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TOPICAL REVIEW

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Passive BCI beyond the lab: current trends and future directions

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Abstract

Over the last decade, passive brain–computer interface (BCI) algorithms and biosignal acquisition technologies have experienced a significant growth that has allowed the real-time analysis of biosignals, with the aim to quantify relevant insights, such as mental and emotional states, of the users. Several passive BCI-based applications have been tested in laboratory settings, and just a few of them in real or, at least, simulated but highly realistic settings. Nevertheless, works performed in laboratory settings are not able to take into account all those factors (artefacts, non-brain influences, other mental states) that could impair the usability of passive BCIs during real applications, naturally characterized by higher complexity.

The present review takes into account the most recent trends in using advanced passive BCI technologies in real settings, especially for real-time mental state evaluations in operational environments, evaluation of team resources, training and expertise assessment, gaming and neuromarketing applications.

The objective of the work is to draw a mark on where we are to date and the future challenges, in order to make passive BCIs closer to being integrated into daily life applications.

1. Introduction

The first attempt to evaluate the feasibility and practicality of employing brain signals in a man–computer dialogue was introduced in 1973 (Vidal 1973). In such a perspective, the machine was considered as a prosthetic extension of the user's brain. In its classical definition, the brain–computer interface (BCI) was considered as 'a communication system in which messages or commands do not pass through the brain normal output pathways of peripheral nerves and muscles' (Wolpaw *et al* 2002).

The original aim of BCI applications was to provide a communication and/or control channel for people with severe motor disabilities (i.e. locked-in people). In fact, because of (i) the low transfer rate (25 bits min^{-1}, Wolpaw *et al* 2002, Aricò *et al* 2014), and depending on the brain feature of the specific user, and also (ii) the long training period (i.e. sensory motor-based BCIs), such types of systems remain a possible effective solution just for patients. Most recently, it was considered possible to explore other applications of BCIs rather than only enhanced communication and additional control channels. In particular, Wolpaw and Wolpaw (2012) defined a brain–computer interface as 'a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment'. From the measure of the CNS activity to the conversion into artificial output, there are few common processing steps for any kind of BCI system. In particular, a BCI records brain signals (e.g. electroencephalography (EEG), functional near infra-red spectroscopy (fNIRS), etc), extracts specific features from such signals (e.g. event-related potentials (ERPs), frequency bands), and converts (i.e. translates) these features into artificial outputs (figure 1).

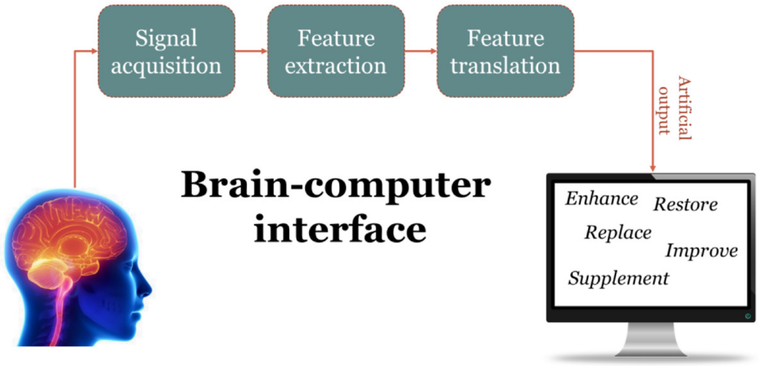

Figure 1. A schematic representation of the basic processing of BCI systems.

Over the last decade, researchers have suggested new application fields for BCI systems, developing applications that also involve healthy subjects in real-life situations. In fact, the meaning of the term 'BCI' (which originally only included the translation of the users' intentions through the classification of their voluntarily modulated brain activity, e.g. Ma *et al* (2017)) was broadened to comprise the monitoring of cognitive and emotional states (e.g. mental workload, attention levels) identified through the users' spontaneous brain activity. In other words, the BCI system itself is able to covertly, or more correctly 'passively' decode, the mental and emotional states of the user by using neurophysiological signals. This type of new concept of the BCI has therefore been called the 'passive brain–computer interface' (pBCI, Arico *et al* 2017a, Zander and Kothe 2011, Blankertz *et al* 2016, Arico *et al* 2017c). Figure 2 shows a brief representation of the pBCI concept.

Over the past few years, pBCI technology has gained popularity in the form of *measurement devices* allowing us to measure, even in real time, mental states such as attention, stress, workload, performance capability, emotion etc, and to use them (i) to provide feedback to the user (Borghini *et al* 2017a), (ii) in a closed loop to modify the behaviour of the interface that the user is interacting with Aricò *et al* (2016a), or (iii) to provide user's insights related to his/her feelings (e.g. emotion or interest) when experiencing specific situations (e.g. advertisements, etc) without any verbal communication (Cartocci *et al* 2016).

Several review papers have been published during the last few years regarding pBCI-based applications highlighting future trends and open issues to introduce such systems in real-life applications. For example, Roy and Frey (2016) focused their work on highlighting different mental states (i.e. cognitive workload, mental fatigue and vigilance, attention, error detection, emotions) the 'brain markers', or features that can be used to classify each of the mentioned mental states, in order to realize pBCI-based real-life applications, such as in air traffic management (ATM), driving and tactile and robotic interfaces. Authors have highlighted an important limitation of pBCIs, regarding the possibility of classifying different mental states at the same time in real settings-based applications, because of the intersection of brain features with respect to different mental states (e.g. P300 ERP is affected both by workload and attention or fatigue, and so on). Regarding the same issue, Fairclough (2009) proposed an interesting review paper on physiological computing, that represents another way to denominate pBCI, in which the attention has been focused on the mapping between mental states and neurophysiological measures, in particular by stressing the complexity of the neurophysiological inference; in other words, the possible inaccuracy in associating variations in neurophysiological features just because of one specific mental state and not of others. For example, frontal EEG theta rhythm variations are sensitive not only to workload, but even to fatigue or effort (Borghini *et al* 2013). Such difficulty in assessing a specific mental state by using neurophysiological activity of the user is increased, especially in real settings, since it is plausible to assume that such settings evoke complex user states that consist of multiple different components having the potential to influence neurophysiological signals used to infer a specific state. In particular, Grissmann and colleagues (2017) investigated the impact of affective valence on the classification of working memory load. The authors' findings revealed that the affective context could significantly affect classification accuracy, concluding that classifiers could fail to generalize across affective contexts, thus highlighting the need for user state models that can account for different contexts or new, context-independent, brain features. In this regard, Roy and colleagues proposed a work demonstrating the impact of mental fatigue on workload assessment, in particular on EEG frequency bands used to evaluate the workload experienced by the users and the related classification performances. In particular, 20 subjects performed an experimental protocol, which involved modulating the workload between two levels and the time on task (i.e. short and long), in order to highlight changes induced by mental fatigue. The experiment demonstrated opposite changes in alpha power distribution between workload and time on task conditions, as well as a decrease in workload level discriminability with increasing time on task in both the number of statistical differences in band power and classification performance (Roy *et al* 2016, 2013).

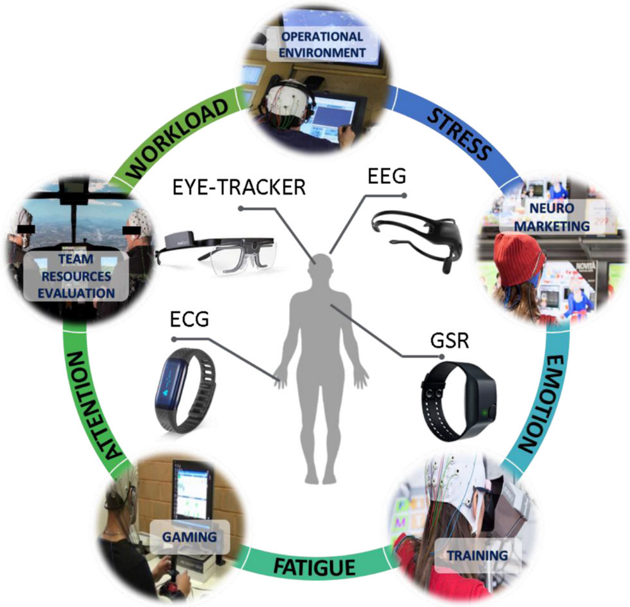

Figure 2. A schematic representation of the passive BCI concept. In particular, a pBCI system is able to collect different types of biosignals (e.g. EEG, GSR, ECG, EYE-TRACKER) and computes them to evaluate different users' mental and emotional states (e.g. workload, attention, etc). Such insights can be used to change the behaviour of the surrounding environment or the technology that the user is interacting with.

Another less recent, but still interesting review paper has been proposed by van Erp and colleagues (2012). The authors identified seven possible BCI applications, beyond the medical application: in particular, device control, user state monitoring, evaluation, training and education, gaming and entertainment, cognitive improvement, safety and security. For each of these applications an estimation of the time to market was provided. The two main gaps to fill to make pBCI systems entering the market were identified as (i) calibration of pBCI classification algorithms need too much data to be calibrated, and (ii) the EEG cap technology is still expensive, not wearable and at the same time reliable (i.e. dry EEG sensors) and uncomfortable. It is interesting to highlight how these issues have not been completely addressed so far (see the following sections), and this aspect induced a broadening of the timing estimation provided by the aforementioned review work of a few years. Although a huge amount of works regarding the potential applications of passive BCI systems have been published over the last decade, most of them have been tested only in the laboratory or, in general, in very controlled settings. Nevertheless, in the last few years, passive BCI systems have improved significantly in terms of reliability and usability with respect to their applicability.

The present review will focus in particular on the steps forward made in terms of the applicability of pBCIs in real settings in recent years, highlighting technological, applicative and methodological aspects.

2. Technologies

Many neurophysiological measures have been considered to be used to evaluate mental and emotional states of the users, e.g. the brain activity analysis by EEG, fNIRS, functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and other types of biosignals such as electrocardiography (ECG), electrooculography (EOG) and galvanic skin response (GSR; Borghini *et al* 2014b). With regards to applying neurophysiological measures to realize daily life pBCI-based applications, issues related to the size, weight and power of equipment impede the use of MEG and fMRI (Gramann *et al* 2014). To give an example of the effort recently produced in this field, different neurophysiological indicators have been developed and tested in real settings applications, for example in aviation (EEG, fNIRS, ECG, EOG and pupil dilation; Izzetoglu *et al* 2015, Aricò *et al* 2016b, Arico *et al* 2017), surgery (EEG; Borghini *et al* 2016a), city traffic monitoring (EEG, fNIRS, ECG, eye tracking; Matthews *et al* 2015, Dehais *et al* 2015b, Gateau *et al* 2018) power plant control centers (EEG, ECG; Fallahi *et al* 2016) and other daily life activities (EEG, ECG, EOG, fNIRS, GSR; Cherubino *et al* 2016, Kong *et al* 2015).

In recent years, many companies have been moving to develop more wearable and minimally invasive biosignal acquisition devices. For example, regarding EEG systems, actual effort is being made to develop dry sensors (i.e. not requiring any conductive gel), or to eventually use water-based solutions instead of the gel, allowing high signal quality and comfort (Mihajlovic *et al* 2015). Easy to apply ring-electrodes with a sponge soaked in water have been proposed to provide reliable EEG signals (von Lühmann *et al* 2017). Moreover, dry electrodes have been proposed through the years, moving from metallic spin electrodes to silicone ones (Yu *et al* 2016) to easily reach the skin on the head, despite the presence of hair. To avoid the disposition of the EEG electrodes on the scalp, the ears often have to be involved. This is the cEEGgrid, consisting of ten electrodes printed on a flexible adhesive around the ear (Debener *et al* 2015), or of soft and thin electrodes placed in the ear (Nguyen *et al* 2016). Wireless and wearable EEG devices have been adopted during different experiments in real driving (Lin *et al* 2017). For example, Zander *et al* (2017a) tested the Brain Product actiCAP Xpress dry EEG cap during an autonomous driving experiment. The authors tested such an EEG system in terms of the usability and comfort from the user's side, and the signal quality in order to implement a pBCI despite movements and artefacts due to the real settings. The authors concluded that the evaluated system was able to provide the essential requirements for an application in an autonomous driving context, since (i) the signal quality was sufficient for standard EEG analysis in both the time and frequency domains; (ii) while the influence of vehicle-induced interferences on data quality was insignificant, driving-related movements led to strong shifts in electrode positions; (iii) in general, the EEG system allowed a fast self-applicability of the cap and electrodes; (iv) the assessed usability of the system was still acceptable (i.e. fast self-applicability of cap and electrodes); while (v) the wearing comfort decreased strongly over time due to friction and pressure to the head. In this regard, many portable and dry EEG recording systems demonstrated similar results, such as g.Nautilus (g.Tec, Amaral *et al* 2017), Enobio (Neuroelectrics, Vourvopoulos *et al* 2017) or Cognionics (Mullen *et al* 2015). In particular, with regards to the Cognionics system, the authors also developed a comprehensive open source framework able to perform online neuroimaging and user's state monitoring. This work proposed such a type of framework applied on a 64-channel dry EEG system. The work provided an example of a robust real-time measurement and interpretation of complex brain activity in the dynamic environment of the wearable setting.

Even hybrid approaches have been proposed. For example, von Luhmann (2017) proposed a mobile, modular and multimodal (EEG, fNIRS, ECG, EMG) biosignal acquisition architecture (M3BA). It consists of a microcontroller that allows integration and customization, a Bluetooth connection and a 3D accelerometer. The use of both wet or dry electrodes is possible thanks to high input impedance and a common mode rejection ratio. Finally, due to the long duration of the biosignal acquisition, radio frequency identification (RFID)-based sensor systems have been proposed: passive RFID technology allows a significant reduction in size for a wearable system thanks to the absence of a battery (Vora *et al* 2017). For other physiological signals, wearable and ergonomic sensor commercialization has grown exponentially over the last few years. For example, wristbands that record heart rate or skin conductance are already available offering a high reliability for daily life pBCI-based applications. In addition, breathing and heart rate can be monitored without attaching sensors to the body, but by using a camera. For example, Procházka *et al* (2016) proposed such an approach by means of Microsoft Kinect for heart rate and breath acquisition.

3. Applications

In the following sections, several applications are reported in which pBCI systems have been successfully tested. As stated above, the most recent works have been considered in order to provide the reader with information regarding state of the art practical attempts at pBCI applications. Table 1 summarizes the main studies that are reviewed in this section to highlight the salient aspects for each application in terms of paradigm, technologies and results.

3.1. Operational environments

One of the main applications in which pBCI systems have been exploited is related to the evaluation of users' mental states during their working activities, in particular to enhance human–computer interactions, human factor assessment and/or predict human errors. In such safety-critical environments, where humans are subjected to multiple sources of information, possibly on the same perceptual channels (e.g. two visual inputs), or even on different channels (e.g. visual and auditory inputs) and with different priorities on the tasks, a user's wrong behaviour could induce serious consequences, since attentional resources are continuously divided between different stimuli (Ma *et al* 2017).

3.1.1. Driving

One of the applications in which pBCI could be very useful is driving. One recent work has been proposed by Brouwer and colleagues (2017), in which they recorded physiological responses (heart rate, eye blinks, and brain signals from 64 sites) of 15 healthy subjects during real driving experiments, with the aim of investigating the drivers experience in terms of mental and emotional states, during the use of automatic cruise control (ACC) technology. The authors demonstrated that physiological responses could be used to evaluate the mental states of the drivers. In another paper, the same authors (Krol *et al* 2017b) demonstrated that it was possible to implement a reliable pBCI application, despite myriad sources of artefacts (i.e. muscle artefacts, mechanical artefacts and noise produced by the car's electrical systems) that could interfere with the signal of interest in a real driving experience, thanks to the recent progress in artefact removal techniques. In particular, they used artefact subspace reconstruction (ASR) and Infomax independent component analysis (ICA) on CUDA architecture, reaching a classification accuracy of 77% (better than chance). In the same application field, Herff *et al* (2017) computed a fNIRS-based workload index to discriminate between two workload levels in a realistic driving scenario. Cognitive load effects on driving have been investigated using a virtual reality driving simulator. In such an environment, Unni *et al* (2017) showed not only is it possible to predict the level of working memory load using fNIRS, but also that, by sampling the whole head with high-density fNIRS, the increasing cognitive load is associated with increasing brain activation in bilateral inferior frontal and bilateral temporal-occipital areas. In another interesting work proposed by Reyes-Muñoz and colleagues (2016), the authors developed an Android-based, real-time low-level attention detection system depending on the actual EEG activity of the driver. Such a system was able to issue warnings of critically low driver attention levels. Other recent works investigated the possibility of predicting drowsiness and fatigue by classifying the users' brain activity. Liang *et al* (2017) proposed a study in which 16 night shift workers undertook two 2 h driving sessions by using a real vehicle on a closed test track. In particular, the authors developed and tested an EEG-based, real-time drowsiness detector able to manage the drowsiness level and avoid related motor-vehicle crashes and loss. The possibility of classifying the effect of sleep deprivation on drivers is due to the fact that power spectral analysis has shown a significant increase in alpha and theta power in cases of sleep deprivation. Such relevant results have been obtained on 24 participants performing a 1 h monotonous highway driving task (Perrier *et al* 2016). In contrast to oscillatory features, Khaliliardali *et al* (2016) proposed the use of ERP pBCI during driving. In particular, the authors investigated the possibility of building in-car pBCI systems to predict specific driver's intended actions (e.g. changes in traffic light signals or preparing to brake or accelerate) through anticipatory EEG brain potentials (i.e. slow cortical potentials). The experiment was conducted on eight subjects, driving an Infiniti Nissan car on a closed road.

3.1.2. Aviation

So far it has been shown that it is possible to record neurophysiological signals during both simulated and real driving tasks (Maglione *et al* 2014). The same can be said for aviation. Although the clear complexity of such an environment, Dehais *et al* (2018a) showed that dry-based EEG systems can be implemented in an actual cockpit. They recorded four aircraft pilots during real flights with the aim to investigate inattentional deafness to auditory alarms, a nagging problem in the aviation field. Also, during real flights, Di Stasi *et al* (2015) found that flight procedures of higher complexity are associated with higher EEG activity over the higher frequency bands of military helicopter pilots. An equally hazardous piloting phenomenon in aviation is the pilot-induced oscillations phenomenon, in which a pilot's control-inputs and the aircraft control-responses have become out of phase. Thanks to a pBCI system, Scholl *et al* (2016) showed that it was possible to detect, with an area under curve (AUC) of 0.7 (Bamber 1975), whether or not an aircraft pilot was experiencing this phenomenon during a challenging precision flight by tracking manoeuvres using a Calspan Learjet in-flight simulator. All these findings suggested that EEG recordings might help to evaluate a pilot's cognitive performance in challenging real and simulated scenarios, thus aiding the prevention of accidents.

Not far from an aviation field, Aricò *et al* (2016b) performed several experiments involving professional air traffic controllers at ENAC (École Nationale de l'Aviation Civile, Toulouse, France) facilities while performing high-ecological ATM tasks at different difficulty levels. Such works demonstrated the possibility of evaluating, in real time, the experienced mental workload of the operators while dealing with the ATM activities by using the controllers' brain activity. Such a workload index was also used to trigger the ATM interface and to run specific adaptive automation solutions if the operator was overloaded. Another recent work has been proposed by Dasari *et al* (2017), in which the authors evaluated EEG correlates to three mental factors (i.e. mental fatigue, workload and effort) using ICA on high-density EEG data. EEG signals were recorded on ten subjects while performing a realistically simulated air traffic control (ATC) task of 2 h. While Di Flumeri *et al* (2015) demonstrated the potential of EEG-based neurometrics of mental workload when compared with subjective measures, by computing an EEG-based workload index on professional Italian air traffic controllers dealing with realistic ATM software and obtaining higher sensitivity in terms of neurometrics. The pBCI system has also been tested in aviation using other technologies apart from EEG. For example, Dehais *et al* (2015b) developed and tested a system, based on eye tracking measurement, able to detect conflicts between the aircraft pilots and automation, that could potentially mitigate the so-called 'automation surprise', with a positive impact on safety. The system has been tested on 16 pilots by the research group of Dehais from the École Nationale Supérieure de l'Aéronautique et de l'Espace (ISAE). Gateau *et al* (2015) used fNIRS to realize a pBCI able to evaluate, even in real time, two working memory levels of 19 aircraft pilots inside a highly realistic simulator, reaching 80% of classification accuracy. Verdière *et al* (2018) investigated fNIRS-based connectivity metrics to realize a pBCI system able to detect pilots' engagement

Table 1. References related to recent applications of pBCI systems, tested in realistic and real-setting scenarios. In particular, for each paper, the specific application field (e.g. aviation), the employed biosignals (e.g. EEG), the number of subjects in the experimental group, the processing chain (e.g. linear discriminant analysis (LDA) classifier), the main results or, if available, the achieved classifier performance (e.g. area under curve (AUC) and number of classes) have been reported. In addition, for each work, we report on whether a pBCI application was actually realized and tested (i.e. full pBCI), or whether the study could potentially be used to realize a pBCI application, but such an application was not yet fully developed within the specific study (i.e. pBCI ready).

Paper	Application	System/biosignals	Mental state/paradigm	Subjects	Processing chain	Results/performance
Aricò (2016b)	Aviation	EEG	Mental Workload during real ATM task	12 ATCOs	PSD on alpha and parietal size in alpha and theta band classified by SWLDA and asSWLDA	Full pBCI; 2 classes asSWLDA maintains high reliability across a month (around AUC 0.78)
Aricò (2016a)	Aviation	EEG	Adaptive automation and workload level during ATM task	12 ATCOs	PSD features classified by asSWLDA	Full pBCI; 2 classes AA is usually activated more often during complex scenarios and it reduces workload when it is activated
Aricò (2018)	Technology comparison	EEG	Workload with augmented technology	10 ATCOs	Frontal theta and parietal alpha ratio	pBCI ready High significant negative correlation between EEG-based work-load and behavioural performance
Ayaz (2012)	Training	fNIRS	Expertise during UAV task	7 college students	Oxygenation changes for each 16 optodes were calculated separately using the Modified Beer Lambert Law (MBLL)	pBCI ready: 3 classes Three levels of expertise influence hemodynamic response in the left dorsolateral prefrontal cortex
Borghini (2017a)	Training	EEG	Assessing of cognitive control behaviour	37 ATCOs	PSD classified by asSWLDA	pBCI ready: 3 classes The proposed work demonstrated a significant discrimination accuracy among SRK levels, and between experts and students
Borghini (2015b)	Technology comparison	EEG	Workload associated with old and new avionic technologies	3 professional helicopter pilots	Frontal theta and parietal alpha ratio	pBCI ready Significant difference among the considered avionic t echnologies in terms of EEG- based workload
Brouwer (2017)	Driving	EEG HR Eye blinks	Mental and emotional states during automatic cruise control	15 healthy subjects	ISI Blink duration ERP	pBCI ready Faster HR and longer blink duration for strong brake; ERPs show an effect of the announced type of braking
Cartocci (2017a)	Neuromarketing	EEG GSR HR	Assessment of antismoking an-nouncement perceptions	22 healthy subjects	Approach Withdrawal, effort and emotional index	pBCI ready Significant difference between announcement by using neurophysiological indexes
Cherubino (2016)	Neuromarketing	EEG GSR HR	Perception of TV advertisement	24 healthy subjects	Approach Withdrawal and emotional index	pBCI ready Difference between young and old group perception

(*Continued*)

Table 1. (*Continued*)

Paper	Application	System/biosignals	Mental state/paradigm	Subjects	Processing chain	Results/performance
Dasari (2017)	Aviation	EEG	Neural mechanism of mental fatigue, workload and effort	10 healthy subjects	ICA	pBCI ready: 2 classes Independent components spectral powers correlated behavioural metrics
Dehais (2015b)	Aviation	Eye tracking	Conflicts with automation	16 pilots	EEG-engagement index; average power in beta [13–30 Hz] Average power in alpha [8–12 Hz] Average power in theta [4–8 Hz]	Full pBCI: 2 classes Short fixations and saccades to the detriment of information processing (fewer fixations) during conflict in comparison to baseline
Dehais *et al* (2018)	Aviation	EEG	Neural correlates of engagement index and inattentional deafness to auditory alarms	4 aircraft pilots	Index based on theta alpha and beta power	Full pBCI: 2 classes The index increased in the difficult flying condition that led to higher miss rate
Di Stasi (2015)	Aviation	EEG	Evaluate cognitive performance	8 military helicopter pilots	EEG delta, theta, alpha and beta bands evaluation	pBCI ready Highly demanding flight stages are associated with higher EEG power over the higher frequency bands
Ewing (2016)	Gaming	EEG	Byocirbernetic loop based on theta and alpha band activity during Tetris game	20 healthy subjects	EEG theta and alpha bands evaluation	Full pBCI: 2 classes Frontal theta is robustly sensitive to game demand; alpha activity only responded to demand at specific sites
Gateau (2015)	Aviation	fNIRS	Working memory load during flying task	19 aircraft pilots	Online SVM classifier	Full pBCI: 2 classes 80% of accuracy on single trial classification
Gauba (2017)	Neuromarketing	EEG	Predict rating of video-advertisement	25 healthy subjects	Multimodal features (EEG + NLP score) Random Forest Regression LOOCV	Full pBCI: 2 classes RMSE = 0.714
Guixeres (2017)	Neuromarketing	EEG HR Eye Tracking	Predict effectiveness of YouTube ad	35 healthy subjects	EEG metrics, pleasantness EEG index, interest EEG index, HRV metrics and eye tracking metrics. Classifier: artificial neural network	Full pBCI: 2 classes 82.9% accuracy
Hemakom (2017)	Cooperation	ECG Respiratory signal	Cooperation in a choir and surgical team	5 singers 3 members surgical team	Intrinsic synchrosqueezing transform (ISC) measure and nested intrinsic phase synchrony (N-IPS)	pBCI ready These indexes revealed accurately and physically meaningful the synchrony in time and frequency

(*Continued*)

Table 1. (*Continued*)

Paper	Application	System/biosignals	Mental state/paradigm	Subjects	Processing chain	Results/performance
Herff (2017)	Driving	fNIRS	2 workload levels during lane change task + auditory n-back task	6 healthy subjects	10-fold cross validation LDA classifier	pBCI ready: 2 classes Significant higher classification accuracy than chance level
Jahng (2017)	Cooperation	EEG	Reading others intentions in game theory paradigms	5 couples	Time-frequencies analysis and phase-locking value	pBCI ready Alpha power in right temporal and parietal regions and the higher inter-brain synchronization allow discriminating of the face-to-face condition
Khaliliardali (2016)	Driving	EEG	Anticipatory behaviour to green and red light	8 healthy subjects	QDA classifier with 4-fold cross validation of Cz potential	pBCI ready: 2 classes AUC 0.64 to red light AUC 0.63 to green light on single trial classification
Ko (2017)	Training	EEG	Sustained attention during university lessons	18 healthy subjects	Spectral analysis	pBCI ready Lower reaction time is preceded by an increase in delta and theta over occipital areas and decrease in beta over occipital and temporal areas
Krol (2017a)	Gaming	EEG eye tracking	Hands-free Tetris based on relaxation and error perception	—	Filter bank CSP features and regularized shrinkage LDA to classify relaxation and windowed-means as error perception classifier	Full pBCI: 2 classes The proposed pBCI classifier recognizes a state of error perception in the player upon landing that block
Krol (2017b)	Driving	EEG EOG EMG ECG	Cortical activity identification in highly noisy data	15 healthy subjects	Artefact subspace reconstruction and Infomax ICA on CUDA architecture	Full pBCI: 2 classes Accuracy of 77% in discriminate strong and weak deceleration with clean data with respect to 94% in case of standard preprocessed data
Liang (2017)	Driving	EEG EOG	Drowsiness detection during close track driving	16 night shift workers	Linear logistic regression testing of lane-crossing model and microsleep model	Full pBCI: 2 classes 88% accuracy for lane-crossing model and 90% per microsleep on 1 min classification
Miklody (2017)	Navigation	EEG	Workload in navigation scenario and n-back task	10 professional captains	Regularized shrinkage LDA	pBCI ready: 2 classes 25% loss in intra-phase classification
Nozawa (2016)	Communication	fNIRS	Natural cooperative communication during a group meeting	12 groups of 4 subjects	Interpersonal neuro synchronization (INS) index	pBCI ready Frontopolar INS increases during natural communication between humans

(*Continued*)

Table 1. (*Continued*)

Paper	Application	System/biosignals	Mental state/paradigm	Subjects	Processing chain	Results/performance
Perrier (2016)	Driving	EEG	Sleepiness deprivation during highway driving test	24 healthy subjects	Spectral analysis in theta alpha and beta bands	pBCI ready: 2 classes Significant increases in alpha and theta power spectra in cases of sleepiness deprivation
Scholl (2016)	Aviation	EEG	Pilot-induced oscillations phenomenon	6 pilots	Fisher linear discriminant applied on spectral features	pBCI ready: 2 classes AUC from 0.7 (raw data) to 0.79 (clean data)
Sciaraffa (2017b)	Cooperation	EEG	Workload affecting cooperation	5 couples	Multi-subject connectivity analysis	pBCI ready Task difficulty affects local properties of the multiple brain network
Shishkin (2016)	Gaming	EEG EOG Eye tracking	Differentiate intentional and spontaneous eye movements during computer puzzle game	8 healthy subjects	Single trial FRP classification with shrinkage LDA and Committee of Greedy Classifier	pBCI ready: 2 classes Intentional gaze fixation of 500 ms is discriminate using 300 ms with a sensitivity of about 0.38. Occipitoparietal negativity is the EEG marker
Toppi (2016)	Cooperation	EEG	Cooperation during simulated flight	6 couples of civil pilots	Multi-subjects connectivity analysis	pBCI ready More links between pilot and co-pilot during the landing phase that is the most collaborative
Unni (2017)	Driving	fNIRSHR	Working memory load	19 subjects	Multivariate cross-validated Lasso regression using all fNIRS sensors, only frontal and HR	pBCI ready: 4 classes Maximum mean person correlation is 0.61 between induced and predicted memory load
Vecchiato (2016)	Gaming	EEG	Analysis of cognitive load during multiple tasks	10 healthy subjects	Frequency bands analysis	pBCI ready It is possible to use a BCI device and simultaneously manage other operational tasks (i.e. flight simulator, TAV)
Verdière (2018)	Aviation	fNIRS	Engagement during manual and automated landing	12 pilots	shrinkage LDA and a stratified cross validation	Full pBCI: 2 classes 66.9% of accuracy on 10 s classification
Zander (2017b)	Clinical	EEG	Workload associated with different and technically challenging task	9 professional surgeons	Regularized shrinkage LDA	Full pBCI: 2 classes Estimated online accuracy 89% for five subjects

Note: AA, adaptive automation; ATCO, air traffic controller; asSWLDA, automatic stop stepwise linear discriminant analysis; CSP, common spacial pattern; FRP, fixation-related potentials; HR, heart rate; HRV, heart rate variability; ISI, inter stimulus interval; LDA, linear discriminant analysis; NLP, natural language processing; PSD, power spectrum density; QDA, quadratic discriminant analysis; SRK, skill-rule-knowledge; SWLDA, stepwise linear discriminant analysis; SVM, support vector machine; TAV, tasks of alertness and vigilance.

during a highly realistic automated versus manual landing scenario, reaching on average 66.9% of classification accuracy.

3.1.3. Other applications

Other operational environments have also acted as a scenario for pBCI applications. For example, Miklody *et al* (2017) developed a system able to measure the workload of operators by using their EEG activity, while using a professional ship simulator bridge and a highly realistic scenario, optimized for tugboat missions.

Another recent application has been proposed by Zander *et al* (2017b). In particular, it implemented a pBCI system to assess the workload of professional surgeons performing surgical training tasks at different difficulty levels. The EEG signal of the nine participants was classified using the BCILAB toolbox (Kothe and Makeig 2013) to estimate whether the operator load was low or high, depending on the specific performed task. Such a classification was even simulated online to demonstrate the possibility of monitoring the user's mental state (i.e. workload) continuously during real applications.

Another interesting application has been proposed by Ko *et al* (2017) that evaluated sustained attention in real classroom settings on 18 healthy students using a 32-channel EEG system (Compumedics NeuroScan, Germany). In particular, students were instructed to recognize, as quickly as possible, special visual targets that were displayed during regular university lectures. This study was important to demonstrate the feasibility of performing a sustained visual attention task in a highly distractive real classroom environment, setting the basis for developing a system capable of estimating the level of visual attention during real classroom activities by monitoring changes in the EEG-related features.

In conclusion, pBCI systems could be used to compare different technologies (e.g. new versus old), for example in terms of required mental workload or attentional resources to be used. In this regard, Borghini *et al* (2015b) performed a study on professional helicopter pilots performing realistic simulated missions carried out at AgustaWestland facilities in Yeovil (UK) with the aim to compare different avionic technologies not only in terms of performance, but also regarding the experienced workload to be used. Aricò *et al* (2018), proposed a work aiming to investigate the possibility of employing neurophysiological-based measures to assess the human–machine interaction effectiveness. In particular, two different interaction modalities (normal and augmented) related to the ATM field have been compared in terms of behavioural performance and an EEG-based workload index (frontal theta and parietal alpha ratio), by involving ten professional air traffic controllers in a control tower simulated environment at ENAC, Toulouse, France. The performance and EEG-based workload index showed a significant negative correlation, confirming the possibility of comparing different technologies from a neurophysiological point of view.

3.2. Training and expertise assessment

Inappropriate training assessment might have high social and economic impacts, especially in operative environments. The importance and the interest in the concept of training in operative environments (e.g. aviation, hospital, public transport) is reflected in the regular publication of scientific reviews in the Annual Review of Psychology since 1971 (Campbell 1971, Goldstein 1980, Wexley 1984, Tannenbaum and Yukl 1992, Salas *et al* 2001, Aguinis and Kraiger 2009). Training could not only result in the acquisition of new skills (Hill and Lent 2006, Satterfield and Hughes 2007) but also in improved declarative knowledge and enhanced strategic knowledge, defined as knowing when to apply a specific knowledge or skill, in particular during unexpected events (Kozlowski *et al* 2001, Borghini *et al* 2017a). Furthermore, despite the time passed from the last training session, there is also the need to assess whether the operator is still able to work while ensuring a proper level of safety; in other words, to assess his/her expertise over time. In fact, although the results in terms of performance should be the same, the cognitive demand for the same operator could not be, and the standard training assessment procedures are not able to provide the information about the amount of cognitive resources requested by the user for the correct execution of a task. In other words, standard training assessment methods (e.g. performance evaluation) cannot be used alone to track a comprehensive profile of the training level of the user. Instead, they have to be integrated with neurophysiological measures to take into account cognitive and physiological aspects of the trainee, such as the development of automaticity (Liu and Wickens 1994). The literature dealing with the effect of practice on the functional anatomy of task performance is extensive and complex, comprising a wide range of papers from disparate research perspectives (Chein and Schneider 2005, Doyon and Benali 2005, Parsons *et al* 2005, Dux *et al* 2009, Parasuraman and McKinley 2014, Sampaio-Baptista *et al* 2014, Taya *et al* 2015, Borghini *et al* 2017a, 2017b, Amo *et al* 2017). Across these studies, three main patterns of practice-related activation change can be distinguished. Practice may result in an increase or a decrease in activation in the brain areas involved in task performance, or it may produce a functional reorganization of brain activity, which is a combined pattern of activation increases and decreases across a number of brain areas (Kelly and Garavan 2005). Trainee assessments and training purposes evaluation are key points of BCI-based cognitive training; in fact, objectively knowing the level of training achieved allows the improvement of usability and customizability of

BCIs to users' characteristics and cognitive capacities (Carelli *et al* 2017) and could enhance patients' motivation and engagement (Cartocci *et al* 2015).

In the field of operational environments, pBCI applications to enhance the training assessment have recently been investigated by Borghini *et al* (2017a, 2016b), where students and professional controllers have been asked to learn new tasks. In each training session, several neurophysiological, behavioural and subjective signals have been gathered. From such data, the authors proposed a pBCI-based neurometric able to consider three fundamental aspects for an objective training evaluation: performance level (the considered task must be performed correctly); stability of the performance over time (every time the user deals with the considered task, he/she must guarantee the same high level of performance); and cognitive stability (once the user is trained, the activations of the brain pattern will be the same when the considered task is executed). Furthermore, such a pBCI-based metric allows one to establish a threshold for each user to objectively assess and better tailor the next phases of the training program.

In Borghini *et al* (2017a), two groups of professional air traffic controllers (ATCOs) (15 experts and 22 students) have been compared in terms of expertise and skill-rule-knowledge (SRK) model-based cognitive control behaviours (Rasmussen 1983) by using EEG-based neurometrics during the execution of highly realistic ATM tasks. The results showed the possibility of characterizing and objectively measuring the expertise level of the operator in terms of brain activations while dealing with realistic activities. As a consequence, such evidence should be used to calibrate a pBCI-based system and to evaluate the expertise of the user during the execution of the considered task with the aim to better train the user or to define an objective criterion for the personnel selection. Finally, a less recent work (Ayaz *et al* 2012), investigated the sensitivity of fNIRS technology in assessing practice in a highly realistic unmanned aerial vehicle (UAV) task. In particular, seven students with no prior flight experience were asked to perform ten repetitions of two scenarios (approach and landing), for a total of 160 trials per participant over 8 d. The authors were able to statistically differentiate three levels of expertise, concluding that the expertise appeared to influence the hemodynamic response in the left dorsolateral prefrontal cortex in complex realistic tasks.

3.3. Team resources evaluation

Another field in which pBCI could have important implications is related to monitoring the team resources under different operative conditions. In this context, most of the activities are based on the interaction between two or more users; therefore, the success of a task is based not only on the highly individual performance, but also on the ability to perform effective teamwork. In this regard, cooperation among team members is defined as two or more subjects coordinating their actions in space and time to pursue the same goal (Sciaraffa *et al* 2017b). In their review on joint action processes, Vesper *et al* (2017) highlighted the necessity for neuroscientific research to use ecological tasks to understand how humans act together in this sense. The objective study of the team capacity in natural settings has been possible thanks to the technological improvement of the biosignal recording systems. The real novelty of the analysis of the cooperation is based on the concept that interactions of two or more subjects cannot be studied considering one person at a time, but only by analysing the entire system (Hari *et al* 2015). This concept is the basis of the hyperscanning technique. The hyperscanning term was introduced in 2002 by Montague, to define the synchronized acquisition of brain signals from two different subjects using fMRI (Montague 2002), while the first application of EEG hyperscanning was by Babiloni *et al* 2007. Using EEG, fNIRS or the less ecological fMRI, the hyperscanning technique allows the provision of information of the neural system at the basis of the interaction (Babiloni and Astolfi 2014). In fact, such neural substrates could only be activated by the interaction, when a subject wants to represent the intention of another human, to coordinate his action, decision or feelings, as in the case of empathy. Although the hyperscanning is essentially based on brain signals analysed together to point out co-modulation or synchronism, different realistic applications have used other autonomic measures. For example, Hemakom *et al* (2017) aimed to quantify the degree of cooperation during cooperation tasks employing the phase synchrony and the intrinsic coherence of the respiratory and cardiac signals in a choir and in a team performing a surgical procedure. According to recent literature, future trends in the field of cooperation analysis could have a strong impact in three main domains: clinical research, communication analysis, and team definition and evaluation.

During the last decade, different hyperscanning paradigms have been inspired by game theory. Most recently, works based on prisoner dilemma paradigms showed that inter-brain synchrony exhibited higher increments in the case of cooperation between humans rather than human–machine interactions during interactive decision making (Hu *et al* 2017), and that face-to-face contact during such paradigm induced inter-brain synchronization across right temporal and parietal regions were connected to the willingness to read others intentions (Jahng *et al* 2017). The aim of this kind of study was to find the brain areas strictly involved in cooperation to highlight the pathological incongruences in their activations. Thus, they have an important relevance in the diagnosis and rehabilitation field connected to research relating to social brain disorders.

Natural cooperative communication has also been investigated using fNIRS during a task reproducing social aspects of creative and productive group meetings. The interpersonal neuro synchronization (INS) was enhanced during natural communication involving multiple individuals (Nozawa *et al* 2016). The INS has since been proposed as an index of the quality of the interaction during social activities, such as teaching, acting and public speaking.

EEG hyperscanning has recently been interpreted as an instrument for selecting a member of a team: higher team performance has been related to higher inter-brain synchronization correlating to social facilitation (Szymanski *et al* 2017). The main objective in this case was to understand the neural basis facilitating team working to overcome the traditional and subjective evaluation that characterizes this field, such as interviews and work quality measurements. Cooperation could then be positive or negative, according to the results that it generates. Difficulties in work environments usually generate difficulty in creating a shared action plan: this could happen, for example, during high workload situations. In this context, Sciaraffa *et al* (2017a) showed that different workload demands impacted differently not only on the single subject, but on the whole team in terms of altered local network features, describing the brain activities that were Granger-caused to each other by two subjects involved in a cooperative task.

In the framework of the hyperscanning, two innovative applications have already proved that it is possible to use this technique in realistic scenarios. Firstly, couples of pilots and co-pilots have been involved in hyperscanning paradigms during a simulated flight: multi-subject connectivity results showed more links between co-pilot and pilot during the more collaborative phase of landing (Toppi *et al* 2016). Secondly, neuromanagement application is the most innovative hyperscanning application aiming to apply neuroscientific methods to management. Using both brain and autonomic signals, Venturella *et al* (2017) investigated the interaction between the leader and an employee, and the study was largely concerned with the employee's reaction to different communication styles of the leader.

Finally, a recent review highlighted the lack of and the necessity of using the hyperconnectivity technique to study the emotional component at the basis of cooperation (Balconi and Vanutelli 2017).

3.4. Gaming

The introduction of more wearable and ergonomic biosignal recording devices encouraged the introduction of pBCIs for commercial applications, such as gaming (Vecchiato *et al* 2016). Works published in such a field sought to detect gamers' affective states to adapt to specific game features (i.e. difficulty level or user's feelings). All of these were investigated using EEG-based emotion recognition systems. For example, Krol *et al* (2017a) proposed a completely hands-free version of Tetris that uses eye tracking and passive brain–computer interfacing. In particular, two mental states (i.e. relaxation and error perception) of the player influenced some game parameters in real time. First, a measure of the player's relaxation was used to modulate the speed of the game. Second, upon the landing of a tetromino, a state of error perception was detected in the player's brain and this last landed tetromino was destroyed. To realize such a pBCI, a 32-channel dry electrodes LiveAmp system (Brain Products GmbH, Gilching, Germany) was used. Another similar work proposed a pBCI system able to predict the difficulty level of a video game. In particular, EEG signals were recorded using a 32 electrode Fast'n'Easy Cap (Brain Products GmbH, Gilching, Germany) from six participants playing a modified Tetris game at ten different difficulty levels. The proposed approach was able to predict the levels with high accuracy, yielding a mean prediction error of less than one level. Another work in this field (Ewing *et al* 2016) proposed the development of an adaptive game system designed to maximize player engagement by utilizing real-time EEG changes to adjust the level of game demand. Twenty subjects participated in the study and the EEG signals were recorded using 64 Ag–AgCl pin-type active electrodes mounted in a BioSemi stretch-lycra head cap. Also, in this field, the current trend is to reduce the system invasiveness by combining EEG technology with other systems, in particular eye tracking devices, as made by Belkacem and colleagues (2015), who performed a preliminary study on five people proponing a hybrid BCI system based on two EEG channels and eye tracking able to enhance (if compared with the use of the two technologies independently) the human capability of controlling a videogame character. Also, Shishkin *et al* (2016), proposed a method based on a combination of eye tracking and EEG signal activity, able to differentiate intentional and spontaneous eye movements. They tested such an approach using a game called 'EyeLines', a simple computer puzzle game, with the goal to construct as many 'lines' from colored balls as possible. Such methodology has been tested on eight healthy subjects, and 13 posterior EEG channels. This study led to the development of a hybrid 'eye–brain computer interface', the EBCI, as an unobtrusive tool for both paralyzed and healthy users.

3.5. Neuromarketing

The ability of the pBCI to detect covert emotions and feelings of the user (i.e. not explicit responses from the subjects) means that it was found to be applicable to the field of marketing. In particular, the so-called *consumer neuroscience* investigates the possibility of accessing information within the consumer's brain during the generation of a preference or the observation of commercial advertisements (Ariely and Berns 2010, Vecchiato *et al* 2012, 2011, Davidson 2004, Vecchiato *et al* 2013) by using a robust approach withdrawal index. Such an index is obtained by measuring the unbalance in the EEG power spectra on the prefrontal cortices (PFC) on the alpha frequency band. In fact, the PFC region is structurally and functionally heterogeneous, but its role in emotion is well recognized (Davidson 2004). Specifically, findings suggest that the left PFC is an important brain area in a widespread circuit that mediates an appetitive approach, while the right PFC appears to form a major component of a neural circuit that instantiates defensive withdrawal (Davidson 2004). Over the last few years, several studies have been published showing how it is possible to detect hidden signs of the memorization process and emotional engagement, such as pleasantness perceived while watching an advertisement by employing neurophysiological recordings (Borghini *et al* 2014b, Yu *et al* 2016, Guixeres *et al* 2017, Cherubino *et al* 2016, Cartocci *et al* 2017a, Vecchiato *et al* 2014). Such indexes have also been successfully applied for the evaluation of stimuli other than visual, such as auditory (Cartocci *et al* 2017b, Marsella *et al* 2017), olfactory (Di Flumeri *et al* 2016b) and tasting (Di Flumeri *et al* 2017).

To measure both the brain activity and the emotional engagement of the users, several experiments have been proposed with the simultaneous use of EEG, GSR and ECG measurements during the observation of TV commercials. In these works, significant variations in EEG, GSR and heart rate (HR) measurements were correlated to the emotion and pleasantness experienced by the subjects during the presentation of experimental stimuli, as successively resulted from the subject's verbal interview (Cartocci *et al* 2017a).

4. Future trends and open issues

The advancements achieved during the last decade in the field of neuroscience regarding technology (i.e. the possibility to record a user's biosignals with wearable, ergonomic and reliable devices) and algorithms (i.e. signal processing, artefact removal and artificial intelligence/machine learning techniques) have encouraged the scientific community to investigate the use of neurophysiological measures, not only for research purposes, but also even for daily life applications (Di Flumeri *et al* 2016a). In other words, it is now possible to acquire, in real time, a person's actual mental and emotional insights, without asking the user or interfering with the considered task and using such information to change the behaviour of the surrounding environment or technology that the user is interacting with.

With respect to the standard methods to evaluate the mental and emotional states of the user, such as behavioural (i.e. performances, reaction times) and subjective (i.e. questionnaires) measures, neurophysiological signals demonstrate several additional advantages (Zander and Jatzev 2012). For example, behavioural measures represent an indirect measure of the investigated mental state (e.g. a decrease in performance could explain an increase in workload), and to be recorded, the user often has to execute a secondary task, implying a certain intrusiveness of the system that could affect the operator's main task performance itself. Regarding the subjective measures, although they provide a direct (i.e. self-reported) measure of the investigated mental or emotional state, it is not possible to collect information in real time (i.e. the subject has to explicitly state his perceived state), and the reliability of the measurement could be affected by the nature of the measurement itself (i.e. the subject may not be fully aware of their mental state, or they might not want to report it). On the contrary, the neurophysiological measures overcome all aforementioned issues, allowing an objective, non-intrusive, and even continuous and instantaneous measure of the actual mental and emotional state of the user (Blankertz *et al* 2016, Aricò *et al* 2016b), paving the way for a whole variety of applications. For example, Zander *et al* (2016) proposed a pBCI application, in particular a neuroadaptive technology, able to decode in real time the user's expectations when moving a cursor towards a specific target, through the classification of brain signals from 64 EEG channels. In particular, the user's 'expectation' model, was computed by collecting and classifying specific brain responses, evoked by violating the operators' expectations to varying degrees. This work was just an example to envision how neuroadaptive technologies could transform work and leisure activities in everyday settings, for example by modelling and evaluating in real time the affective state of the user. Many other studies have proposed pBCI applications, demonstrating the high sensitivity of neurophysiological measures for retrieving certain aspects of perception or cognition. Although such effects are valid under highly constrained experimental settings, in more complex (and less controlled) situations, it is possible that variables (i.e. other mental states, artefacts) unrelated to the investigated user's insights could change the behaviour of neurophysiological indicators, thus inducing misinterpretations (Blankertz *et al* 2016, Arico *et al* 2017c). In this regard, Fairclough (2009) in his review work on physiological computing systems, stressed such an issue to export neurophysiological measures from the laboratory to more realistic setting-based applications. In particular, these measures must be tested with a full range of the target population in the field, hence the requirement to establish neurophysiological validity. Neurophysiological measures should be selected on the basis of diagnostic (ability of the variable to index the target mental state and remain unaffected by related states), sensitivity (ability of the variable to respond rapidly to changes in the mental state) and reliability (consistency of the neurophysiological inference across different individuals and environments). In the present review, we chose to refer only to such works in which pBCI applications have been tested in real settings (i.e. real environments and daily life tasks; highly realistic simulators) to focus on the maturity of such systems. All discussed works, performed in different fields, demonstrated that pBCI technology could be ready to realize applications in real settings, since such techniques were able to achieved high-performing results, even without all the constraints imposed in laboratory setting experiments. This result is mainly due to the recent advancements in signal processing and machine learning techniques that are able to isolate the mental or emotional state of interest being investigated from the 'noise' elicited by the surrounding environments. Nevertheless, the majority of these techniques (i.e. supervised machine learning algorithms, e.g. linear discriminant analysis (LDA), stepwise linear discriminant analysis (SWLDA), support vector machine (SVM), Lemm *et al* 2011) require frequent calibration using training data related to the user's insight to measure, before their use to extract the specific user's neurophysiological features able to discriminate the mental state of interest and to maintain high performance over time. This represents one of the main limitations for pBCIs to enter the market. Several efforts are being made in this direction to mitigate such an issue. For example, Aricò and colleagues (2016b) proposed a machine learning technique (i.e. automatic stop stepwise linear discriminant analysis (asSWLDA), Aricò *et al* 2016b) able to evaluate the workload of air traffic controllers in operational environments without recalibrating the system for up to a month (Arico *et al* 2015). Also, Schultze-Kraft *et al* (2016) developed and tested an unsupervised (i.e. that does not need any calibration phase) algorithm able to classify the workload of operators achieving high performance. In a recent study proposed by Wei and colleagues (2018), the authors proposed a method for obviating inter- and intra-subject variability in EEG-based drowsiness detection, and consequently too long calibration data (and time). In particular, this study proposed to apply hierarchical clustering to assess the inter- and intra-subject variability within a large-scale dataset of EEG collected in a simulated driving task, and to investigate the feasibility of transferring EEG-based drowsiness detection models across subjects. Compared with the conventional within-subject approaches, the proposed framework remarkably reduced the required calibration time for a new user by 90%, without compromising performance.

Lotte *et al* (2018) proposed an interesting review about classification algorithms employed in BCI-based applications during the last ten years. The authors highlighted different methodologies that could be used if a limited calibration dataset was available, such as transfer learning, sLDA, Riemannian minimum distance to the mean (RMDM) classifiers or random forest. In addition, they suggested adaptive classification approaches with respect to static ones, for both supervised and unsupervised approaches. In this regard, a very recent work, (Ma *et al* 2018), not related to the pBCI field but interesting as perspective, proposed an adaptive calibration framework for the BCI with the motion-onset visual evoked potential (mVEP) as a control signal. This framework was able to update the training set adaptively for classifier training (i.e. adding new samples to the training set and removing the older ones) by combining a support vector machine and fuzzy C-mean clustering. It was demonstrated that the proposed method was able to significantly outperform the standard methods (without adaptation).

Regarding supervised and unsupervised learning, the former is still preferred to the latter since it allows achievement of higher accuracies (Blankertz *et al* 2016). To speed up the resolution of such an issue, and to stimulate the work in this emerging field, data repositories to test developed algorithms and advancements have been created, as well as a communication platform for researchers to exchange experiences (http://www.bnci-horizon-2020.eu, http://www.passivebci.org, Huggins *et al* 2017).

Another issue reflected by the proposed review that is slowing down the entry of pBCI in daily life use is related to the employed EEG sensor technology. In fact, although technology advancements allowed scaling down of the EEG recording systems (i.e. bioamplifiers), the stumbling block remains the sensors for the biosignal acquisition. As has been highlighted throughout the cited works, a lot of effort has been made in this direction, by developing gel-free (i.e. dry) electrodes. A lot of commercial products, even cheap and fancy, have been proposed by several companies (i.e. Neurosky, Emotiv, Uncle Milton, MindGames, and Mattel), but the advantage of having no gel is generally compromised by a decrease in signal quality (van Erp *et al* 2012). Nevertheless, such systems are still suitable for gaming and entertainment applications. Many other companies proposed very high level (but more expensive with respect to the former) systems with dry electrodes (e.g. BrainProduct, g.Tec, Neuroelectrics, Quasar), reaching even comparable quality of the wet-based systems. However, this technology still suffers from several disadvantages. For example, they need a certain amount of pressure to maximize the conductivity with the skin, which can be uncomfortable or even painful over time. In addition, such systems seem to be very sensitive to the surrounding noise (i.e. electrical interferences, other people and the subject's movement artefacts) with respect to conventional wet systems (Saab *et al* 2011), making them unusable in real contexts. Also, many works tested their systems with a huge number of EEG electrodes (e.g. 64) at the expense of duration of the setup and subject preparation, while for a user-friendly system, a low number of sensors is mandatory.

In conclusion, it would be very useful to validate existing signal processing chains and classification techniques (Bigdely-Shamlo *et al* 2015) to find the best algorithm for each investigated mental state and application, so much so that basic knowledge such as the EEG channels reference has been the subject of debate during the last decades (Yao 2017, 2001). However, a discussion about this issue deserves deep and devoted work and is out of the scope of the present paper, which aims to give a high level overview of the open issues with respect to bridging the gap for a practical use of pBCI systems and to provide several examples of pBCI attempts in real/realistic settings.

In conclusion, because of the high number of pBCI-related works performed in real settings that have been published over the last few years, and the big effort that is being made to address the above-mentioned issues, we could infer that pBCIs are not too far from being introduced as a new consumer product, and in the near future it will not be science fiction to imagine smart devices that adapt their behaviour depending on the user's insight.

Starting from the (still) open issues highlighted in the present review, we could infer and summarize a few recommendations to speed up the introduction of pBCI systems to real-life applications.

- Misinterpretation of neurophysiological measures: as in real-life applications (i.e. outside of the lab) there could be the simultaneous coexistence of many mental and emotional states. Thus, each proposed neurophysiological measure should be further investigated using the three aspects suggested by Fairclough (2009): diagnosticity, sensitivity and reliability.
- The classification/regression algorithms calibration need: research groups in machine learning should take advantage of available data repositories and communication platforms for research (e.g. Huggins *et al* 2017) to test cutting edge algorithms able to minimize, or even remove the calibration phase, or at least readapt calibration datasets online (Ma *et al* 2018, Schettini *et al* 2014), thus maintaining a high classification accuracy. In addition, as suggested in Lotte *et al* (2018), there is thus a need to study and validate new classification algorithms not only offline, but online as well, to ensure they are sufficiently computationally efficient to be used in real time, can be calibrated quickly enough to be convenient to use and to ensure that they can withstand real-life noise in EEG signals (Borghini *et al* 2014a, Arico *et al* 2014).
- Bio-sensors: companies devoted to bio-sensor development should focus their efforts to maximize the comfort of both the sensors and the related support, minimizing the price, while of course maintaining a high quality of the recorded signals, in order to enhance the acceptability of such technology. Few technologies have already reached a good result, such as bracelets or smartwatches for the measures of heart activity or GSR, and they are already present on the market. On the contrary, other technologies (e.g. EEG sensors) are backward, especially in terms of comfort and price (Mihajlovic *et al* 2015).

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