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Trends in EEG-BCI for daily-life: Requirements for artifact removal

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ABSTRACT

Since the discovery of the EEG principles by Berger in the 20's, procedures for artifact removal have been essential in its pre-processing. In literature, diverse approaches based on signal processing, data mining, statistic models, and others compile information from multiple electrodes to build filters for artifact removal in the time, frequency or space domains. For almost one century, EEG acquisitions have required strict experimental conditions that included an isolated room, clinical acquisition systems, rigorous experimental protocols and very precise stimulation control. Under these steady experimental conditions, artifact removal techniques have not significantly evolved since then. However, in the last decade technological advances in brain-computer interfaces permit EEG acquisition by means of wireless, mobile, dry, wearable, and low-cost EEG headsets, with new potential daily-life applications, such as in entertainment or industry. New aspects not considered before, such as massive muscular and electrical artifacts, reduced number of electrodes, uncontrolled concomitant stimulus or the need for online processing are now essential. In this paper, we present a critical review of EEG artifact removal approaches, discuss their applicability to daily-life EEG-BCI applications, and give some directions and guidelines for upcoming research in this topic. Based on the results of the review, existing artifact removal techniques need further evolution to be applied in daily-life EEG-BCI. The use of multiple-step procedures is recommended, combining source decomposition with blind source separation and adaptive filtering, rather than using them separately. It is also recommendable to define and characterize most of artifacts evoked in daily-life EEG-BCI for a more effective removal.

Contents

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1. Introduction

A brain-computer interface (BCI) provides a communication channel that interconnects the brain with an external device. In particular for BCI based on electroencephalogram (EEG), electric potentials recorded from electrodes placed on the scalp provide direct measure of brain activity. However, EEG recordings are usually contaminated by undesired signals called artifacts. Artifacts are a source of noise in EEG acquisitions and they are caused by endogenous (e.g., physiological sources such as eye, muscle and cardiac activity) and exogenous (e.g., non-physiological sources such as impedance mismatch, power-line coupling, etc.) reasons. Since Hans Berger reported the first acquisition of human EEG in 1929 [1], different methods have been used to handle EEG artifacts. These include three different groups of techniques, namely (i) artifact avoidance (e.g., telling subjects to avoid moving or blinking during the experiment and gaze at a central fixation point), (ii) artifact rejection (e.g., discarding contaminated trials by visual inspection or by automatic procedures), and (iii) artifact removal based on preprocessing of the EEG data [2]. In this review we focus on the third group. It comprises a huge variety of algorithms that combine EEG recordings with information about the experimental conditions to obtain the most efficient filter for artifact removal.

Classical EEG-BCI experiments require strict laboratory conditions far from those of daily-life. Almost all the studies found in literature for this review were carried out following rigorous experimental protocols, including very precise stimulation control. Most of them were performed within isolated environments and used clinical acquisition systems [3–8]. Under these strict conditions there are methods that efficiently remove artifacts such as those caused by eye blinks, eye movements or teeth clenching (see reviews [2,9–12]).

Thanks to technological advances, EEG headsets have dramatically evolved in the last years. Current portable-wearable-wireless EEG acquisition systems permit ubiquitous acquisition outside a laboratory. In addition, the development of dry electrodes [13–18] may facilitate the use of EEG-BCIs in daily-life environments. Apart from hardware, progress in signal processing is also essential for the deployment of these modern systems. In particular, artifact removal in daily-life applications is one of the decisive areas for that goal [19]. Nevertheless, artifact removal techniques have not evolved accordingly. For instance, most studies found in the literature only focused on removal of in-lab artifacts (e.g., the removal of ocular artifacts [20–22]). However, EEG in daily-life environments is affected by both in-lab well-known artifacts (e.g., ocular, cardiac, power-line noise, etc.), and outdoor not well-known artifacts caused by massive movement (e.g., muscular and mechanical artifacts) and a variety of electromagnetic causes.

In summary, existing approaches for artifact removal have become impractical in daily-life scenarios. Thus, new techniques need to be investigated and developed. Despite some incipient contributions, there is no commonly accepted methodology for artifact removal in daily-life EEG-BCI applications. In this paper we present a review of existing EEG artifact removal approaches and discuss them in this new context. After analyzing the main aspects of daily-life EEG-BCI applications in Section 2, we establish the main requirements for artifact removal in daily-life in Section 3. In Section 4, we summarize most of artifact removal approaches in the last decade and discuss about their applicability to the daily-life requirements. In Section 5, we suggest some directions and guidelines for future solutions.

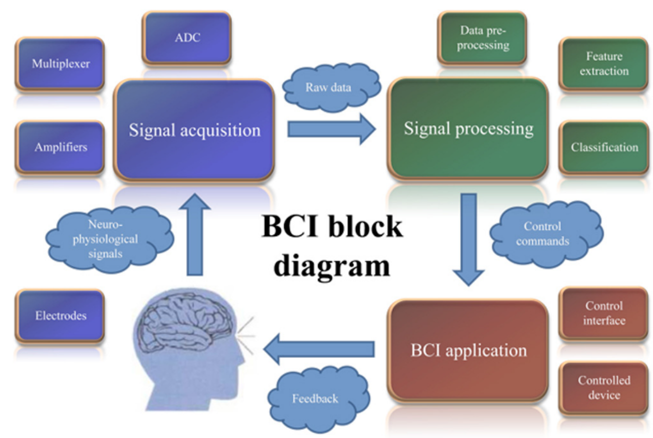

Fig. 1. Basic block diagram of a BCI. The first block is signal acquisition (blue). It is composed of electrodes, amplifiers, multiplexer and analog to digital converter and it is responsible for the acquisition of neurophysiological signals and their conversion to digital values. The second block is signal processing (green). It translates the raw data received from the first block into construable control commands. The translation usually requires three steps, namely data preprocessing, feature extraction and classification. The data preprocessing adapts the raw data to further processing. The feature extraction obtains the relevant parameters from the preprocessed information. Finally these features are classified to generate suitable control commands. These are sent to the third functional block, the BCI application (red). This block includes a control interface in charge of interpreting the control commands and producing the necessary signals to control and communicate with the final device. The information transfer between the functional blocks is performed by communication interfaces and a synchronization system. Information usually flows from the BCI application to the subject resulting in a closed-loop. Single or 1.5-column fitting image. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2. Daily-life EEG-BCI applications

Since the first papers using the term 'brain-computer interface' appeared in the early 90's [23,24] the study of BCIs has grown dramatically [25]. EEG-BCIs decode electrical potentials recorded on the scalp and convert them into valuable pieces of physiological and cognitive information. The translation of neurophysiological signals into information enables the user to control electronic devices and establish bidirectional communication with them. This translation is performed throughout different blocks within the BCI (see Fig. 1).

The design of a BCI requires every single element (e.g., electrodes, communication channel, processing methods, etc.) to be chosen from all the available technological options according to the final application. Thus, the evolution of EEG-BCI applications is bound to the changes and advances in technology, together with other important factors such as people activities and necessities. Since their origin, researchers have mainly used EEG-BCIs as a communication tool for disabled people such as patients in a complete locked-in state [26–28] or patients with severe motor

(a) (b)

Fig. 2. Example of daily-life EEG-BCI applications. The graphical user interface proposed in Ref. [48] for EEG-BCI gaming control is displayed in (a). The mobile EEG system proposed in Ref. [56] for outdoor activity is displayed in (b). Single-column fitting image.

impairment [29,30]. EEG-BCIs have been also used as rehabilitation tools [31,32], as assistive technology [33–36], and others [37]. For instance, a P300 speller EEG-BCI was proposed in [38]. Another example of classical use is the control of neuroprostheses [8] with potential application for restoring movement. However, current EEG-BCIs are not intended to work exclusively in health applications but also in daily-life environments.

Although the interest in health applications remains, the development of portable-wearable-wireless hardware and the appearance of improved techniques for EEG processing have motivated the emergence of novel EEG-BCI applications. These applications challenge the classical definition and functional structure of a BCI (e.g., open-loop operation in some applications). For example, the interest in neuromarketing has grown in the last years [39] and some studies related to the attention to human speech [40–44] have suggested EEG-BCIs as a useful tool for that. In arts, EEG-BCIs have been applied as translators from brain activity into music (Neural Music program [45], or the 'Concert: Music and Brain', as part of the IWINAC2015 Congress). In defense, an example is the DARPA Augmented Cognition technology [46,47]. In entertainment, gaming control has been proposed as an EEG-BCI application [48] (see Fig. 2a). In addition, some applications in smart living environments have been reported [49–52]. In cognitive neuroscience, various EEG-BCIs have been proposed for brain workload [53] and conscious awareness [54] measurement, and for drowsiness detection [55]. Finally, sport professionals have become more and more interested in the potential advantages of neuroimaging [56] (see Fig. 2b).

Despite the number of studies reporting advances in EEG-BCI research, some aspects are still lacking. In the next subsections, some of the more relevant aspects of EEG-BCIs (e.g., EEG acquisition systems and headsets, processing, physiological signals, working environment, and EEG features) are analyzed under the framework of daily-life applications.

2.1. EEG acquisition systems and headsets

Both EEG acquisition systems and headsets have undergone some changes in recent years. In particular, portable-wearable-wireless acquisition systems and headsets with a few dry electrodes have been commercialized. They are analyzed in the next subsections.

2.1.1. EEG acquisition systems

Traditional EEG acquisition systems consist of several electrodes attached to the scalp and connected to a front-end amplifier by leads [57]. Those systems do not facilitate the execution of motion tasks due to the cables, size, weight, and portability of the devices. Hence traditional acquisition systems may be appropriate for daily-life applications during the prototype phase, but they may be less appropriate in final implementation (products).

Fortunately some companies and research groups have created modern systems that use wireless communication such as Bluetooth (see Fig. 3a–c). Moreover, they are small in size and efficient in power consumption, thus providing portability and wearability. These features allow modern EEG headsets to be assembled in user friendly styles such as headbands or baseball caps (see Ref. [25] for a thorough review). Various commercial products and research prototypes are presented in Fig. 3. It must be taken into account that these wireless systems may be inconvenient for applications that need synchronization between the stimulus and the recording. Some commercial products include a supplementary module that provides synchronization by using proprietary software, but not between the stimulus player and the headset. Therefore wireless headsets are still not intended for paradigms in which synchronism is essential (e.g., evoked potentials). In addition, the usage of an extra module implies extra hardware that limits portability. These could justify why most daily-life applications work with brain rhythms or steady-state responses (see subsection 2.5 for further information).

2.1.2. EEG headsets

Since the extended international 10–20 system for EEG electrode location [58] was published in 1958, the number of channels recorded during EEG experiments typically did not exceed 64. New standards such as 10–10 (ten percent) [59] and 10–5 (five percent) [60] allowed for high density EEG studies with 128–256 channels [5,61]. That is useful for spatial filtering such as common average reference (CAR) which uses information from many channels to reduce noise. Laplacian montages have been proved to be highly effective in, for example, artifact identification and elimination [12], saccadic spike potentials reduction [62], and one-dimension cursor control [63]. Nevertheless, the cost in terms of preparation time and usability rule out the use of high density EEG headsets to execute daily-life activities. The necessity of a simple and rapid electrical montage for daily-life applications is evident. Simple electrode montages have been implemented in modern EEG headsets such as the EEG headband of Cognionics (see Fig. 3c), the EPOC and Insight wireless acquisition systems of Emotiv (see Fig. 3d and e respectively) or the MindWave mobile acquisition headset of NeuroSky (see Fig. 3h).

Another evolved aspect is the electrode type. Traditional wet EEG electrodes are considered the gold standard [13]. They require the use of skin prep and conductive gel to improve impedance of the electrode-scalp interface. This preparation takes time, contributes to user fatigue, and requires support from technical staff. It seems to

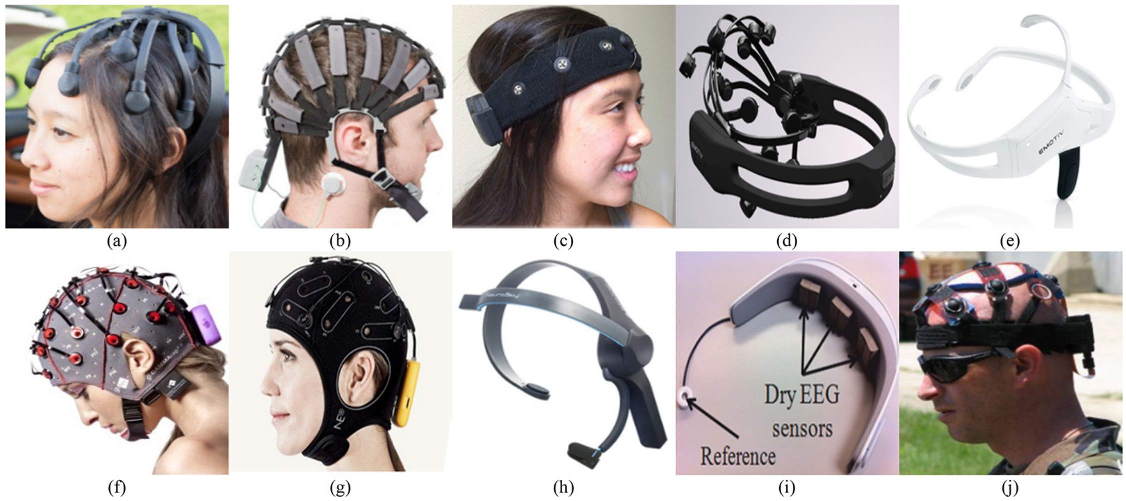

Fig. 3. Various portable wireless headsets and acquisition systems for EEG recording. (a–c) Miniature Wireless Acquisition Systems by Cognionics with Quick-20 Dry EEG Headset, 72-Channel Dry EEG Headset and Multiposition Dry EEG Headband respectively, (d and e) EPOC and Insight wireless EEG acquisition systems by Emotiv, (f) g.Nautilus wireless EEG acquisition system by g.tec, (g) ENOBIO 8 wireless EEG system by Neuroelectrics, (h) MindWave Mobile EEG acquisition headset by NeuroSky, (i) wearable EEG acquisition headset [48], and (j) wireless EEG sensor headset by Advanced Brain Monitoring used in Ref. [47]. Double-column fitting image.

be unsuitable for daily-life applications. Dry EEG electrodes are a must for daily-life. In the literature, different dry EEG electrodes have been proposed [14–18] (see commercial dry EEG headsets in Fig. 3a–c). Ideally, they are able to record potentials from the scalp without preparation. Dry EEG electrodes have been tested under alpha-beta rhythms [64], steady-state visual evoked potentials (SSVEPs) [65,66], and auditory event-related potentials (ERPs) paradigms [67]. Nevertheless, there still are some lacks regarding them. Traditional wet EEG electrodes provide much better quality of recorded signals in comparison with current dry EEG electrodes. In addition, evaluation procedures are questionable [13].

2.2. Processing

The online capability of an EEG-BCI application depends on, between others, the computing efficiency of the processing block. In this context, the term 'online' refers to real-time operation of the application (i.e., processing and output are performed during the experiment with acceptable delay for the specific application); the term 'offline' implies that processing and output are performed after the experiment, or during it but with an unacceptable delay for the specific application. Offline processing has been generally utilized in EEG studies. Its main advantage is that it does not need high performance in terms of processing time. Nevertheless, automatic real-time operation is fundamental for daily-life applications such as gaming [48] or cell-phone control [49]. Fortunately, advances in both hardware and processing methods have made online operation a reality [3,68]. For instance, novel feature extractors and classifiers which have improved EEG processing (e.g., fuzzy-logic [69,70], neural-networks [71,72], etc.).

2.3. Physiological signals

Among the different types of BCIs, hybrid systems have been proposed in recent studies. They are based on the simultaneously acquisition of EEG and other physiological signals. For example, near-infrared spectroscopy (NIRS) provides information about local neural activity by measuring the level of oxygen saturation in blood. NIRS BCIs [73] and hybrid NIRS-EEG BCIs [74–76] have been used in motor imagery applications. In addition, electromyography (EMG) signals were used for error correction during spelling tasks in a P300-based BCI [77]. Other BCIs have been used in combination with eye trackers [78,79]. Also typical artifact sources such as teeth clench [79,80] and ocular movements [20,22,81–85] have been combined with EEG activity for BCI control and artifact removal respectively.

2.4. Working environment

The vast majority of EEG-BCI studies found in the literature were performed within isolated environments (e.g., laboratories), and participants were instructed to limit their movements [3,6–8]. Thanks to this, the presence of external interferences and massive movements that penalize the quality of the EEG (i.e., artifacts) is reduced. On the contrary, daily-life applications are supposed to work while performing everyday-life tasks outdoors, for instance, walking on the street among other people. However, limited success has been obtained with EEG-BCIs working in these conditions. Even some applications intended for daily-life environments such as smart living environmental auto-adjustment [50] or drowsiness detection [55] were exclusively tested using in-lab virtual reality.

Although the evolution from laboratory to daily-life environment is still challenging for researchers, some authors reported promising results. A recent study proposed a classifier of single-trial auditory ERPs with EEG during real and simulated flight [67]. A cell phone-based EEG-BCI for communication in daily-life was tested with ten volunteers located in an office room without electromagnetic isolation [49]. In addition, an EEG-BCI for freely moving humans was successfully examined with ten subjects walking a treadmill in a naturalistic environment [65]. Nevertheless, both cell phone and freely moving human EEG-BCIs utilized SSVEPs probably due to their artifact-robustness (see Section 3.1 for detailed information).

2.5. EEG features

EEG-BCIs can be classified into three main groups regarding the EEG features that they utilize: brain rhythms, evoked potentials (EPs) and steady-state responses.

2.5.1. Rhythms-based EEG-BCIs

When an EEG is analyzed, low amplitude periodic signals (microvolts) at different frequencies (i.e., rhythms) are observed as a result of neuron interactions (see Table 1). Rhythms-based

Table 1
EEG rhythms.

Rhythm	Frequency (Hz)
Delta	<4
Theta	4–7
Alpha	8–13
Beta	13–30
Gamma	>30
Mu	8–12

EEG-BCIs (e.g., alpha-based, mu-based, etc.) do not require external stimulation for their elicitation. The so-called thought translation device (TTD) is an example [86]. Regarding the mu rhythm, one of the first works consisted in the vertical shifting of an object displayed on a screen [23]. A mu rhythm was also employed in the control of a hand orthosis by a tetraplegic patient [87] as well as in binary motor imagery EEG-BCI applications [36]. Beta and theta rhythms have been utilized in neurofeedback for assessment and effective intervention of attention deficit hyperactivity disorder (ADHD) [88].

Regarding daily-life applications, theta rhythm have been employed together with alpha in sporting performance [89], drowsiness detection [55], smart living environment [50,51] or gaming control [48] (see Ref. [90] for a review). However, user training [91,92] is needed in this type of EEG-BCI [93,94]. The training time leads us to think that they may be not appropriate for daily-life applications. Furthermore, some of the cited daily-life rhythms-based EEG-BCIs were only tested under unrealistic conditions, for example, using virtual reality and/or within a laboratory. Their applicability in daily-life environments was not verified.

2.5.2. EP-based EEG-BCIs

Evoked potentials are electrical signals in the EEG produced as response to stimuli (e.g., auditory and visual). One of the most utilized EPs in EEG-BCI is the P300 (positive deflection at least 300 ms after the stimulus onset). In the EEG-BCI context, P300 is usually produced by a physical sensory stimulus followed by a cognitive task (e.g., count of stimuli). Spelling [7,38,95], 2-D cursor control [96] and humanoid robot control [97] are examples of classical P300-based EEG-BCI.

Few EP-based daily-life applications have been found in the literature [67]. One of the main advantages of EP-based EEG-BCIs is that they do not require user training. However, there can be some users unable to control EP-based EEG-BCIs due to the 'BCI illiteracy' [98–102]. In addition, precise synchronization between the stimulus player and the acquisition system is required in EP paradigms since evoked potentials appear a short time (milliseconds) after the stimulus presentation. Moreover, EPs are usually denoised by trial averaging, thus the significance of the synchronism. As mentioned in previous sections, the synchronization between the stimulus player and the acquisition system is still lacking in wireless EEG-BCIs.

2.5.3. Steady-state-based BCIs

A train of repetitive stimuli can cause periodic responses; the so-called steady-state evoked potentials. Depending on the stimulation, they can be either SSVEPs for visual stimuli or auditory steady-state responses (ASSRs) for auditory stimuli. SSVEPs have been utilized in classical EEG-BCI applications such as spelling [78,103–105], prosthesis [8], and wheelchair control [34]. Characterization of SSVEPs and stimulation enhancement have been object of research in the last years [106–108].

Some daily-life applications are based on SSVEPs, for instance, EEG-BCI for freely moving humans [65], tele-services accessing [79] and cell phone-based EEG-BCI [49]. ASSRs were employed in studies for selective attention [44,72,109]. The extended use of steady-state-based EEG-BCIs might be because they combine the 'plug and play' feature (i.e., no user training is needed) of EP-based EEG-BCIs with the robustness of rhythms-based BCIs in presence of artifacts (see Section 3.1 for detailed information).

3. EEG artifact removal in daily-life

As mentioned, artifact removal is one of the decisive areas for the deployment of daily-life EEG-BCIs. Once the main aspects of daily-life EEG-BCIs applications have been analyzed, it may be interesting to set up the main requirements for artifact removal methods in this context. In the next subsections we report those requirements together with a brief survey of EEG artifact removal.

3.1. Requirements for daily-Life

Each aspect of daily-life EEG-BCIs analyzed in Section 2 results in certain requirements and limitations for artifact removal methods. These are related to both the algorithm to remove artifacts and the experiment to record the EEG.

- *EEG acquisition systems and headsets*: the use of portable-wearable-wireless EEG acquisition systems in daily-life suggests testing artifact removal approaches with EEG recorded by that type of system. In addition, the necessity of a simple and rapid electrical montage suggests that algorithms should be able to work with a single active channel (channel + reference + ground) on the one hand, and that EEG for testing has to be recorded by using simple montage (e.g., three or less electrodes, apart from reference and ground). It would also be desirable to use dry electrodes.
- *Processing*: online processing is mandatory for daily-life applications. As part of the processing block of an EEG-BCI, artifact removal algorithms must be able to work under real-time requirements.
- *Physiological signals*: despite the combined use of EEG with other physiological signals may result advantageous in some cases, it requires the use of multiple electrodes, thus it is contrary to a simple montage. Therefore, artifact removal algorithms for daily-life applications must be able to work with EEG signals exclusively, and the EEG used to test them must have been real (i.e., not simulated EEG).
- *Working environment*: the daily-life environment suggests testing approaches with EEG recorded outdoors while performing everyday-life tasks (e.g., walking, running, etc.). Under these circumstances, complex artifacts (i.e., those resulting from massive movement and a variety of electromagnetic causes) are present together with well-known artifacts (e.g., ocular, cardiac and 50/60 Hz power-line artifacts). Therefore, artifact removal algorithms are required to eliminate complex artifacts.
- *EEG Features*: rhythms-based and steady-state-based EEG-BCIs have an advantage regarding the artifacts. Whilst ocular artifacts are usually located at low frequencies (see Fig. 4a), muscle artifacts are normally related to higher frequencies [110]. Indeed, all the artifacts resulting from daily-life tasks such as walking or running (e.g., ocular, muscular, electrical, mechanical, etc.) are present at a wide frequency band, and their spectral power directly depends on the quantity of movement (see Fig. 4b). Rhythms-based and steady-state-based EEG-BCIs are less sensitive to artifacts than others due to the gathering of power at narrow frequency bands; hence they have high signal to noise ratio (SNR) at those frequencies. Only high power (compared with the signal power) artifacts occupying the same narrow band might be problematic. A simple band-pass filtering might be enough to remove the rest. Therefore, some EEG features (e.g.,

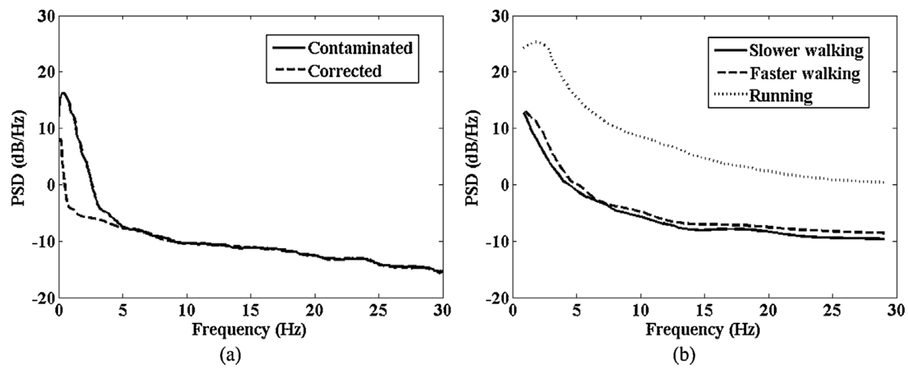

Fig. 4. Artifacts localization in the frequency spectrum. The power spectral density (PSD) of EEG containing ocular artifacts (continuous line) and the PSD of corrected EEG (dashed line) is displayed in (a). The figure has been created from findings in Ref. [130]. The PSD of EEG containing artifacts resulting from real-life tasks (running, faster walking and slower walking) is displayed in (b). The figure has been created from findings in Ref. [5]. Double-column fitting image.

Table 2
Requirements for EEG artifact removal in daily-life applications.

Related to experiment	Performed outdoors Use of portable-wearable-wireless device Use of real EEG signals Performance of daily-life tasks Use of simple electrical montage Use of dry electrodes
Related to algorithm	Removes complex artifacts Works with EEG signals exclusively Works online Works with single active channel

rhythms and steady-state responses) may be more appropriate for daily-life in terms of artifact removal complexity. However, we do not set up any special requirement related to the features (Table 2).

3.2. Survey of EEG artifact removal

In this subsection a brief summary of the main EEG artifact removal approaches is reported. The aim of this work is not to review the state of the art of EEG artifact removal (see Ref. [9] for a recent and thorough review) but to compile and discuss the principal methods in the last years in the context of daily-life EEG-BCIs. However, it may be proper to provide some comments on artifact removal approaches in order to facilitate the subsequent discussion.

They are usually classified in different categories:

– *Filtering*: it is frequently used in EEG preprocessing. Filter coefficients are estimated and applied to a signal according to the desired order (i.e., filter aggressiveness), frequency response (e.g., low-pass, high-pass, band-pass, etc.), impulse response (e.g., FIR, IIR, and TIIR), etc. Filtering is non-adaptive if its coefficients are static; filtering is adaptive if they iteratively change according to an optimization criteria. Among the non-adaptive filters, Wiener FIR filter is one of the most utilized. It minimizes the mean square error between the desired signal and the estimated signal. Wiener filtering is more appropriate for linear time-invariant signals; it cannot work with EEG in real-time. Adaptive filters continuously adjust their coefficients in order to minimize the error between the desired and the estimated signal by using algorithms such as the least mean squares (LMS) or the recursive least squares (RLS). These are more appropriate for linear time-variant signals (e.g., EEG) than non-adaptive filters. They are efficient in real-time artifact removal but a priori knowledge of artifacts is required [20,83]. Sometimes a reference signal is used; e.g., electro-oculogram (EOG) for ocular artifacts. Alternatively, the a priori can iteratively be estimated (without a reference signal) by probabilistic filters after initial calibration. Kalman filters are the linear approximation of probabilistic Bayesian filters. They have been utilized in removal of transcranial magnetic stimulation (TMS)-induced artifacts [111,112].
– *Linear regression*: it is based on the superposition principle. It is assumed that the signal of every single EEG channel is the sum of clean EEG signal (i.e., from non-noisy sources) and a portion of one or several artifact signals (i.e., from artefactual sources). These artifact signals are available by means of reference channels (e.g., EOG, EMG, ECG, etc.) or artifact templates. Thus regression aims to estimate the optimal value for the factor that determines the portion of the artifact signal within each EEG channel. Linear regression has been widely used in ocular [84] and movement [5] artifact removal.
– *Blind source separation*: blind source separation (BSS) provides a matrix of estimated sources (each column corresponds to the time-signal of a source) from a matrix of observations (each row corresponds to the time-signal of a recorded EEG channel) without using any artefactual reference. Once the sources have been estimated, those corresponding to artifacts can be identified and extracted, thus recomposing the EEG with the non-artefactual sources. Several assumptions need to be met for success in separation. Principal component analysis (PCA) is a BSS method. It provides a set of linearly uncorrelated variables (i.e., principal components) by using the orthogonality of the observed variables. The most used BSS method in artifact removal is the so-called independent component analysis (ICA) [85,113–115]. It is based on the assumption that the recorded EEG signals are a lineal combination of several unknown and statistically independent sources. ICA has been proved to be more efficient than PCA in artifact removal. It is probably due to the better adaptation of its assumptions for the nature of the sources (i.e., artifacts and brain activity are usually independent enough). However, PCA is often applied for dimension reduction during the ICA preprocessing. There are some derivative ICA methods such as temporally [116] and spatially [81] constrained ICA. Apart from PCA and ICA, there are other BSS-based methods that have been used for artifact removal: canonical correlation analysis (CCA) [110,117,118], sparse component analysis (SCA) [119], singular spectrum analysis (SSA) [120], etc.
– *Source decomposition*: it aims to decompose every single EEG channel into basic waveforms. As for BSS, these components (i.e., waveforms) can represent either brain activity or artefactual activity. Hence signals can be recomposed without artifacts components. Unlike BSS methods, source decomposition can independently be performed in every single channel. Wavelet

decomposition has been widely utilized for artifact removal [21,82,121,122]. The discrete wavelet transform (DWT) provides time-frequency signal breakdown (i.e., time coefficients at different frequency bands) by using a mother wavelet. The empirical mode decomposition (EMD) is also located in this category. It provides several zero-mean amplitude-frequency-modulated components, the so-called intrinsic mode functions (IMFs). EMD has been used for artifact removal in recent years [123–125]. Other derivative methods such as stationary wavelet transform (SWT) [126,127] and ensemble empirical mode decomposition (EEMD) [117,118,128] have also been used for artifact removal with success.

– *Others*: some authors have used neural networks (NN) [129,130] and adaptive neural fuzzy inference systems (ANFIS) [131,132] in their methods to remove artifacts.

According to the above references, we notice that combining methods is very frequent. Indeed, some authors have compared the efficiency of different methods [133]. This fact might indicate that there is no universal method for artifact removal. The election of the artifact removal procedure deeply depends on the individual problem or application. We discuss about that in the next section.

4. Summary and discussion

In this section we report a summary table (see Table 3) containing the most relevant methods on artifact removal found in literature in the last decade. In particular, forty eight proposals were collected. We focus on proposals in which the artifact removal method is the main task during the EEG preprocessing. Other interesting works focused on feature extraction/classification were not considered.

Some features of the collected methods are also reported in the table. In total, ten features were analyzed for the gathered methods according to the main requirements for daily-life EEG-BCIs described in the previous section; the first six are related to the experiment employed for the evaluation of the approach and the last four concern important capabilities of the utilized algorithm. In particular, 'Performed outdoors' means the experiment was performed in a non-isolated environment (no laboratory); 'Portable-wearable-wireless device' means the employed EEG headset and acquisition system were wireless, user friendly style, and small size, 'Real EEG signals' means the processed data were real EEG acquired signals (not simulated), 'Daily-life tasks' means the EEG was recorded while performing any daily-life task (e.g., walking), 'Simple electrical montage' means the EEG was recorded from three or less electrodes (apart from reference and ground), 'Dry electrodes' means the EEG was recorded using dry EEG electrodes, 'Complex artifacts' means the algorithm can remove some artifacts related to daily-life tasks such as those resulting from massive movement (e.g., muscular and mechanical artifacts) and a variety of electromagnetic causes, 'Only EEG signals' means the algorithm can work using EEG data exclusively (without using other physiological signals such as EMG or EOG), 'Online' means the algorithm can be used under real-time requirements, and 'Single active channel' means the algorithm can work with single-channel EEG data.

It is remarkable that no method was tested in a daily-life environment; all of them were only tested to work within a laboratory. In addition, the EEG was recorded by wet electrodes in all cases. Just 2 out of 48 cases used portable-wearable-wireless devices. Real EEG data were utilized in 46 cases; simulated EEG data were employed in 2 experiments. In only 8 studies EEG was recorded while executing daily-life tasks. Simple electrical montage was employed in 3 experiments, 2 of them match with the portable-wearable-wireless device-based studies. Regarding the capabilities of the algorithms, all the collected methods can eliminate well-known artifacts (i.e., ocular, cardiac and 50/60 Hz power-line artifact) at least. However, only 19 procedures are able to remove complex artifacts, but nonetheless just 6 of them were tested using daily-life task-based EEG. Most algorithms (39) can work merely using EEG sources. Less than half (20) can work online. Finally, 23 algorithms can eliminate artifacts using single-channel EEG data.

The fact that no author has tested his method outdoors [5,20–22,81–85,110,113,114,117,118,120,121,123–131,134–156] (despite some of them handled complex artifacts) indicates the difficulty when handling artifacts in a real situation (i.e., daily-life environment). For example, movement artifacts considerably vary across subject, speed and electrode location while walking [157]. Even so, it would be desirable that researchers test their methods outdoors, what would add important value to their works.

Regarding the low quantity of studies that used portable-wearable-wireless devices [121,136], it might be caused by the recent commercialization of these systems. Indeed, both studies are from 2013 and 2014. Another fact to take into account is the synchronization problem of wireless EEG headsets. The lack of precise synchronization might have a negative effect on some artifact removal studies. For example, those that utilize evoked potentials to demonstrate the efficiency of the method. More artifact removal works using portable-wearable-wireless devices may be expected next years.

To the best of our knowledge, all the studies on artifact removal used wet electrodes. In some cases, they were active wet electrodes [5,85] which include a pre-amplifier, with or without gain, which reduces the noise induced in the cables [158]. It is understandable taking into account the current limitations of dry electrodes. Worse results might be expected by using dry electrodes.

The requirement of simple electrical montage (used in [121,126,136]) limits the use of procedures that require information from multiple channels. It is indispensable to employ methods capable of operating with a few channels or even with a single active channel. However, most of the algorithms found in literature are based on multichannel BSS techniques (e.g., ICA). These cease to be suitable under this new scenario. In order to overcome this limitation, several authors proposed procedures for single-channel artifact removal. They are based on single-channel ICA [148], EMD [123,125] or wavelet decomposition [121,129,136]. The latter has low computing cost and takes advantage of the fact that ocular artifacts are localized at low frequency bands [136]. However, in these wavelet-based approaches, EEG electrodes were placed on frontal areas, typically Fz, Fpz, F1, and F3 in the 10–20 system. At these locations ocular activity is powerful, thus the ocular component in the recorded EEG is evident. Testing those methods with central EEG activity might be recommendable in order to corroborate their robustness. The deployment of portable-wearable-wireless devices with simple electrical montages and dry electrodes will probably increase the number of artifact removal studies on daily-life tasks.

Although all the compiled proposals obtained promising results, most of them handled a very limited set of target artifacts (e.g., eye blinks and eye movement). They were not proved to be efficient with all the massive electrical, mechanical and muscular artifacts resulting from daily-life environments. However, there are some methods that were proved to eliminate more complex artifacts. For example, artifacts resulting from daily-life tasks such as walking/running [5,157] or cycling [117,128]. In addition, CCA was proved to be robust in SSVEP-based EEG-BCIs working under daily-life conditions in two studies [49,65].

As mentioned before, all the algorithms running in the processing block of a daily-life EEG-BCI must have online capability. Numerous algorithms for artifact removal can be considered offline methods [85,137,144] due to their high computing cost which

Table 3
Summary of the main EEG artifact removal methods proposed in the last decade (since 2006) and their principal features according to the requirements of daily-life EEG-BCI applications. Each column represents one artifact removal procedure, named as first author and year of publication. Each row represents one of the main desirable features for artifact removal techniques in daily-life EEG-BCI applications. Grey color indicates accomplishment and white color indicates no accomplishment or not mentioned. *This reference has been included despite being 2002 because of its high degree of adaption to the requirements. Indeed, several methods in this table have been inspired by it. [154,130,137,117,128,141,148,81,152,20,5,82,131,83,113,127,138,21,144,135,125,114,150,123,110,129,85,121,156,140,142,134,22,84,151,118,139,120,147,145,149,143,146,153,124,155,136,126].

	Acharjee et al., 2015	Burger et al., 2015	Castellanos et al., 2006	Chen et al., 2014 (1)	Chen et al., 2014 (2)	Cho et al., 2007	Davies et al., 2007	Geetha et al., 2012	Gu et al., 2014	Guerrero-Mosquera et al., 2009	Gwin et al., 2010	Hsu et al., 2012	Hu et al., 2015	Klados et al., 2011	Kong et al., 2013	Krishnaveni et al., 2006 (1)	Krishnaveni et al., 2006 (2)	Kumar et al., 2008	Ma et al., 2011	Mammone et al., 2012	Mijovic et al., 2010	Mognon et al., 2011	Mourad et al., 2007	Mourad et al., 2013
Performed outdoors																								
Portable-wearable-wireless device																								
Real EEG signals	■	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■	■	■		■	■	■	■
Daily-life tasks				■	■				■		■										■			
Simple electrical montage																								
Dry electrodes																								
Complex artifacts				■	■		■				■		■							■	■	■		
Only EEG signals	■	■	■	■	■	■	■		■		■				■	■	■	■	■	■	■	■	■	■
Online		■				■		■	■	■			■			■	■	■					■	
Single active channel				■	■	■	■						■			■	■	■			■			■

	Mowla et al., 2015	Nguyen et al., 2012	Nolan et al., 2010	Peng et al., 2013	Porcaro et al., 2015	Puthusserypady et al., 2006	Raduntz el al., 2015	Romo et al., 2012	Sameni et al., 2014	Schlogl et al., 2007	Shao et al., 2009	Sweeney et al., 2013	Sziboo et al., 2012	Teixeira et al., 2006	Teixeira et al., 2007	Teixeira et al., 2008	Tiganj et al., 2010	Wang et al., 2014	Yong et al., 2009 (1)	Yong et al., 2009 (2)	Zeng et al., 2013	Zhang et al., 2015	Zhao et al., 2014	Zikov et al., 2002*
Performed outdoors																								
Portable-wearable-wireless device				■																			■	
Real EEG signals	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Daily-life tasks		■			■													■						
Simple electrical montage				■																			■	■
Dry electrodes																								
Complex artifacts	■		■		■		■	■			■	■						■	■	■	■			
Only EEG signals	■	■		■	■		■	■			■	■	■	■	■	■	■	■	■	■	■	■	■	■
Online	■	■		■			■		■	■			■				■						■	■
Single active channel		■		■								■	■	■	■	■	■		■	■	■		■	■

causes unacceptable delays for these applications. Fortunately, alternative solutions have been proposed. Among these proposals, adaptive filtering and wavelet decomposition are suitable procedures for real-time artifact removal.

Table 4 is included in order to elucidate which methods might be more appropriate for daily-life EEG-BCI applications and to give some guidelines for future research. Within the group of very appropriate methods, there are three of them based on a combination of BSS and source decomposition, in particular, ICA or CCA joined with EEMD. The other four approaches are wavelet-based combined with adaptive filters or neural networks.

As mentioned in [9], most researchers prefer to use ICA because they believe that the assumption of independence models the brain activity better than others. Unfortunately, to the best of our knowledge and according to recent publications [9,12,159], there is no standardized and universally efficient artifact removal method. This has motivated the pursuit of alternative solutions such as research paradigms intending to extract narrow-band EEG features [41,42,160], or precautionary protocols to avoid artifacts during the experiments. For example, EEG-BCI studies usually require many trials in order to rule out artefactual activities. Long experiments may increase subject fatigue, hence provoking undesirable results. Improvement of existing methods might help to reduce the number of trials needed as well as their duration by improving feature extraction and classification. This is a particularly delicate matter when dealing with artifacts in daily-life context. The continuous appearance of noise coming from multiple artifact sources is not a trivial problem, especially when artifact sources have different natures and features (e.g., movement artifacts [157]). It is understandable that artifact removal is still lacking in daily-life EEG-BCI but it is important to progress in this area for the deployment of these modern systems [19]. In addition, advances in hardware are still essential. For example, improvement of current dry electrodes might help to reduce the number of artifacts in daily-life applications.

5. Conclusion

A critical review of existing artifact removal approaches and their applicability to daily-life EEG-BCIs is presented in this paper. The main requirements for EEG-BCIs in daily-life context were established. After compiling the principal artifact removal methods in the last decade, several reasons indicate that there is no definitive artifact removal technique for these applications. First of

Table 4
Each method in Table 3 is classified in this table depending on its adaption to the daily-life EEG-BCI requirements considered in this paper: less appropriate, appropriate, very appropriate. Under no circumstance are we questioning the validity of the methods for their original purpose.

Very appropriate	Chen et al. [117,128] Zikov et al. [126]	Mijović et al. [125]	Nguyen et al. [120]	Peng et al. [121]	Zhao et al. [136]
Appropriate	Burger et al. [130] Hu et al. [131] Mourad et al. [123] Shao et al. [151] Teixeira et al. [145]	Cho et al. [141] Krishnaveni et al. [127,138] Rakibul Mowla et al. [110] Sweeney et al. [118] Tiganj et al. [149]	Davies et al. [148] Kumar et al. [21] Porcaro et al. [156] Szibbo et al. [139] Wang et al. [143]	Gu et al. [152] Mognon et al. [114] Radüntz et al. [142] Teixeira et al. [120] Yong et al. [146,153]	Gwin et al. [5] Mourad et al. [150] Romo et al. [134] Teixeira et al. [147] Zeng et al. [124]
Less appropriate	Acharjee et al. [154] Klados et al. [83] Puthusserypady et al. [140]	Castellanos et al. [137] Kong et al. [113] Sameni et al. [22]	Geetha et al. [81] Ma et al. [144] Schlögl et al. [84]	Guerrero-mosquera et al. [20] Mammone et al. [135] Zhang et al. [155]	Hsu et al. [82] Nolan et al. [85]

all, none of the collected approaches accomplished all the requirements; some of them reached 6 out of 10 required features but, in general, low accomplishment was achieved. Secondly, most of the procedures were only tested using well-known artifacts such as ocular and cardiac. In addition, some of the complex artifact-capable methods were never proved to work using EEGs resulting from daily-life tasks and outside a laboratory. Dealing with artifacts in daily-life context is a complex problem due to the continuous appearance of noise coming from multiple artifact sources (with different natures and features) during recordings. Although it is understandable that artifact removal is still lacking in daily-life EEG-BCI, it is important to progress in this area for the deployment of these modern systems. Advances in hardware (e.g., dry EEG electrodes) are still essential. It would be desirable that researchers continue to work on daily-life artifact removal, with special attention to the requirements analyzed in this paper. As guideline and according to results reported in Tables 3 and 4, we would recommend the use of multiple-step procedures, combining source decomposition (in particular, wavelet or EMD) with blind source separation (in particular, CCA) and adaptive filtering. It may also be interesting to define and characterize most of artifacts evoked in daily-life EEG-BCI in order to use them as reference or template in the cited methods. Despite BCIs have been studied for decades, there is only little effort to apply them in daily-life. Further research in this topic should be focused on considering the lacking aspects mentioned before.

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