engaged in piloting a robot indoor. By means of voluntary eye blinks, the robot state could be changed between (i) idle state, (ii) change direction, and (iii) move forward (Fig. 3.b). In the “change direction” state, the child could choose the direction (left or right) by means of flickering icons evoking SSVEPs. Resulting mean accuracy and latency for SSVEP and eye-blink detection are reported in Table II. The latency in eye-blink detection is also reported. This considers either the fact that, in detection, the EEG amplitude must be below a threshold for a non-zero amount of time, and then there is a latency related to the interrupt routine sending the command associated with the detected eye-blink.

TABLE II
Mean classification accuracy and latency of SSVEP and eye-blink signals.

	accuracy (%)	latency (%)
SSVEP	78.5 ± 6.5	1.22 ± 0.42
eye-blink	93.0 ± 4.6	0.22 ± 0.02

C. Active BCI

Motor imagery (MI) is probably the most adopted paradigm within active BCIs. It consists in imagining a specific movement without executing it, and then acquiring and classifying the associated sensorimotor rhythms [24]. Several researches have shown MI-BCI suitability in communication, control, and rehabilitation [25], [26]. Such BCIs are easy to use and comfortable because they rely on spontaneous brain activity. However, performance is limited by inter-subject and intra-subject variability [27]. Moreover, wearability and portability are limited by the relatively high number of channels required in many paradigms.

In this regard, the research focus at ARHeMLab has been dedicated to decrease the number of required channels. A "filter-bank common spatial pattern" (FBCSP) approach was exploited in processing EEG signals [28]. By doing so, signals were represented through logarithmic band-power features containing both spectral and spatial information. The developed selection method adds a non-uniform embedding strategy [29] to evaluate the contribution of each channel to the final performance. As a result, the channel selection returns the classification accuracy as a function of the number of selected channels. Moreover, a specific sequence for channels to select is also achieved. This method was validated on the dataset 2a of BCI Competition IV [30]. The accuracy in classifying motor imagery tasks was assessed with a 6-fold cross-validation. The results in terms of mean cross-validation accuracy among 9 subjects are reported with a blue line in Fig. 4 with specific regard to the imagination of left hand or right hand movement. In the figure, the sequence of channels resulting from the algorithm is represented on the x-axis. These channels are located according to the 10-20 standard for EEG electrodes placing [31]. Meanwhile, the classification accuracy is represented in percentage on the y-axis, and a light-blue area also depicts the standard deviation associated to the mean accuracy.

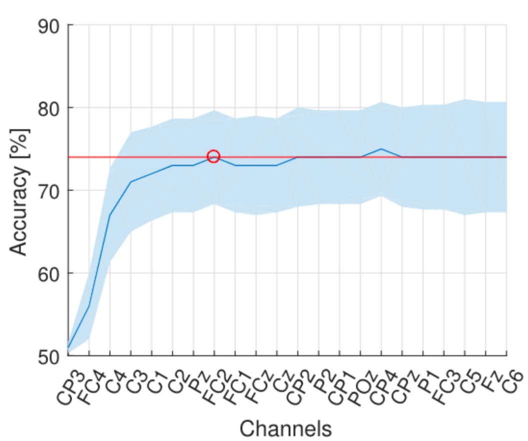

Fig. 4. Mean classification accuracy and associated standard deviation as a function of selected channels, in the case of left hand versus right hand imagery. The red line represents accuracy at maximum number of channels (22), while the red circle corresponds to the minimum number of channels for which this same accuracy is reached (8 in the present case).

The significance of this representative results is in the fact that 8 channels can be used, instead of 22, without losing in classification performance. On the other hand, the performance still remains inadequate for many applications. Therefore, future studies will deal with EEG non-stationarity and feedback will be also exploited in trying to improve such a BCI.

D. Passive BCI

1) stress detection: systematic alterations in frontal EEG asymmetry, in response to specific emotional stimuli, can be exploited to analyze emotional response [32]. In particular, EEG asymmetry proved to be capable of predicting state-related emotional changes and responses. For example, a greater self-reported happiness or positively-valued stimuli might be expected to be associated with greater relative left frontal activity. Therefore, greater relative right frontal activity would be expected in response to negative stimuli [33]. However, fear or happiness response to stimuli may either be attenuated or amplified according to any given individual's trait pattern of frontal EEG asymmetry [33].

The architecture of the proposed method is shown in Fig. 5, in an example of interaction with a cobot. Prefrontal asymmetry is measured by two electrodes as the difference of brainwaves from position FP1 and FP2, according to 10/20 system. The differential signal is referred to the earlobe. Analog signal is digitized by the acquisition unit and it is sent, via wires, to the wi-fi transmission unit. Digital data arrives at the processing unit through wireless communication for real-time elaboration. Preliminary experiments in frequency domain highlighted poor accuracy results. Therefore, data analysis was carried out in the time domain. According to the state of the art [34], an EEG time window of 2 s was chosen as the optimal solution considering the trade-off accuracy vs latency. In time domain, EEG tracks are divided into 2–s records of 512 samples. In this way, raw data are composed of 512 features, i.e. each feature corresponds to just one sample. Feature extraction was carried out by a standard machine learning technique, the PCA.

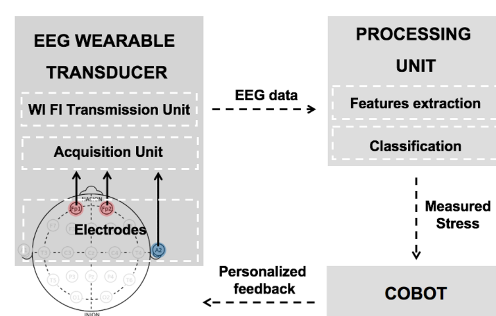

Fig. 5. BCI architecture for stress detection [35].

Ten healthy young volunteers (average age 25 years) of whom five women and five men, participated in the study. Participants were divided equally into control and experimen-

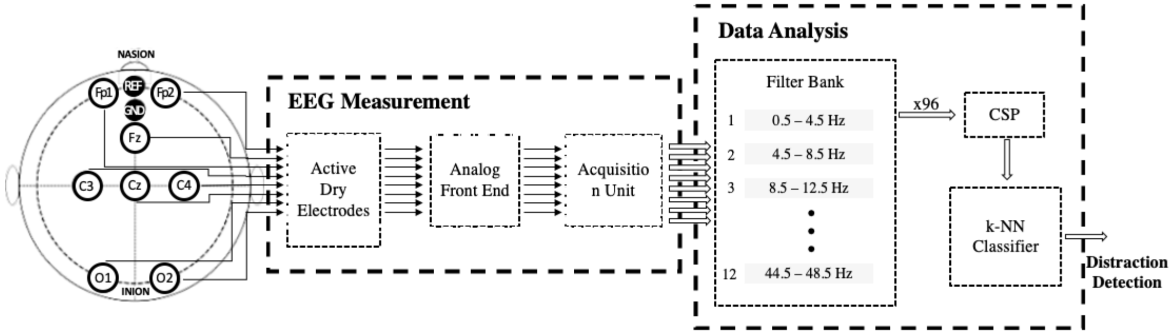

Fig. 6. BCI architecture for distraction detection.

tal groups, to complete a task, which induces mental load, together with (experimental group) or without (control group) negative social feedback. In particular, the Stroop experimental and clinical purposes, aimed to challenge subject using a complex cognitive task. As triple metrological references, standardized stress tests, observational questionnaires given by psychologists, and performance measurements were exploited. Four different machine learning classifiers were used for validating the proposed method, by distinguishing stressed subject signals from no-stressed subject signals: (i) SVM (linear kernel), (ii) k-nearest neighbors (n_neighbors = 9), (iii) random forest (criterion = 'gini', max_depth = 118, min_samples_split = 49) , and (iv) ANN (one hidden layer, activation function for hidden node = hyperbolic tangent, loss function = cross entropy cost, post processing = soft max, training algorithm = Resilient Propagation). Each classifier was fed with both raw data (2-s EEG epoch) and PCA pre-processed data. Generally, PCA allows to obtain a better noise robustness. The results show the adequacy of the proposed solution based on a single-acquisition channel and time domain-based feature selection. In the worst case, the linear-kernel SVM classifier succeeded in discriminating stress conditions with an accuracy of $97.5 \pm 0.6\%$ and a latency of 2 s. For latency above 4 s the accuracy reaches 100%. Noise robustness was tested in order to exclude the impact of bias during signal acquisition and to empower generality to the results.

2) distraction detection: in everyday life, many types of distracting effects (visual, auditory, and their combinations) divert attention when performing any task, especially if engaging [36]. Diez et al. identified attention just as the ability to select interesting stimuli, by ignoring other distracting stimuli in the surrounding environment [37]. These distractors play a fundamental role in analyzing the attentional process [38]. Changes in cognitive processes related to attention activate different parts of the brain. Concurrent distracting events deactivate certain brain areas by activating other ones [39].

The measurement method is illustrated in Fig. 6. The EEG signals are acquired by active dry electrodes from the scalp. Each channel is differential with respect to AFz (REF), and referred to Fpz (GND), according to 10/20 international system. Analog signals are first transduced by the active dry electrodes and then conditioned by the analog front-end. Next, they are digitized by the acquisition unit and transmitted to the data analysis stage. Here, suitable features are extracted by the chain of a 12-component filter bank and a CSP algorithm. The k-NN classifier receives the feature arrays and detects distraction.

Experimental validation was realized on nine volunteers. The commercial EEG acquisition system *Ab Medica Helmate* [8] was employed. The device, composed of ten dry electrodes, guarantees eight acquisition channels. The EEG signal is acquired by dry electrodes made of conductive rubber with an Ag/AgCl coating at their endings [9]. Different features extraction from spatial, temporal, and frequency domain and classification strategies were compared. The performances of five supervised classifiers in discriminating between attention on pure movement and with distractors were compared. The higher accuracy, 89.4 ± 3.0 %, was obtained by a k-nearest neighbors classifier when the features extraction is based on a custom 12 pass-band filter bank and the CSP algorithm. The latency of the device, of only 1.5 s, is suitable, for example, to improve the main motor rehabilitation therapies and allows the therapist or an automated system to know when to stimulate the patient's attention for enhancing the therapy effectiveness.

IV. Conclusion

In this paper, a five-year research activity on BCI at ARHeMLab of University Federico II of Naples was presented. All the BCI paradigms were explored: reactive, active, and passive. Standard benchmark dataset and data from custom experimental campaigns (more than 200 volunteers involved in five years) were used. Custom device conceived with off-the-shelf components and CE marked EEG instrumentation were employed. The major goals of the investigated measurements methods were:

- *enhanced wearability*: low number of channels, dry electrodes, and wi-fi connection allow daily-life applications;
- *low-cost solutions*: off-the-shelf components based devices will expand the end-user market;
- *BCI for control and monitoring*: among the bio-signal based interfaces, BCI guaranties simultaneously control and monitoring. It is a particularly effective interface in connecting humans to the cyber-physical systems.

Results showed that machine learning based solutions are successful in extracting information from highly wearable EEG devices based on few channels and dry electrodes. As a general consideration, the promising results achieved so far anticipate a strong potential of BCI systems for practical applications and motivating further research dedicated to improving wearability and identifying low-cost implementation solutions. This would ultimately lead to a large-scale adoption of BCI in daily activities.

References

[1] S. K. Sowe, E. Simmon, K. Zettsu, F. de Vaulx, and I. Bojanova, "Cyber-physical-human systems: Putting people in the loop," *IT professional*, vol. 18, no. 1, pp. 10–13, 2016.

[2] B.-C. Pirvu, C.-B. Zamfirescu, and D. Gorecky, "Engineering insights from an anthropocentric cyber-physical system: A case study for an assembly station," *Mechatronics*, vol. 34, pp. 147–159, 2016.

[3] G. Schirner, D. Erdogmus, K. Chowdhury, and T. Padir, "The future of human-in-the-loop cyber-physical systems," *Computer*, vol. 46, no. 1, pp. 36–45, 2013.

[4] I. Zolotová, P. Papcun, E. Kajáti, M. Miškuf, and J. Mocnej, "Smart and cognitive solutions for operator 4.0: Laboratory h-cpps case studies," *Computers & Industrial Engineering*, vol. 139, p. 105471, 2020.

[5] 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.

[6] T. O. Zander, C. Kothe, S. Jatzev, and M. Gaertner, "Enhancing human-computer interaction with input from active and passive brain-computer interfaces," in *Brain-computer interfaces*, pp. 181–199, Springer, 2010.

[7] Olimex, "Schematics of the EEG-SMT device for electroencephalography." https://www.olimex.com/Products/EEG/OpenEEG/EEG-SMT/resources/EEG-SMT-SCHEMATIC-REV-B.pdf.

[8] "Ab-medica s.p.a.." https://www.abmedica.it/, 2020. Accessed: June 01, 2020.

[9] H. Hinrichs, M. Scholz, A. K. Baum, J. W. Kam, R. T. Knight, and H.-J. Heinze, "Comparison between a wireless dry electrode eeg system with a conventional wired wet electrode eeg system for clinical applications," *Scientific Reports*, vol. 10, no. 1, pp. 1–14, 2020.

[10] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update," *Journal of neural engineering*, vol. 15, no. 3, p. 031005, 2018.

[11] L. Angrisani, P. Arpaia, D. Casinelli, and N. Moccaldi, "Single-channel, steady state visually evoked potential-based brain computer interface: a proof of principle for biomedical daily use," in *Journal of Physics: Conference Series*, vol. 1065, p. 132005, IOP Publishing, 2018.

[12] L. Angrisani, P. Arpaia, D. Casinelli, and N. Moccaldi, "A single-channel ssvep-based instrument with off-the-shelf components for trainingless brain-computer interfaces," *IEEE Transactions on Instrumentation and Measurement*, 2018.

[13] D. Thiyam and E. Rajkumar, "Common Spatial Pattern Algorithm Based Signal Processing Techniques for Classification of Motor Imagery Movements: A Mini Review," *IJCTA*, vol. 9, no. 36, pp. 53–65, 2016.

[14] I. T. Jolliffe, "Principal components in regression analysis," in *Principal component analysis*, pp. 129–155, Springer, 1986.

[15] C. M. Bishop, *Pattern recognition and machine learning*. springer, 2006.

[16] L. Fraiwan, K. Lweesy, N. Khasawneh, H. Wenz, and H. Dickhaus, "Automated sleep stage identification system based on time–frequency analysis of a single eeg channel and random forest classifier," *Computer methods and programs in biomedicine*, vol. 108, no. 1, pp. 10–19, 2012.

[17] B. Hu, X. Li, S. Sun, and M. Ratcliffe, "Attention recognition in eeg-based affective learning research using cfs+ knn algorithm," *IEEE/ACM transactions on computational biology and bioinformatics*, vol. 15, no. 1, pp. 38–45, 2016.

[18] K. Fukunaga, *Introduction to statistical pattern recognition*. Elsevier, 2013.

[19] Y. Wang, R. Wang, X. Gao, B. Hong, and S. Gao, "A practical VEP-based brain-computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 2, pp. 234–240, 2006.

[20] I. Volosyak, F. Gembler, and P. Stawicki, "Age-related differences in SSVEP-based BCI performance," *Neurocomputing*, vol. 250, pp. 57–64, 2017.

[21] H. Cecotti, "A self-paced and calibration-less SSVEP-based brain–computer interface speller," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 2, pp. 127–133, 2010.

[22] L. Angrisani, P. Arpaia, A. Esposito, and N. Moccaldi, "A wearable brain-computer interface instrument for augmented reality-based inspection in industry 4.0," *IEEE Transactions on Instrumentation and Measurement*, 2019.

[23] P. Arpaia, L. Duraccio, N. Moccaldi, and S. Rossi, "Wearable brain-computer interface instrumentation for robot-based rehabilitation by augmented reality," *IEEE Transactions on Instrumentation and Measurement*, 2020.

[24] M. Hamedi, S.-H. Salleh, and A. M. Noor, "Electroencephalographic motor imagery brain connectivity analysis for BCI: a review," *Neural computation*, vol. 28, no. 6, pp. 999–1041, 2016.

[25] S. De Vries and T. Mulder, "Motor imagery and stroke rehabilitation: a critical discussion," *Journal of rehabilitation medicine*, vol. 39, no. 1, pp. 5–13, 2007.

[26] R. Ron-Angevin, F. Velasco-Álvarez, Á. Fernández-Rodríguez, A. Díaz-Estrella, M. J. Blanca-Mena, and F. J. Vizcaíno-Martín, "Brain-Computer Interface application: auditory serial interface to control a two-class motor-imagery-based wheelchair," *Journal of neuroengineering and rehabilitation*, vol. 14, no. 1, p. 49, 2017.

[27] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, "The non-invasive berlin brain–computer interface: fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, no. 2, pp. 539–550, 2007.

[28] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b," *Frontiers in neuroscience*, vol. 6, p. 39, 2012.

[29] L. Faes, G. Nollo, and A. Porta, "Information-based detection of nonlinear Granger causality in multivariate processes via a nonuniform embedding technique," *Physical Review E*, vol. 83, no. 5, p. 051112, 2011.

[30] C. Brunner, R. Leeb, G. Müller-Putz, A. Schlögl, and G. Pfurtscheller, "BCI Competition 2008–Graz data set A," *Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology*, vol. 16, 2008.

[31] G. H. Klem, H. O. Lüders, H. Jasper, C. Elger, *et al.*, "The ten-twenty electrode system of the International Federation," *Electroencephalogr Clin Neurophysiol*, vol. 52, no. 3, pp. 3–6, 1999.

[32] J. A. Coan and J. J. Allen, "Frontal EEG asymmetry as a moderator and mediator of emotion," *Biological psychology*, vol. 67, no. 1-2, pp. 7–50, 2004.

[33] I. Papousek, E. M. Weiss, G. Schulter, A. Fink, E. M. Reiser, and H. K. Lackner, "Prefrontal EEG alpha asymmetry changes while observing disaster happening to other people: cardiac correlates and prediction of emotional impact," *Biological psychology*, vol. 103, pp. 184–194, 2014.

[34] J. Minguillon, M. A. Lopez-Gordo, and F. Pelayo, "Stress assessment by prefrontal relative gamma," *Frontiers in computational neuroscience*, vol. 10, p. 101, 2016.

[35] P. Arpaia, N. Moccaldi, R. Prevete, I. Sannino, and A. Tedesco, "A wearable eeg instrument for real-time frontal asymmetry monitoring in worker stress analysis," *IEEE Transactions on Instrumentation and Measurement*, 2020.

[36] S. Aliakbaryhosseinabadi, E. N. Kamavuako, N. Jiang, D. Farina, and N. Mrachacz-Kersting, "Classification of eeg signals to identify variations in attention during motor task execution," *Journal of neuroscience methods*, vol. 284, pp. 27–34, 2017.

[37] P. F. Diez, A. G. Correa, L. Orosco, E. Laciar, and V. Mut, "Attention-level transitory response: a novel hybrid bci approach," *Journal of neural engineering*, vol. 12, no. 5, p. 056007, 2015.

[38] M. Noam, N. Mor, S. Arjen, R. T. Knight, and A. Perry, "Behavioral and eeg measures show no amplifying effects of shared attention on attention or memory," *Scientific Reports (Nature Publisher Group)*, vol. 10, no. 1, 2020.

[39] N. Hill and B. Schölkopf, "An online brain–computer interface based on shifting attention to concurrent streams of auditory stimuli," *Journal of neural engineering*, vol. 9, no. 2, p. 026011, 2012.