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Topical Review

EEG artifact removal—state-of-the-art and guidelines

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Abstract

This paper presents an extensive review on the artifact removal algorithms used to remove the main sources of interference encountered in the electroencephalogram (EEG), specifically ocular, muscular and cardiac artifacts. We first introduce background knowledge on the characteristics of EEG activity, of the artifacts and of the EEG measurement model. Then, we present algorithms commonly employed in the literature and describe their key features. Lastly, principally on the basis of the results provided by various researchers, but also supported by our own experience, we compare the state-of-the-art methods in terms of reported performance, and provide guidelines on how to choose a suitable artifact removal algorithm for a given scenario. With this review we have concluded that, without prior knowledge of the recorded EEG signal or the contaminants, the safest approach is to correct the measured EEG using independent component analysis—to be precise, an algorithm based on second-order statistics such as second-order blind identification (SOBI). Other effective alternatives include extended information maximization (InfoMax) and an adaptive mixture of independent component analyzers (AMICA), based on higher order statistics. All of these algorithms have proved particularly effective with simulations and, more importantly, with data collected in controlled recording conditions. Moreover, whenever prior knowledge is available, then a constrained form of the chosen method should be used in order to incorporate such additional information. Finally, since which algorithm is the best performing is highly dependent on the type of the EEG signal, the artifacts and the signal to contaminant ratio, we believe that the optimal method for removing artifacts from the EEG consists in combining more than one algorithm to correct the signal using multiple processing stages, even though this is an option largely unexplored by researchers in the area.

Keywords: EEG, artifact, ICA, PCA, regression, EMD, WT

(Some figures may appear in colour only in the online journal)

1. Introduction

The electroencephalogram (EEG) represents the electrical activity of the brain recorded by placing several electrodes on the scalp [1] (note that single-channel recording only uses two electrodes). The EEG is nowadays used extensively in neuroscience, cognitive science, cognitive psychology, neurolinguistics and psychophysiological research. This is besides its more traditional place in clinical assessment or consciousness research, among other uses. More specifically it is often employed for the diagnosis of various brain conditions such as determining the type and location of epileptic activity or for analyzing sleep disorders [2, 3], as well as other neurological dysfunctions like encephalopathies, neurological infections, dementia, etc [4]. The various waveforms of the EEG convey clinically valuable information; hence it is important to develop methods for the detection and objective quantification of the characteristics of the signal, to facilitate its interpretation [3].

The activity of a single cortical neuron cannot be measured on the scalp; in contrast, the joint activity of millions of cortical neurons produces an electrical field that is sufficiently strong to be detected on the scalp [1, 5–7]. The amplitude of the EEG signal is related to whether the excitation of the generating neurons is synchronized or not. The measured activity has a broad spectral content with a shape similar to that of pink noise, but also reveals oscillatory behavior in specific frequency bands, hence giving rise to the well-known EEG rhythms [3]. Many other neurological phenomena may be recorded [8]: changes in brain rhythms, movement-related potentials, slow cortical potentials, evoked potentials, etc.

Artifacts are undesired signals that may introduce changes in the measurements and affect the signal of interest. While the ideal way of working with an EEG signal is to avoid the occurrence of artifacts when recording [9] (for instance via artifact prevention [10, 11]), the EEG signal is unfortunately often contaminated with various physiological factors other than cerebral activity, which are typically not of interest. For instance, cardiac activity, ocular movements, eye blinks and muscular activity are among the most common kinds of artifacts [12–16]. Due to the sources of noise being very diverse and having different characteristics, most authors focus on removing single kinds of artifacts. The cancellation of noise and artifacts is an important issue in EEG signal processing, and is normally a prerequisite for the subsequent signal analysis to be more reliable (for clinical applications raw signals may still suffice for separating groups of good and bad prognoses, but other applications require data to be as free of artifacts as possible).

Artifact processing techniques range from rejection [10, 11, 17], in which a marker is created to identify the artifact and the goal is to remove segments of poor quality, to cancellation of the artifact from the EEG signal. Although rejection is still an alternative for segments which contain excessive interference [18], it is often desirable to retain as much of the data as possible [3]. The requisites for artifact cancellation are very varied and depend on the context in which the algorithm may be used. On the one hand, when the goal is to improve signal quality for visual interpretation, then no clinical information should be lost and no distortion should be introduced. On the other hand, when noise reduction is a preprocessing step, then requirements may be relaxed, even though performance should still be such that the overall process is enhanced by the artifact removal step.

The literature on EEG artifact removal is very broad; however to date researchers in the area have not agreed on optimal methods for improving the quality of the recorded signal. This is due to at least three factors that are normally overlooked: for example, there are multiple kinds of EEG signals with different characteristics (see section 2 for more details) to which similar denoising techniques tend to be applied; to the best of our knowledge, the public datasets available are scarce, and hence comparisons among methods tend to be done on the basis of reduced amounts of data that in addition differ from one paper to another; and there are no objective performance measures used consistently among publications, which makes fair comparisons very hard to carry out, in particular when analyzing results given by distinct sets of authors.

During the last decade only a few novel methods have been proposed in the artifact removal area, in addition to classic existing approaches such as regression [17], ocular artifact correction [13], filtering [19] and the more widely used blind source separation (BSS) techniques [20, 21]. Rather, the area has evolved with authors either improving on existing algorithms, combining different methods or trying to make the denoising process automatic and devising more realistic simulations and more objective performance metrics. In our opinion, this seems to indicate that in fact most of the modern artifact removal methods converge in terms of results, at least to the extent of providing equivalent denoised signals of enhanced quality for a following application.

In this paper we first provide, in section 2, an overview of the kinds of EEG signals and artifacts, of the EEG acquisition model and of tools available for measuring the performance of artifact removal algorithms. Then, in section 3, we give a comprehensive review of the main methods proposed in the literature for removing artifacts from the EEG. In section 4 we make an attempt at comparing the most relevant artifact removal algorithms on the basis of conclusions drawn by other authors in the literature and, in part, on our own experience. We leave detailed explanations of our experiments for a subsequent publication. Finally, we conclude the paper in section 5 where, in addition to summing up our recommendations, we also highlight open problems in the artifact removal area.

2. Background

In this section we give an overview of the measured EEG signal, the different kinds of artifacts that may affect the recordings, how these sources combine in the scalp and, finally, existing ways for validating artifact removal methods.

2.1. Characteristics of the EEG background activity

An EEG has a frequency content ranging from 0.01 to around 100 Hz and varies from a few microvolts to approximately 100 μV, but the amplitude may be well above this, especially when corrupted by non-cerebral activity. The slow components around 0.01 Hz correspond to slow cortical potentials that in clinical routine are usually not recorded (they are filtered out); however, they may be of interest for brain–computer interfaces (BCI) [8]. The energy of background EEG is more concentrated in the lower range of the spectrum [22]. In fact, its frequency content is known to present a decay inversely proportional to the frequency ($1/f^{\alpha}$, with α approximately 1) [23, 24].

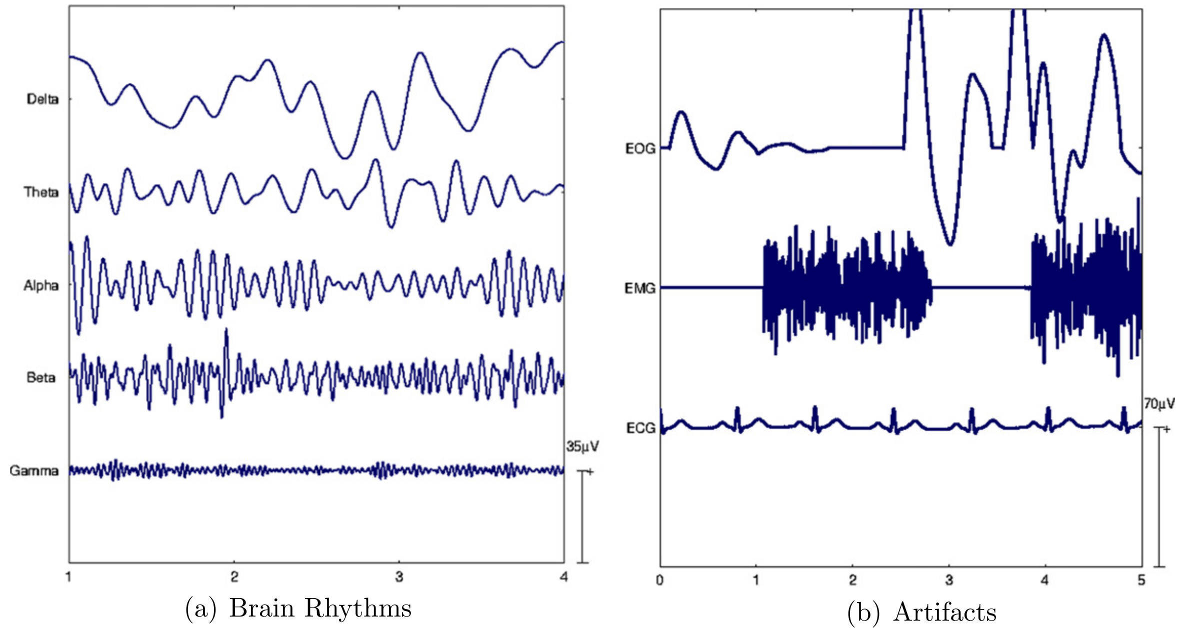

Figure 1. (a) *Five normal brain rhythms, from low to high frequencies.* Delta, theta, alpha, beta and gamma rhythms comprise the background EEG spectrum. (b) *Three different kinds of artifacts.* Ocular, muscular and cardiac artifacts are the most frequent physiological contaminants in the literature on EEG artifact removal.

Electroencephalographic or background rhythms are classified into five different frequency bands: delta (~0.5–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz) and gamma (>30, but typically <100 Hz). The study of the EEG is key to diagnosis of many neurological disorders. Some clinical conditions may be inferred from the characteristics of these bands; however, the interpretation of the bands as 'normal' or 'abnormal' depends on the age and mental state of the subject [2]. Oscillatory activity can also be used for brain–computer interfaces, in which subjects can control an external device by changing the amplitude of particular brain rhythms. Figure 1 (a) shows typical brain rhythms with usual amplitude levels.

A fundamental question for EEG signal processing is that of whether the EEG should be viewed as a (nonlinear) deterministic or stochastic signal. Evidently, the characterization of the EEG signal has direct implications for the methods considered suitable for artifact removal. In general, it is not possible to predict the exact characteristics of the EEG signal in terms of amplitude, duration, or morphology, and a 'pure' EEG signal cannot be recorded. Hence, it seems reasonable to treat the EEG as a stochastic process [3, 25], even if some characteristics of the signal are known [22].

When considering long time periods, thus, multiple factors make it necessary to treat the EEG signal as a non-stationary, stochastic process, i.e. one whose mean, correlation and higher order moments are time-varying. Short intervals, on the other hand, can reasonably be considered stationary, that is of time-invariant statistical properties, the validity of which depends on the type of signal. Stationarity really depends on the recording conditions, with statistical tests revealing that the EEG may be stationary for just a few seconds to several minutes [26].

2.2. Additional EEG waveforms

EEG signals change dramatically during sleep and show a transition from faster frequencies to increasingly slower frequencies (like alpha waves). In fact, different sleep stages are regularly characterized according to their spectral content. A number of transient waveforms occur during the different sleep stages: vertex waves, sleep spindles and K complexes [2, 3]. The study of these waveforms and sleep stages, along with the analysis of other physiological measurements and the medical history of the patient, are important for evaluating disorders such as sleep apneas and narcolepsy.

Another relevant type of waveform that is examined independently from background EEG activity is the evoked potential (EP). EPs are 'deterministic' signals, in the sense that they are evoked and not spontaneous like the rhythms. EPs are also frequently called event-related potentials (ERPs), although some authors differentiate evoked from event-related cases, the former being not necessarily caused in response to any event. ERPs constitute a transient form of brain activity generated in the brain structures in response (and time-locked) to specific events or stimuli [27], with amplitudes so small that they are not clearly visible to the human eye when found along with a background EEG [2]. However, simple signal processing techniques including averaging over consecutive realizations can reveal their shape and allow their analysis. Many forms of evoked potentials exist: movement-related potentials (MRPs), slow cortical potentials (SCPs), auditory evoked potentials (AEPs), somatosensory evoked potentials (SEPs), visual evoked potentials (VEPs), etc [28].

There are several other EEG waveforms that differ from background EEG rhythms and may be of interest for particular research and clinical assessment aims. In general, any deviation from spontaneity may indicate some underlying medical condition. Just as a final example, in patients with epilepsy, seizure activity appears as rapid spiking waves (an ictal EEG). Moreover, patients with brain lesions, which can result from tumors or stroke, may have unusually slow EEG waves. EEGs may also be used to identify (and diagnose) Alzheimer's disease and certain psychoses.

Depending on the specific research area, the actual signal of interest may be any of the ones that we have described so far. For instance, if the goal is to study background activity, then any other kinds of signals, in addition to the artifacts that we describe later on, may be considered as unwanted interference. The same applies if the goal is to detect ictal EEGs; then even background activity is unnecessary and may be distorted or even completely removed as long as the detection algorithm preserves the quality of the ictal EEG (see for example [29, 30]).

2.3. The main kinds of artifacts

In order to minimize the influence of artifacts on the EEG signal, it is key to acquire knowledge on what are the most common types that may be recorded. Among other possible categorizations, artifacts can be coarsely separated into those of physiological and non-physiological or technical origin [3, 31]. The latter can be reduced by proper attachment of the electrodes, by recording in a controlled environment, etc [9]. In other than clinical environments, for instance with healthcare systems for in-home monitoring, extraneous sources of noise may exist. However, we do not treat these in detail since a recent review by Sweeney *et al* [19] deals with such non-controlled recording environments. The former, on the other hand, can rarely be avoided and most of the algorithms developed for EEG artifact processing are intended for the reduction of physiological artifacts. We next describe the most prevalent contaminants in the literature on EEG artifact removal.

2.3.1. Ocular artifacts: eye movement and blinks. The electrooculogram (EOG) measures the electrical activity produced by eye movement, which is normally strong enough to be recorded along with the EEG [13]. These movements are primarily picked up by the frontal electrodes, although they also extend further [15, 31]. The strength of the interference depends on the proximity of the electrodes to the eyes and the direction in which the eye is moving. Blinking also causes the EEG recording to become contaminated, usually with a change more abrupt than that produced by eye movement, which is associated with higher frequency interference. Moreover, the amplitude of the blinking artifact is generally much larger than that of the background EEG activity [13]. Ocular artifacts in the literature are referred to as OAs or EOG artifacts even though we only use the latter in this text.

From a practical point of view, having reference EOG waveforms, measured simultaneously with the EEG, is very advantageous for ocular artifact cancellation. In fact vertical (VEOG), horizontal (HEOG) and radial (REOG) measurements are advisable [10, 17] since these signals propagate differently across the scalp [15]. Note, however, that some authors point out that the EOG is in turn contaminated by the EEG [12, 14, 15]; hence there is bidirectional interference that has to be removed from the EOG or taken into account in the denoising process.

2.3.2. Muscle artifacts: myogenic activity. The electromyogram (EMG) measures the electrical activity on the body surface caused by contracting muscles. This artifact is typical of patients who are awake and occurs when the patient swallows, talks, walks, etc [3], being more detrimental in uncontrolled environments. The shapes and amplitudes of the interferences depend on the degree of muscle contraction and on the type of muscle contracted; hence they are hard to stereotype. Muscular artifacts are termed MAs or EMG artifacts, although we only use the latter throughout this review.

A number of properties of cranial EMG are responsible for its adverse effects on the EEG background activity [32, 33] and make it more difficult to correct for than other kinds of artifacts [34]: EMG presents a wide spectral distribution, thus perturbing all classic EEG bands; in particular it considerably overlaps with beta activity in the 15–30 Hz range [3] but may be as low as 2 Hz [24], making the widely used alpha band also vulnerable to muscle artifacts [35]. EMG can often be detected across the entire scalp [24] due to volume conduction of myogenic activity independently generated by muscles across the head, face and neck [32]. EMG is temporally mixed with a variety of experimental manipulations like cognitive load and vocalization [32]. Finally, EMG also exhibits less repetition than other biological artifacts and is thus more difficult to characterize, since it arises from the activity of spatially distributed, functionally independent muscle groups, with distinct topographic and spectral signatures [24].

2.3.3. Cardiac activity. The electrocardiogram (ECG) measures the electrical activity of the heart. The amplitude of the cardiac activity on the scalp is usually of low amplitude; however this greatly depends on the electrode positions and differs for certain body types [3]. The ECG has a very characteristic repetitive and regular pattern, which unfortunately may sometimes be mistaken for epileptiform activity when the ECG is barely visible in the EEG [36]. The ECG is routinely measured along with cerebral activity, making this artifact easier to correct since a reference waveform is usually available. Cardiac artifacts are called CAs or ECG artifacts, but we only use the latter in this text.

Pulse artifacts occur when an EEG electrode is placed over a pulsating vessel such as a scalp artery, generating slow periodic waves that may resemble EEG activity [31]. The pulse activity is thus much harder to correct than the ECG since it may be similar in time and frequency content to the measured EEG itself; however it only occurs on one electrode and can be minimized by proper sensor positioning [9]. A direct relationship exists between the ECG and the pulse activity [36]; in fact pulse waves are easily recognizable due to their regular occurrence and since they precede the ECG by a constant interval.

2.3.4. Less common physiological artifacts. In addition to the artifacts described before, two interferences may arise from skin potential: perspiration artifacts, which are slow waves caused by shifts of the electrical baseline of certain electrodes; and, to a smaller extent, the sympathetic skin response, which also consists of slow waves and is an autonomic response produced by sweat gland and skin potentials [31].

Other possible artifacts include movements of the tongue, dental restorations with dissimilar metals [31], breathing artifacts in the lower part of the spectrum [31] and electrodermal interferences due to sweating, chest movements, etc [9].

We do not deal with these artifacts further since they are rarely treated in the literature that we have surveyed.

2.4. The linear mixture of sources model

A typical approach to artifact removal from an EEG is to adopt the standard assumption that the measured cerebral activity $x(n)$ is the sum of the cerebral activity $s(n)$ and the noise $v(n)$. This type of model is associated with simple subtraction methods that have a reference waveform, as well as to linear filtering methods [3].

The most widely used model assumes that measured EEG signals are linear mixtures of electrical waveforms originating from multiple brain sources and artifacts, and propagating instantaneously to the scalp [34, 37]. It is a generalization of the basic additive model and comes from the formulation of the EEG forward problem that allows one to compute the resulting electrical activity on the scalp resulting from the activity of neuronal and other physiological sources [34, 37]. The forward problem for the EEG is solved by starting from given electrical sources that are assumed dipolar and calculating the potentials that reach the electrodes after propagating through consecutive head tissues or compartments [38]. The model, which provides a useful description of the underlying biophysics of the generation and propagation of brain potentials [39], can be described mathematically by the following equation:

$$\mathbf{X} = \mathbf{AS} + \mathbf{V}, \tag{1}$$

where: $\mathbf{X} = [\mathbf{x}(1),..., \mathbf{x}(N)] = [\mathbf{x}_i(j)]_{n\times N}$ is the EEG data matrix, in which each row is one measured EEG channel; N is the number of samples; $\mathbf{A}$ is an $n\times m$ unknown mixing matrix; $\mathbf{S} = [\mathbf{s}(1),..., \mathbf{s}(N)] = [\mathbf{s}_i(j)]_{m\times N}$ is a matrix of unknown sources, whose rows represent brain sources and artifacts; and $\mathbf{V}$ is an $n \times N$ noise matrix.

Note that (1) is also a linear model for a class of denoising techniques based on what is known as the blind source separation problem (see figure 2). In addition, equation (1) is a general form of the linear relation used to model the measured EEG for regression analysis, the latter of which may be obtained by simply setting $\mathbf{A} = \mathbf{I}$ (the identity matrix) [19]. Moreover, the recovery of the exact cortical

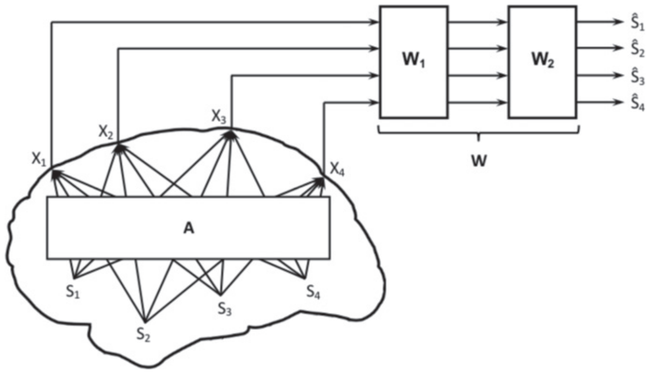

Figure 2. *Linear mixture concept: combination and blind separation of the EEG sources* [2, 21]. Given a linear mixture ($\mathbf{A}$) of the four brain sources $\mathbf{S}_1$ to $\mathbf{S}_4$ and having the same number of measurements as sources, $\mathbf{X}_1$ to $\mathbf{X}_4$, the linear blind source separation problem consists in finding the unmixing matrix $\mathbf{W}$ with no prior information on the mixing process. The figure accounts for $\mathbf{W} = \mathbf{W}_1\mathbf{W}_2$ since this is an instance of how some ICA algorithms work (they first decorrelate the signals using W1, then unmix them using W2).

distribution (source position, orientation and potential value) of an EEG source region is known as the EEG inverse problem [40] and is not solvable with the solution to the BSS problem.

The BSS problem is typically ill-posed unless further assumptions are made [41], since many source configurations may lead to the same measurements [42]. One way to restore the well-posedness of the problem is by imposing certain diversity conditions among sources, for instance that they are temporally independent and identically distributed (i.i.d.) but not Gaussian, or the other way around [41] (when both conditions hold simultaneously, then the problem has no solution). In real scenarios there are likely to be more cerebral sources than sensors ($m > n$), which leads to an underdetermined system (1), although decomposition methods can provide at most n sources [43]. This is normally not an issue since most methods are able to extract a linear combination of sources belonging to the same subspace instead of estimating the sources themselves [34], hence properly separating the signal from the artifacts [43, 44].

As we explain later on in the text, blind source separation algorithms such as independent component analysis (ICA) and principal component analysis (PCA) jointly exploit the information provided by all electrodes, $\mathbf{X}$, simultaneously, whereas other denoising methods such as regression, filtering, empirical mode decomposition and the wavelet transform process each channel separately and do not explicitly solve the BSS problem.

Once the estimated sources $\hat{\mathbf{S}}$ are identified, an artifact-free matrix $\hat{\mathbf{X}}$ is obtained by projecting $\hat{\mathbf{S}}$ back onto the subspace of observations. In reality, (1) is a simplistic representation of a more general mixing model, which makes no assumptions on the linearity of the mixing. However, inverting the unknown mixing process while having no information on the properties of the sources or the mixing process is evidently intractable [20]. In what follows, we follow the typically accepted assumptions that the mixing is linear, as assumed in (1), that it is noiseless, with $\mathbf{V} = \mathbf{0}$, that it is square, i.e. $n = m$, and that it is stationary, that is $\mathbf{A}$ does not change over time [20].

2.5. Performance evaluation

Performance evaluation is a relevant part of EEG signal processing that is required before a method can be used reliably in a clinical context. The greatest challenge for evaluating the performance of algorithms that work with EEG measurements is that the noiseless signal is not known *a priori*. This can be avoided to some extent by creating simulated signals and artifacts, either computer generated or obtained from 'clean', controlled recordings. Regardless of the fact that simulated data can be used to develop and evaluate artifact removal algorithms to obtain preliminary indications, the methods need to be assessed with real data.

Therefore, there is a necessity to develop tools (or standardize one of the existing approaches that we comment on next) that allow researchers in the field to objectively measure and compare the performance of new and current algorithms in order to select the optimal one for a certain scenario.

2.5.1. Simulated versus acquired EEGs. Simulated EEG activity can be generated in several ways by using very simple to much more complex methods, with varying degrees of similarity to the real EEG being achieved. While some characteristics of a recorded EEG can be replicated quite accurately [45], synchronization among channels, time-locking to ERPs, contamination by different kinds of artifacts produced in a realistic manner, etc, are harder to mimic. In fact, the assumptions underlying artifact 'injection' may not characterize real contamination, biasing the results in favor of techniques that adopt similar premises [17, 32, 46, 47]. Simulations in which all of these properties are considered valid are, however, very typical [15, 34, 48–51]. Some attempts at achieving simulations of better quality include [52] and, more recently [34], in which 3D models of the brain, skull and scalp are implemented, and the measured EEG is generated by considering dipolar sources and solving the electromagnetic forward problem.

In our opinion, methods can be first assessed and compared to other methods by using simulations, since it is more straightforward to obtain preliminary results that serve as a guide. But one has to use recorded EEG data as the final testbed for evaluating the true performance, reliability and reproducibility of any artifact removal approach.

2.5.2. Validation for simulated EEGs. One advantage of using simulated EEGs is that the quality of the signal before and after artifact removal can be assessed through standard performance measures. The metrics commonly employed to represent the energy of the signal compared to the energy of the artifacts are the signal to noise ratio (SNR) [53], the signal to artifact ratio (SAR) [15] and the brain to contamination ratio (BCR) [50], the latter being energy ratios equivalent to the well-known SNR but with only biological artifacts as sources of contamination. In order to obtain a mathematical expression for the SAR/BCR, we first rewrite (1) as follows:

$$\mathbf{X} = \mathbf{AS} = \mathbf{X}^{(\mathrm{s})} + \mathbf{X}^{(\mathrm{a})}, \tag{2}$$

where $\mathbf{X}^{(\mathrm{s})} = [x_{i,j}]^{(\mathrm{s})}_{n\times N}$ represents the signal only and $\mathbf{X}^{(\mathrm{a})} = [x_{i,j}]^{(\mathrm{a})}_{n\times N}$ represents the artifact component at the scalp. Here, we have assumed that there are no sources of contamination other than physiological artifacts; consequently $\mathbf{V} = \mathbf{0}$ in (1). Then, the brain to contamination ratio for channel i is simply [15]:

$$\mathrm{SAR}_i = \mathrm{BCR}_i = 10\log_{10}\left(\frac{\sum_{j=1}^{N}\left|x_{i,j}^{(\mathrm{s})}\right|^2}{\sum_{j=1}^{N}\left|x_{i,j}^{(\mathrm{a})}\right|^2}\right). \tag{3}$$

The signal to artifact ratio may also be computed for the entire signal by summing over all channels in both the numerator and the denominator above. The SAR can be used to evaluate the extent of contamination over the scalp, by showing topographical error maps, and to compare the ratio after denoising to the original ratio of the artifactual EEG signal.

The metric most prevalently used to verify the effectiveness of a noise removal method is the normalized mean squared error (NMSE) [34, 54, 55], which measures the deviation between the channel estimate $\hat{\mathbf{x}}_i^{(\mathrm{s})}$ and the clean channel signal $\mathbf{x}_i^{(\mathrm{s})}$:

$$\mathrm{NMSE}_i = 10\log_{10}\left(\mathrm{E}\left\{\frac{\sum_{j=1}^{N}\left|\hat{x}_{i,j}^{(\mathrm{s})} - x_{i,j}^{(\mathrm{s})}\right|^2}{\sum_{j=1}^{N}\left|x_{i,j}^{(\mathrm{s})}\right|^2}\right\}\right)\ [\mathrm{dB}], \tag{4}$$

where $\mathrm{E}\{\cdot\}$ denotes the expectation operator that averages over various runs and estimated signals $\hat{\mathbf{x}}_i^{(\mathrm{s})}$. This is equivalent to the relative root mean squared error (RRMSE) of [29, 56–58].

Another popular measure of performance is the (relative/percentage) error of the signal in various frequency bands of interest; see for instance [14, 15, 49]. A few other ways of determining how well an algorithm works have been proposed. For example, the authors of [50] use a 2×2 matrix of coefficients of correlation between recovered and original brain and contaminant sources. Correlation measures are also employed in [48, 49], where the authors test the efficacy of different algorithms on the basis of Pearson's correlation coefficient and mean square error (MSE) measurements. Furthermore, mutual information on estimated and original clean data is used in [55] to determine how closely the reconstructed EEG resembles the noiseless activation. The mutual information has also been used in [7, 59], where the EEG is assumed to share less information with the EOG after correction than the raw uncorrected data.

2.5.3. Validation for acquired EEGs. Multiple validation procedures for real-life EEG signals have been proposed in recent years; however authors do not seem to agree on choosing a single mechanism for evaluating and comparing the performance of artifact removal algorithms. Possibly the strongest attempts at resolving the issue have been developed by the group of Croft and Barry [10, 17] for ocular artifacts and EOG correction methods, and by McMenamin *et al* [32, 60] for myogenic artifacts. In what follows, we explain several alternatives with decreasing levels of relevance and we postpone our recommendation to section 4.8.

Croft *et al* [10] validate four techniques by measuring the correlation between the corrected data and the reference EOG channels ('regression validation') and the consistency of ERPs associated with eye movements in the EOG channels ('standard deviation validation'). Pham *et al* [17] build upon Croft's work and propose improved versions of both validation measures to address some of their limitations. The problem with this validation scheme is that it depends entirely on having recorded reference EOG channels and on ERP consistency. Thus, it must be used with carefully acquired signals obtained from participants following a specific recording protocol.

The more general approach proposed by McMenamin *et al* in [32, 60] consists in evaluating the sensitivity (whether the method attenuates the artifacts) and specificity (whether it preserves neurogenic signals) of an artifact removal process using regions of interest (ROIs). Although this is an attractive approach, it is not straightforward to implement. Establishing the sensitivity and specificity requires data in which the presence and absence of artifacts is definitive or can be reasonably assumed [47]. This may involve for instance scripted data, in which participants alternate eyes closed or fixed with movements and blinks (to produce EOG), or tense and relax in response to instructions (to produce EMG). Moreover, defining ROIs determined by areas of peak myogenic and neurogenic activation is an arduous and subjective task.

Metrics with which the EEG signal and artifacts may be characterized are important, since they allow researchers to implement simple tests in order to validate processed signals. To mention just a few cases: Daly *et al* [22] propose typical values for characteristics of resting state background rhythms such as their mean power and its standard deviation, their maximum amplitude and its standard deviation, and the kurtosis and skewness of their amplitude; Mognon *et al* [61] compute some features intended to best capture the behavior of components associated with ocular artifacts, such as kurtosis and spatial average difference for eye blinks, or maximum epoch variance for vertical eye movements; Delorme *et al* [51] use extreme values, linear trends, data improbability, kurtosis and spectral patterns to parameterize a greater variety of artifacts. The three studies report excellent performances for the detection of artifacts using the aforementioned statistical characterizations, with the consequence that they may also be employed quite reliably to check whether the cleaned signal resembles a noise-free EEG.

A novel idea for scenarios in which the researcher has full control of the EEG recording is given by Sweeney *et al* [62]. The authors propose a methodology for producing two highly correlated signals: one that is considered a reference artifact-free 'ground-truth' and another that is intentionally corrupted with artifacts. Given this controlled scenario, it is possible to apply artifact removal methods to the noisy EEG and compare the correlation between either the noisy or the resulting signal and the ground-truth.

Finally, the performance of a certain method for noise removal from recorded EEG data may be evaluated by visual inspection of the time, frequency and spatial characteristics of the denoised signal, usually compared to those of the measured signal. Even though this is a subjective method, since it depends on expert revision of the results, it may give an indication as regards whether the algorithm has improved the quality of the EEG signal or has distorted one or more time intervals or frequency bands. In effect, some authors use this simple validation method to compare the performance of certain algorithms; for instance: De Vos *et al* look for a $1/f^{\alpha}$ decay in the denoised spectrum and for a frontal activation when plotting the topography of the removed EMG components [23]; Kirkove *et al* do a qualitative evaluation of their results [11] by plotting segments with ocular activity before and after artifact removal; Crespo and García visually check that most of the high frequency muscle contamination was eliminated in all sleep stages after artifact removal [48]; Croft *et al* resort to 'face validity' to justify the revised aligned-artifact average method as compared to that given by Gratton *et al* [17]; among other cases [15, 49, 56].

2.5.4. Remarks. Note that while performance evaluation is mostly concerned with accuracy, it is also important to study the reproducibility of an algorithm [3]. The reproducibility describes the ability of an algorithm to produce repeated measurements which are coherent, obviously under the assumption that the same signal conditions apply to all measurements. Although reproducibility is best investigated by sequentially repeating an experiment on the same patient, simulated signals also represent a powerful and much more manageable means of evaluating the reproducibility of an algorithm.

Reproducibility, as well as performance, should ultimately be tested with measured EEGs. In order to determine whether the results given by an algorithm are reproducible, a series of measures can be obtained under the same recording conditions, producing equivalent EEG plus artifact combinations. By showing that the algorithm performs in the same way for each dataset, we also demonstrate its reproducibility.

2.6. Computational complexity

An important attribute of an algorithm is its computational complexity, defined as the number of floating point operations (flops) required to execute the algorithm. In practice, knowing whether an algorithm is computationally efficient is as important as knowing what its performance is for certain (online) applications. Typically, there exists a trade-off between speed and accuracy; thus if two methods provide similar results in terms of the quality of the denoised signal, then the faster method should be preferred.

In this paper we do not deal with this subject any further for various reasons; in practice, the execution speed of an algorithm is directly related to its implementation, and not just dependent on the theoretical computational cost. The problem is that most authors do not report the computational cost of their algorithms, either theoretically or in practice. What is more, speed is of prime concern for online applications (for instance patient monitoring in real time), whilst we want to determine which algorithm provides the denoised EEG of best quality. The interested reader may find detailed derivations of the complexity of some artifact removal algorithms in [34, 54].

3. A survey of denoising techniques

In this section we give a comprehensive overview of techniques that can be used for the removal of artifacts from an EEG. For each method, we cite publications on its early use in EEG processing; we also explain the reasoning behind its use for the removal of artifacts from an EEG and highlight some of its advantages and deficiencies. Additionally, we mention extensions of the algorithms, if they exist.

Simple low pass, band pass or high pass filtering represents one of the first classical attempts at removing artifacts from a measured EEG. However this is only effective when the frequency bands of the signal and interference do not overlap [19]. With spectral overlap, which is commonplace for typical artifacts recorded along with the EEG, alternative techniques are needed such as adaptive filtering, Wiener filtering and Bayes filtering [19], as well as regression [63], EOG correction [13], blind source separation [20] and more modern attempts like the wavelet transform (WT) method [64], empirical mode decomposition (EMD) [65] and nonlinear mode decomposition (NMD) [66].

BSS techniques are also known as component based methods since they find principal or independent components equivalent to the input EEG channels and perform processing in the transformed domain. The process is reversed by applying the inverse transformation to the corrected components, with the consequence that all EEG channels are processed and estimated simultaneously. In contrast, filtering, regression, EOG correction, the WT method, EMD and NMD (with the exception of multi-channel EMD, which is not used in the EEG literature) estimate each artifact-corrected channel independently, in the time, frequency or time–frequency domain.

3.1. Linear regression methods

Regression algorithms were arguably the most frequently used EEG artifact correction techniques up to the mid 1990s, especially for ocular interferences, thanks to their simplicity and reduced computational demands. When one or more reference channels are available and on the premise that they properly represent all interference waveforms, then artifacts may be corrected for by subtracting a regressed portion of each reference channel from the contaminated EEG (see the next section and [13, 63] for EOG correction procedures). Regression may be done either in the time or frequency domain, by estimating the influence of the reference waveforms on the signal of interest.

Linear regression assumes that each EEG channel is the sum of the non-noisy source signal and a fraction of the source artifact that is available through a reference channel. Then, the goal of regression is to estimate the optimal value for the factor that represents such a propagation fraction. In multiple linear regression the measured signal at each electrode is influenced by more than one (fraction of the) reference waveforms—for instance, vertical, horizontal and radial ocular artifacts.

Regression methods have been replaced by more sophisticated algorithms primarily because the former need one or more reference channels, a disadvantage that limits their applicability to removing mainly EOG [13] and ECG [67] artifacts (note that the authors in [68] have been able to record EMG activity as a reference channel; however this type of measurement is not routinely performed). Since other potentially more efficient algorithms emerged, like PCA and ICA that have become commonplace in most recent publications (from [44, 69] to [7, 11, 14–16, 34, 50, 54, 70]), regression has no longer been the default choice for EOG or ECG removal of artifacts from an EEG. We remark, however, that no publication has yet shown that BSS algorithms are optimal with measured EEG data; only [71] has preliminary results on them producing denoised EEG of quality equivalent to that from optimal EOG correction methods. Therefore, despite its drawbacks, regression is still used as the ‘gold-standard’ technique to which the performance of other algorithms may be compared; see for instance [14, 15] for ocular contamination.

3.2. EOG correction methods

Even though EOG correction is a general term, in the EEG artifact removal literature it refers to EOG subtraction methods that assume that the measured EEG is a linear combination of the true signal and the ocular artifact, and are based on linear regression [13]. Regression calculates **B**, the proportion of one or various EOG references that are present in each particular EEG channel (the time domain approach). Correction is then performed by subtracting the regressed portion(s) of the EOG reference waveform(s) from each EEG channel, resulting in an estimation of artifact-free measurements in the scalp.

Bidirectional contamination, which refers to brain signals being measured in the reference EOG as well as the other way around, is the main drawback of the early EOG correction techniques. Many of these procedures do not take bidirectional contamination into account and, consequently, certain possibly relevant cerebral information is cancelled in the EEG recordings upon linear subtraction. More advanced EOG correction methods overcome this issue in a number of ways, the simplest of all being low pass filtering of the EOG channels [15]. This is supported by some studies that argue that most high frequency content in the EOG is of neural origin [72]. However, others argue that in fact all frequency bands (alpha, beta, delta and theta) are contaminated bidirectionally [73]. Alternatively, the aligned-artifact average procedure obtains the **B** coefficients from an average EOG waveform that has minimal forward EEG contamination (the ratio of EOG to EEG power increases with averaging) [13]. The procedure was later revised (RAAA) to account for both eye movements and blinks [13, 74].

For comprehensive reviews on the subject, we refer the reader to [12, 13, 75]. From the validation papers [10, 17] the revised aligned-artifact average procedure stands out as the best multiple-regression technique for accounting for ocular artifacts such as blinks and eye movements.

3.3. Filtering methods

Simple filtering is normally not an option for removing artifacts from EEG recordings, except for narrow band artifacts like environmental line noise (50/60 Hz interference can be removed with a notch filter). Thus, numerous artifact removal techniques described in this section try to adapt the filter parameters $\mathbf{w}$ to minimize the mean square error between the estimated EEG $\hat{\mathbf{X}}$ and the desired original signal $\mathbf{X}$. To overcome the limitation of the artifact-free signal being unknown, each method implements strategies following certain optimization criteria. In what follows, we briefly describe some of the main filtering techniques employed in the removal of artifacts from the EEG.

3.3.1. Adaptive filtering. Adaptive filtering assumes that the signal and artifacts are uncorrelated. The filter generates a signal correlated with the artifact using a reference signal and then the estimate is subtracted from the acquired EEG [19]. The choice of the artifact reference is key to the proper functioning of the algorithm and may be obtained from EOG recordings for the removal of eye movements or blinks [13], or from EMG recordings for the removal of muscle artifacts [70].

Adaptive filters iteratively adjust a vector of weights according to an algorithm of optimization. These weights model the contamination of the artifact on the EEG activity [49, 76]. Adaptive filtering represents an improvement over linear regression since propagation factors do not need to be constant or frequency independent [3, 49].

The most prevalent family of algorithms is based on the least mean squares method, which is linear in complexity and convergence. Another well-known family is based on the recursive least squares (RLS) method, which is quadratic in complexity and convergence. According to [77], RLS-based filters are superior in accuracy at removing ECG artifacts from EMG recordings.

3.3.2. Wiener filtering. Wiener filtering is another type of parametric technique, based on a statistical approach, which produces a linear time-invariant filter that minimizes the mean square error between the desired signal and its estimate [19]. The minimization is done using an estimation of the power spectral densities of the signal and artifact; hence it does not need a reference waveform.

The disadvantages are that calibration is needed prior to usage and that it cannot run in real time. On the other hand, when properly calibrated, it can achieve a better SNR for corrected data as compared to the adaptive filter [19].

3.3.3. Bayes filtering. Bayes filtering is a probabilistic system estimation method starting from noisy observations, based on assuming that the system is Markov [19]. These filters overcome some of the limitations of the aforementioned techniques in that they are capable of working without a reference signal and operate in real time. Bayes filters are not directly implementable due to their complexity; however they are approximated through Kalman filters and particle filters, the former of which have been used for EEG artifact removal in for instance [78] and in a nonlinear fashion in [79].

Bayes filters first estimate the state at a given time and then obtain a feedback in the form of noisy measurements [19, 80], which is used to predict a new *a priori* estimate. The algorithm needs to be calibrated.

3.3.4. Filtering in practice. Using different forms of filtering for the removal of artifacts from an EEG dates at least as far back as 1976, when Wright [81] obtained the best linear filter for removing EMG from EEG recordings: a least squares Kalman filter that exploits *a priori* knowledge.

Although other kinds of filters exist and have been used in the EEG artifact removal literature, adaptive filtering is the most common. It is still in use, for instance in [82], where three least mean squares adaptive filters are employed in cascade to eliminate line interference, ECG artifacts and EOG spikes separately. More generally, they are often used for comparison with other artifact removal methods, for instance in [11, 49].

Filtering approaches such as adaptive, Wiener or Bayes filtering have the advantage that they can be automized [62]; however they need a measured or reliably estimated reference in order to operate. Some of these methods can operate on single channels, a characteristic that makes them attractive for the personal healthcare environment [62].

3.4. Blind source separation methods

Blind source separation estimates $\mathbf{S}$ from the observations $\mathbf{X}$ in equation (1), without the need for a reference waveform for either the desired signal or the unwanted artifacts, jointly exploiting the information provided by all electrodes.

The effectiveness of BSS techniques is subject to various assumptions being borne out, at least to a certain extent: uncorrelatedness, independence, non-Gaussianity, instantaneous propagation, linearity, etc [20, 83]. The more closely the hypotheses advanced by a certain algorithm are satisfied, the better the method is meant to separate the components. Success hence critically depends on good source separation and on correct identification of the sources as brain or artifact components.

3.4.1. Principal component analysis. Principal component analysis uses an orthogonal transformation to convert the observations of possibly correlated variables into values of linearly uncorrelated variables called principal components, less than or equal in number to the original variables. The transformation is defined for the principal components to have the largest possible variances while being orthogonal to each other. PCA is also known as the discrete Karhunen–Loève transform and is equivalent to the singular value decomposition of $\mathbf{X}$ or the eigenvalue decomposition of the correlation matrix $\mathbf{X}^{\mathrm{T}}\mathbf{X}$. A reliable source separation is based on the assumption that the dataset is jointly normally distributed and that sources are (approximately) uncorrelated.

PCA was introduced into EEG analysis in [69], where the authors use it to empirically determine the spatial distribution of eye activity, and has since been used extensively for artifact removal [50, 84, 85]. Berg and Scherg [69] report PCA as being more effective at removing ocular artifacts than other non-BSS methodologies including regression, and for source localization [50, 86]. The greatest problem with PCA is that the assumption of orthogonality between neural activity and typical physiological artifacts does not generally hold. In fact, it has been demonstrated that PCA is unable to separate some artifactual components from brain signals, especially when they have similar amplitudes [50, 84].

Many extensions to this method have been proposed, for instance with the goal of making standard PCA more resilient against certain kinds of noise. Some such algorithms include robust PCA [87] as well as kernel PCA [88, 89]. Even though PCA may be useful for certain types of artifacts in various EEG contamination scenarios [14], the majority of the current literature on EEG artifact removal employs other methods. In fact, PCA is often used just as a first decorrelation or whitening step of a complete ICA algorithm [44], since most authors agree with the idea that artifacts and brain signals are better modeled as independent rather than orthogonal [20, 43, 44, 83].

3.4.2. Independent component analysis. Independent component analysis comprises several related methods for unmixing linearly mixed signals using only recorded time information, by imposing statistical independence of the sources. Independence is a stronger assumption than uncorrelatedness and, while the former implies the latter, the converse is not necessarily true. ICA algorithms can be separated into those based on exploiting higher-order statistics (HOS) of the signals and those based on using second-order statistics (SOS), the latter also known as time structure based methods. Not all authors consider time structure based methods as among the ICA techniques [83]. However, we follow the classification of [20] in which the authors explain that independence of the sources implies that the waveforms have no spatial, temporal or time–frequency correlations, which is why time structure based methods are also able to provide independent components by decorrelating the input channels.

The frequently used ICA algorithms are based on HOS [20, 90–92]. The first step in most *HOS-ICA* algorithms is to prewhiten the covariance matrix of the data (using PCA), so that the sought mixing matrix is orthogonal afterwards [21] (adding stability to the process). HOS-ICA approaches find a linear transformation $\mathbf{W}$ for the estimated sources $\hat{\mathbf{S}} = \mathbf{WX}$ to be as independent as possible. Independence measures can be directly related to the probability density function of each column vector $\hat{\mathbf{s}}(j)$ of $\hat{\mathbf{S}}$, for instance via the mutual information (MI) [93], or using the normalized version of the differential entropy, called the negentropy [92] which is connected to the MI [54]. For their part, *SOS-ICA* methods are based on decorrelating the data in the time domain, and an attractive framework for dealing with this problem is the simultaneous diagonalization of properly defined matrices [21]. Specifically, the second-order blind identification (SOBI [93, 94]), the algorithm for extraction of multiple unknown signals (AMUSE [95]) and the temporal decorrelation separation (TDSEP [96]) are methods that estimate the BSS mixing matrix by diagonalizing time-lagged correlation matrices [21].

ICA was introduced to EEG study simultaneously by different groups in [43, 44, 97] and has mostly replaced other approaches for the removal of artifacts from an EEG. In contrast to the possibly incorrect assumptions of PCA [85], it is the case that artifacts and brain activity are usually sufficiently independent, which explains the success of ICA for artifact removal [44, 85]. In practice, nowadays only a few ICA algorithms such as SOBI [93], (extended) InfoMax [98] and fastICA [90, 99] are used to process biomedical signals [7, 54]. Recently, the adaptive mixture of independent component analyzers (AMICA) [100] has emerged as an interesting alternative to the former methods [7, 101]. Many more methods exist, but we do not deal with these algorithms in detail in this paper since the interested reader can find in-depth explanations elsewhere (see for instance [54] and references therein).

The effectiveness of ICA is based on statistical independence of the sources and the full column rank of the mixing matrix $\mathbf{A}$. Even if the sources are not exactly independent, ICA based algorithms have been reported to be successful at removing artifacts from the EEG signal of interest. Due to ICA being based on statistical features, results will not be reliable if the amount of data given to the algorithm is insufficient [43]. It would be best to use all the available data, provided the artifacts and cerebral activity were spatially stationary through time; however this may not be the case. The goal then becomes using the maximum amount of data when the sources are reasonably stationary. Some authors suggest that 10 s epochs usually give good results [43], and others that the number of samples should be a few times the square of the number of channels [15, 102]. On the other hand, temporal decorrelation based methods have the advantage that they work well with far fewer samples; for example the authors in [15] report that the performances of AMUSE and SOBI are quite insensitive to the duration of the data segments. Other studies [48, 103, 104] support this same idea.

3.4.3. Constrained ICA. Constrained ICA (cICA) [20] or ICA with a reference (ICA-R) incorporates prior knowledge about the source signals, making (1) become a semi-blind source separation problem. This is done by imposing temporal or spatial constraints on the source mixture model. It is often the case that temporal, spectral or time–frequency information from the biomedical measurements is available, such as heart beat morphology, frequency bands of EEG activity and temporal dynamics of certain high amplitude artifacts [20].

Temporally constrained ICA: The goal in this case is to obtain an output that is statistically independent of other sources but closest to a reference signal [20]. In [105] this is done by solving a constrained optimization problem through an augmented Lagrangian function. Moreover, prior knowledge can be introduced into the model by means of reference channels that make the original matrix **X** become augmented by a number of rows equal to the references [15, 20]. Other attempts at solving the temporally constrained ICA problem are [106–108], where prior information from some source waveforms is used.

Spatially constrained ICA: The idea here is to define a set of spatial constraints on the mixing matrix **A** to represent prior knowledge or assumptions of the spatial topography of some source sensor projections [20]. The method described in [39] has been reported to show excellent performance in denoising certain kinds of EEG signals [55]. To be precise, the algorithm incorporates reference or constraint topographies, such that some source sensor projections are approximately known, hence limiting the degree to which certain columns of the mixing matrix may deviate from the known projections. The idea is not new; in fact in [85] the authors use spatially constrained ICA (SCICA) [109], but this latter method involves a more computationally expensive optimization.

We end by noting that using any form of constraint to solve the BSS problem involves the relaxation of strict assumptions regarding the statistical, temporal or spectral properties of the associated waveforms, in order to satisfy the temporal or spatial constraints [39].

3.4.4. Other component based techniques. Other component based techniques that have appeared in the literature for removal of artifacts from an EEG include multiple-source eye correction (MSEC) [69, 86, 110], multivariate singular spectrum analysis (MSSA) [16], canonical correlation analysis (CCA) [56] and sparse component analysis (SCA) [111, 112], among others.

MSEC determines signal topographies by spatiotemporal dipole source analysis in the presence of predefined artifact topographies [85]. Using the resulting spatial vectors together with a brain model, eye activity in the EEG and event-related response data can be estimated and corrected in the presence of brain activity [110].

Singular spectrum analysis (SSA) is a nonparametric spectral estimation method based on embedding a signal into a higher dimensional space, the latter represented by the signal trajectory matrix formed with time-delayed versions of the signals. Artifacts are removed by clustering the columns of this trajectory matrix and applying singular value decomposition. For MSSA the trajectory matrix is constructed by concatenating the trajectory matrices from each individual signal in the multivariate signal set [16, 113].

CCA measures the linear relation between two multi-dimensional random variables and can be applied to solve the BSS problem by taking the source vector as the first multi-dimensional random variable and a temporally delayed version of the source vector as the second multi-dimensional random variable [34, 114].

SCA assumes sparsity of the sources in some (transformed) domain in order to solve the BSS problem. Authors who have studied the application of sparse factorization in EEG data analysis include Li *et al* [115], while others like Georgiev *et al* [112] and Gribonval *et al* [111] deal with SCA for BSS in general.

3.5. Source decomposition methods

Alternatively, the problem of finding an artifact-free matrix $\hat{\mathbf{X}}$ from the observations **X** in equation (1) can be tackled directly by decomposing each individual channel into basic waveforms that represent either the signal or the artifact, thus removing the latter. Successful algorithms of this type are based on the fact that some source (either the signal or artifacts) can be represented by a single decomposition unit, such as an intrinsic mode function (IMF) for empirical mode decomposition, or resemble certain wavelet basis for the wavelet transform.

3.5.1. Wavelets. Wavelets are ideal for biomedical applications because of their versatility, in that they allow one to design methods that are robust and work in most circumstances, and for their finely tunable time–frequency trade-off, such that they can accommodate biomedical signals that generally combine features with good time or frequency localization [64]. The WT has been widely used in the context of EEG denoising, probably commencing in the early 1990s. By the time that the review [64] was published, the subject was evolving very rapidly. The WT is defined as the inner product of the signal $f(t)$ with the time scaled and shifted version of the wavelet function $\Psi(t)$ [64]. The WT decomposes the signal into a set of coefficients, for various scales, which represent the similarity of the signal with the wavelet at that scale. The discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled in time, that is $t = mT$. A common form of the DWT employs a dyadic grid where the amplitude and time scales are $a = 2^j$ and the time shift is $b = k2^j$, with both j and k integers.

The continuous-time wavelet transform can be obtained by using $W_\Psi f = \left\langle f, \Psi_{a,b} \right\rangle$, where $\Psi_{a,b}(t) = |a|^{-1/2}\Psi\left(\frac{t-b}{a}\right)$. The discrete-time wavelet transform is usually calculated by filtering the input vector through a series of low pass and high pass filters that provide one approximation and D detail coefficients respectively.

Denoising is done following three steps: first, decompose the signal into a number of levels D; second, threshold the detail coefficients; and third, reconstruct the signal from the filtered representation. Artifact removal based on the WT relies on the sources of interest being decomposable in a wavelet basis, whereas artifacts cannot be (depending on the type of signal; it may be the artifacts that have a better defined wavelet decomposition—for instance consider background EEGs and blinks). This implies that only a few wavelet coefficients with high absolute value should represent the signal and that wavelet coefficients with low absolute value correspond to the artifacts. Evidently, good separation of the signal and noise depends on the wavelet basis and its similarity to the source signals to be preserved. Thus, the mother wavelet, the shrinkage rule and the noise level rescaling are important to the design of the noise removal method [34].

The DWT is often accompanied by threshold selecting criteria, such as Stein's unbiased risk estimate (SURE) [116] implemented in [34] or other forms of thresholding [11], such that only large enough coefficients are kept. Even though the DWT remains an interesting tool for EEG processing on its own [117–120], nowadays it is more often found combined with other denoising techniques such as ICA [55], one reason for this being that the DWT is in fact unable to remove completely artifacts that overlap in the spectral domain like ECG on an EMG signal [19].

3.5.2. Empirical mode decomposition. Empirical mode decomposition [65] is a heuristic one-dimensional technique that aims at decomposing a signal into its basis functions, called intrinsic mode functions (IMFs), which are amplitude and frequency modulated zero-mean components, plus a non-zero-mean low degree polynomial remainder [34]. The modes have a well-defined instantaneous frequency, which can then be computed utilizing the Hilbert transform. The combined instantaneous frequencies produce a time–frequency representation of the signal known as the Hilbert spectrum [121]. The technique is intended for nonlinear signal processing and is well suited to non-stationary signals. EMD has been criticized due to its low robustness against noise [66] (its performance is greatly influenced by white noise), but has gained a lot of attention in the last few years in many fields [122] and in particular for processing biomedical signals. The robustness of the original algorithm has been improved with the ensemble empirical mode decomposition (EEMD) [123].

EMD sequentially computes K IMFs and the remainder such that $x_n[m] = \sum_{k=1}^{K} s_{n,k}[m] + r_n[m]$. Each IMF is obtained via an iterative procedure, called a sifting process, that consists in identifying the local maxima and minima of the residual (or the signal in the first iteration), interpolating between them to find the upper and lower envelopes, and computing the mean envelope of the residual (or the signal) and subtracting it from the residual. The process is repeated until some convergence criterion is met, resulting in IMFs of decreasing frequencies, until no more components can be extracted.

The key to the success of EMD is that the signal and the artifacts can be represented by one or more IMFs. Specifically, each source should be the sum of AM–FM modulations and they should be different from one another [34]. EMD has been used rather successfully for the removal of artifacts from an EEG on its own [34, 124, 125] and also along with BSS methods [57, 58], when the signal and the artifacts can be represented by one or more IMFs. EEMD has likewise been used in the context of EEGs [126] (in this case in conjunction with CCA). EMD also requires thresholding in order to select the components of interest—such as the methodology proposed in [34, 127]. To end, EMD has been adapted to the multivariate environment, for example with the multivariate EMD (MEMD) [128, 129] and the turning tangent EMD (2 T-EMD) [130]; however these methods are not often used for EEGs due to their computational complexity.

3.5.3. Nonlinear mode decomposition. Nonlinear mode decomposition [66] is a novel adaptive decomposition tool for time domain signal analysis based on the synchrosqueezed wavelet transform (SWT) [131]. The technique decomposes a signal into its so-called nonlinear modes, which are its fully oscillatory components and their harmonics. The authors in [66] claim its qualitative and quantitative superiority over the EMD and EEMD methods, in that it has a solid mathematical background (EMD and EEMD are empirical) and since it is more robust against noise. The authors further illustrate the application of their proposed algorithm to the removal of artifacts from a human EEG recording.

The NMD procedure consists of four parts [66]: adaptive curve extraction (of the first harmonic) from the synchrosqueezed wavelet transform, identification of possible harmonics, reliable identification of the true harmonics and reconstruction of the nonlinear modes from the SWT. The first step relies on the construction of the SWT, which is capable of providing a time–frequency representation with much better frequency resolution than and the same time resolution as the WT [66, 131]. Adaptive curve extraction is equivalent to finding the region of the SWT that contains the required component (of the form $A(t)\cos\varphi(t)$). Candidate harmonics are then extracted by inspecting regions of peaks at harmonic frequencies and then finding the corresponding supports. To conclude, the SWT of each nonlinear mode is reconstructed by summing the SWT of the main curve and those of all its true harmonics (values not belonging to the supports of the extracted curves are set to zero).

The only reference in the literature on the applicability of NMD to EEG artifact suppression and, in general, to any form of denoising is in the original work [66]. It seems, however, a potentially interesting new tool for improving the results achieved by using the simpler WT [117, 118, 120].

3.6. Combinations of different algorithms

Using a combination of algorithms to remove artifacts from the EEG is an option that has gained attention in the recent literature for multi-channel [55, 132, 133] and single-channel processing [57, 58, 126]. The former are characterized by using a BSS algorithm, the components of which may be refined by a single-channel method in a second stage. The latter, which prevail in terms of number of publications, follow a completely different approach, by first decomposing each channel into simpler components and then applying a BSS algorithm to the decomposition.

Multi-channel processing is performed in [55], where wavelet denoising is applied to the components obtained from applying spatially constrained ICA [39] to remove ocular activity from background EEG activity. Similarly, in [134] the authors employ regression to denoise the components related to ocular activity obtained by applying ICA to the EEG recordings. The idea behind both procedures is to filter out cerebral activity that may be leaked into the artifact components and would be lost by simply removing the unfiltered components. The authors in [135] invert the procedure, first applying wavelets and then ICA to the EEG signal. Their WICA algorithm first partitions the EEG recording into four EEG subbands, then selects the artifact-linked wavelet components and passes them through ICA. To end, the independent components related to the artifacts are found and cancelled out.

Combining techniques for single-channel processing is far more common; for instance in [57] the authors combine EEMD and FastICA. When applied to a real EEG, EEMD-ICA seems to correctly separate seizure activity from artifactual components despite its very low SNR. Another example is given in [58], where the authors develop an alternative method that only varies in the calculation of extrema for EEMD, but obtains more precise separation results. Finally, in [126] the authors combine EEMD and CCA and test the technique against wavelet and EEMD-ICA, producing significantly improved results. For more details and algorithms that operate on single-channel measurements (which is not the primary focus of this paper), we refer the reader to [19].

One option that remains largely unexplored is a combination of methods in cascade, examples of which are not very numerous (see for instance [82] for various adaptive filters applied to the EEG signal in succession). The idea may, however, be used for any combination of different methods that process the measured EEG one after another, such that each algorithm targets the artifact that it removes best.

In figure 3 we show the three kinds of combinations described before, among which (a) and (b) are regularly found in the literature, while (c) is not so commonly used.

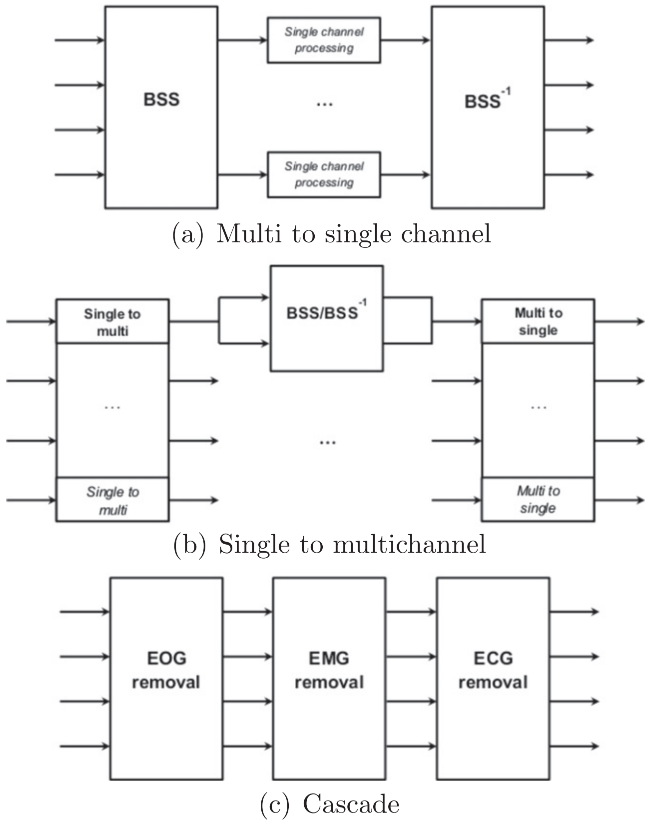

Figure 3. *Combinations of artifact removal algorithms.* (a) Multi-channel–single-channel processing normally begins with a BSS algorithm, as pictured. (b) Single-channel–multi-channel processing usually starts with EMD, the components of which may then be processed by a BSS method. (c) Cascade artifact removal, shown as processing EOG, EMG and ECG—but these could be in any order.

3.7. Further artifact correction methods

For cardiac interference there exist algorithms such as ensemble average subtraction (EAS) that are sometimes still in use [136]. The method incorporates a simultaneously measured ECG channel. It first performs peak detection, then partitions the signal into segments around each peak, averages the segments to estimate the artifact and subtracts the mean artifact from each segment. But due to other methods being much more common, we do not deal with EAS any further.

The literature on the removal of artifacts from an EEG is so broad that if we tried to be comprehensive, we could not explain all existing methods for lack of time and space. Otherwise, we have explained the most habitually used approaches for removing EOG, EMG and ECG contamination from the EEG.

3.8. Semi-automated and automated execution

Artifact removal algorithms can be classified as semi-automated or automated, depending on whether there is a need for human intervention or not. Semi-automatic methods require visual inspection of the measured signal or of the components obtained by the artifact removal method; hence they can only be used for offline applications. Therefore, to be able to run an algorithm in an online application and, in general, to avoid introducing subjectivity in the process, automated execution is normally preferred.

Multiple procedures for automatic identification of and correction for artifacts have been developed; however no single one stands out among them. Automating existing algorithms is not easy since, as commented throughout the text, there are multiple kinds of signals and contaminants that are mixed in undetermined ways in real-life measurements, thus limiting the applicability of standard methods unless they can be readily adapted to specific scenarios. Regression and filtering approaches need a reference channel if they are meant to operate automatically [19, 137]. On the other hand, component based methods are more versatile in that they can be made automatic via a reference signal and also based on values for typical characteristics of the EEG signal or artifacts and deviations from normality [22, 51, 61].

When a reference waveform exists or a prototype signal can be generated, viable automation may be performed by computing the correlation of certain ICs with the reference channel [14, 85], or by combining signal features and correlation [15, 49]. More generally, spatial and temporal probabilistic characteristics of the components derived from decomposition of the EEG signal compared to standard values for the background EEG and artifacts may serve to automate an algorithm on the basis of a combination of thresholds. A completely automatic ICA-based algorithm for identification of artifact-related components in EEG recordings, ADJUST [61], works quite reliably following this idea. Similar approaches are presented in [22, 51]. Another alternative, implemented in [16, 138], consists in performing a training phase followed by a clustering step. The training phase needs a reference channel that is either measured or obtained from clean epochs of the same recording or from epochs of a different recording that contains signal or artifact components similar to those of interest. Clustering is performed on the basis of the similarity of the temporal dynamics of ICs as described via their auto-mutual information.

To conclude, WT and EMD can be automated more easily and in a common manner using thresholds [34]. For the WT, the SURE [116] shrinkage rule and a soft thresholding strategy seem to provide good results [34]. With regard to EMD, inspired by wavelet thresholding, the authors of [127] use an algorithm that evaluates the noise level and filters each IMF.

4. Discussion and guidelines

The vast majority of the literature that we have reviewed extracts conclusions on the effectiveness of a certain artifact removal method (or of its superiority compared to other algorithms) on the basis of simulations or, at best, visual inspection and subjective interpretation of the results. As we remarked in section 2.5, in our opinion measured EEG signals should be the relevant testbed for artifact removal experiments. Thus, in what follows, we separate out the algorithms that have been shown optimal for artifact removal from either simulated or real EEG signals for EOG, EMG, ECG and a mix of contaminants. Note that denoising results differ when reference waveforms are available as compared to when they are not [15], the former being the preferable scenario.

Blind source separation techniques are possibly the methods most widely used to remove any type of artifact from an EEG. Many comparative studies concerning various kinds of BSS algorithms and other methods can be found in the literature [11, 14–16, 19, 34, 46, 59, 139]; however they sometimes lead to contradictory results. In the following subsections our goal is to clarify this on the basis of the existing literature and some preliminary conclusions extracted from our own work that we mean to support in a continuation paper, the results of which are still being derived.

4.1. Assumptions for the comparison

In order to provide meaningful guidelines, we need to define the scenario considered in this review in more detail. In short, and to some extent in order to sum up the previous sections, we primarily consider EEG rhythms but also consider event-related potentials as the signals of interest that are to be cleaned. That is, we do not distinguish between these two signal types, even though we acknowledge that denoising may not affect them equally. Since this distinction is not properly reported in the literature, we cannot extract conclusions except from our own experience, and this may only be part of the continuation paper for the current review.

Furthermore, we describe techniques meant to deal with ocular, muscular and cardiac artifacts, first appearing in isolation and then simultaneously. This separation can only be ensured with simulated signals or, to a lesser degree, with controlled recording environments. However, conclusions should be easily adaptable to clinical environments, taking extra care that extraneous artifacts may be present and hence make some intervals of the recordings unusable. What is more, we always assume that the measured EEG is a linear combination of brain signals and one or more kinds of artifacts. Finally, we do not take into account the number of electrodes when comparing results reported by different authors, even though it is a relevant design feature: more electrodes provide increased robustness due to redundancy of information [53], but they may also lead to overfitting if not dealt with carefully [21].

4.2. Ocular artifacts

As commented on throughout the review, eye movements and blinks have been treated extensively in the EEG artifact removal literature. This is motivated by the fact that they are always present in EEG recordings, and also because they possess more predictable time, spatial and frequency characteristics than other kinds of artifacts.

If we attend to publications that use real EEGs, the revised aligned-artifact average solution [13] is possibly one the best methods for removing blinks and saccades from EEG measurements, as validated in [10, 17]. Importantly, this approach, just like using any other regression algorithm, depends on having a reference channel for removing the ocular activity from the EEG (up to vertical, horizontal and radial EOG references for optimal performance [13]). On the other hand, ICA has also been shown to perform satisfactorily as regards removing ocular artifacts in experimental scenarios [7, 39, 44, 108, 140], of which possibly that of [140], using extended InfoMax, is the most thoroughly justified. More recently, however, the same research group as validated RAAA has presented preliminary results showing that ICA is able to produce a denoised EEG of quality equivalent to that from the EOG correction methods [71].

According to simulations and visual inspection of results on acquired EEGs, SOBI stands out as the best performing method for removing ocular artifacts from background EEG activity and ERPs in multiple publications [15, 38, 49, 53, 104]. Moreover, it can be used to facilitate source analysis from EEGs [141] and magnetoencephalographic (MEG) data [142–144], since it has been shown to be robust across subjects [141] and over large time intervals [145]. In addition, SOBI has very lenient requirements regarding the data and their sources, which makes it attractive for fitting the BSS problem.

In our experience, SOBI, AMICA and, to a lesser extent, extended InfoMax perform satisfactorily in the correction for artifacts in simulated and real EEGs. We thus recommend the use of either RAAA, SOBI, InfoMax or AMICA to remove ocular interference from the EEG when reference channels are available and the last three methods when they are not. In particular, SOBI is integrated in EEGlab [102], is fast, easy to use, reliable, and reproducible, and does not need a reference channel.

4.3. Muscle artifacts

The presence of muscle artifacts poses a more challenging scenario than that of ocular interference, since a reference waveform is rarely available [140] and because spatial topographies need not be as well defined as with contamination coming from the eyes. Unlike ocular artifacts that can be removed by the aforementioned ‘EOG correction methods’, as well as by other more general approaches such as BSS, there exist no ‘EMG correction methods’, i.e. authors in the literature have not developed algorithms designed specifically to cancel out muscular interference.

Recently, Muthukumaraswamy [139] presented a literature review on several techniques that help suppress muscle artifacts and other high frequency interference from EEG and MEG activity. According to his survey, disagreement exists in the literature about the effectiveness of ICA in removing EMG activity from data, a fact that is also reported elsewhere [32, 33, 47, 60, 146]. The author concludes that even though a number of techniques are available for the reduction of EMG artifacts, at present none can guarantee processed data free of high frequency artifacts.

Despite the previous statements, EMG has been removed quite successfully from contaminated EEGs in a number of publications. To name just a few cases, muscular artifacts are cancelled in [23, 56] by using CCA, in [68, 147] by using InfoMax, in [48, 70] by employing SOBI and in [34] by using EMD for low SNR, CoM_2 (and ICA algorithm) and CCA for intermediate SNR and DWT for high SNR. Among these, the cases in [34, 48, 56, 70] are mainly based on simulations. Then, in addition to the previous papers, [23, 43, 68, 70, 147, 148] analyze the results visually and [32] validates ICA on the basis of its sensitivity and specificity. Evidently, the performances obtained with simulated data and the results corroborated by visual inspection need to be properly validated, as in [32], or by extending an ocular artifact validation procedure [17, 149], but existing studies do not yet provide a unified method for doing this.

Clearly, then, EMG artifact removal is not as straightforward as EOG correction—among other reasons, because reference signals are rarely available. Even though CCA is widely used in the literature, according to our practical experience it does not outperform ICA. On the basis of experimentation, we believe SOBI, extended InfoMax and AMICA are as good as CCA at removing myogenic activity from the EEG. We therefore recommend SOBI for ease of use, code availability, speed of execution and reproducibility of results, even though CCA is also fast and easy to find online, for instance it is implemented in function bsscca of the AAR plugin for EEGlab available at www.germangh.com/eeglab_plugin_aar/index.html.

4.4. Cardiac artifacts

There are not as many publications that deal with cardiac interference as there are dealing with ocular and muscular artifacts, and fewer methods have been developed to target cardiac artifacts. Moreover, ECG has a very specific temporal morphology and a simple time–frequency characterization, which is why it does not pose as great a challenge as other artifacts as regards its removal from an EEG. In general, also, ECG is routinely measured along with the EEG and is less likely to present bidirectional contamination than EOG. Like for muscular interference, ‘ECG correction methods’ have not been categorized per se in the literature, even though some publications are devoted exclusively to removing this interference [150].

Early methods attempting to correct for ECG interference in an EEG, like subtraction (see [151] and references therein) and ensemble average subtraction (EAS) [152], are no longer used often, with exceptions [136]. The correction techniques more typically used nowadays include adaptive filtering [153] and ICA [148, 150, 154–156]. Note that ECG artifacts may be minimized by means of a linear model given a reference signal; however one should take into account that ECG is time-variant, and thus time-varying coefficients are needed [9]. Most authors use a reference ECG waveform to remove the cardiac interference; however the process can also be made automatic without a reference [150, 157].

In our experience, HOS-ICA methods perform well, as indicated by several studies [148, 156], but SOS-ICA methods such as SOBI perform better, in line with what is reported in [16]. Hence, once more we recommend the use of SOBI for the removal of cardiac interference from EEG measurements.

4.5. Multiple artifacts

We consider here publications where authors have tried to remove various artifacts of the aforementioned types that occur in the same recording. To mention just a few cases: Jung *et al* deal with ocular and muscular artifacts in [43] via extended InfoMax; Iriarte *et al* evaluate joint approximate diagonalization of eigenmatrices (JADE) to eliminate electrocardiogram, eye movement, 50 Hz interference, muscle, or electrode artifacts from interictal activity [148], reporting an evident clearing of signals with minimal distortion; Daly *et al* [16] employ simulations for contaminating EEG rhythms with EOG, EMG and ECG artifacts and report that lagged auto-mutual information clustering (LAMIC: an ICA algorithm based on second-order statistics) generally performs best, and when they consider real EEGs, the contrast to noise ratio, which determines the improvement in magnitude of the ERP component, indicates that MSSA is preferable, while the signal quality index metric, which measures the improvement in quality over the entire signal, indicates that LAMIC is superior; Delorme *et al* [7] experimented with measured EEG background activity and multiple contaminants (mainly EOG and EMG) in order to evaluate different ICA algorithms according to the pairwise mutual information, the overall mutual information reduction and decomposition 'dipolarity', and on the basis of such indicators, they found that the algorithm showing the worst performance was principal component analysis, while AMICA and extended InfoMax showed the best performance—however, these authors do not use validation methods that can completely justify their findings.

In our opinion, and, once more, relying in part on our own experience, ICA algorithms (extended InfoMax, AMICA and SOBI) are possibly the safest bet for artifact reduction in EEG signals without any prior knowledge of the characteristics of the brain signal (whether it is composed of EEG rhythms, ERPs or other things); and of the type of artifacts that are affecting the measurements.

4.6. Other artifacts

As commented in section 2.3, there exist multiple other sources of potential contamination for the recorded EEG [8, 19], among which line noise of 50 Hz (or 60 Hz) is most frequently treated in the publications that we have reviewed. This is an environmental artifact that originates from power leads that surround the body and can additionally arise from electromagnetic interference. Such artifacts can be suppressed with a simple notch filter due to the narrow frequency band of the line artifact [19], while low frequency trends in the EEG may be removed via a high pass filter [16]. Note that line noise can also be removed as part of the ICA process [43, 85, 138].

We end by highlighting that 'complete' ICA decompositions, such that the number of ICA components equals the number of channels, return components that have interpretable scalp maps and activations, along with other components that may correspond to non-physiological artifacts but may also account for mixtures of (unimportant) low energy sources that are combined to satisfy the linear mixture model [158]. These components can be discarded with no loss of information.

4.7. Is there a single best artifact removal algorithm?

As it turns out, there is no algorithm that is optimal for every possible scenario. The performance rather varies according to the type of EEG signal, the artifacts present in the measurements and the brain to contaminant ratio, among other factors.

Despite the fact that some contradictory studies exist, ICA based procedures are the main accepted solution for obtaining a clean EEG of improved signal quality [32], although they do not always completely separate artifactual from cerebral sources [32, 139]. In fact, leading researchers in the field have been using ICA and improved variations for the last 15 years—for example Vigário [21, 44, 159, 160], Hÿvarinen [161, 162], Oja [21, 159, 161, 162], James [20, 39, 55, 108], Makeig [43, 52, 97, 102], Jung [43, 52, 97], Comon [41] and Cichocki [83, 163], among others. PCA, on the other hand, may be better employed to extract features of the brain signal or of the artifacts to be removed in a pre-processing stage [85] or to whiten the signal prior to applying ICA [21, 44, 159].

Depending on the scenario, a certain ICA algorithm may stand out among the others as regards its effectiveness. SOBI is repeatedly reported to outperform other artifact removal methods [15, 49, 53, 103, 104] especially for a background EEG contaminated by EOG, barely distorting any frequency band, even when an EOG reference is not available or when the data length is short. It is noteworthy that the only studies that have validated EOG correction with real signals to date [17, 32, 71] conclude that RAAA is the best performing EOG correction method when reference channels are available, and that ICA with and without a reference proved effective and not statistically different from RAAA.

More variability exists for EMG and ECG contaminations. For the former, even though SOBI has been used satisfactorily in [70], other BSS algorithms, such as InfoMax [43, 147] and CCA [56], have been found to perform successfully too. The latter may be corrected by several ICA variants [16, 148, 150, 156], all of which work well, especially when a reference waveform is available. As explained before, our choice is SOBI for both kinds of contaminants.

Finally, for mixtures of artifacts, AMICA and extended InfoMax seem to be the best choices according to [7]; however the authors point out that SOBI components look just like AMICA ones. SOBI, in fact, performs just as successfully, but possibly did not behave as well according to the selected performance measures. We summarize our preferred artifact removal choices in table 1.

Furthermore, when prior knowledge is available, then some form of spatially constrained ICA [39] is preferred as compared to using ICA alone, since it improves the estimation and allows one to automate the artifact identification and removal process [55]. For offline applications and, even more so, for scenarios in which human intervention is admissible,

Table 1. Artifact removal algorithms.

Artifact	Method
EOG	RAAA, SOBI
EMG	SOBI, AMICA
ECG	SOBI, AMICA
Combination	AMICA, InfoMax, SOBI

learning phases may provide valuable information on the kinds of artifacts present in the recorded EEG, such that experimental spatial constraints can be inferred from the data.

4.8. The recommended validation scheme

We end this section by outlining a possible validation scheme for each of the main artifact types considered in this review, based principally on the approach of Pham *et al* [17] for EOG correction methods. This has not received much attention in the literature, but we believe that it can be quite helpful for comparing algorithm performances.

Considering a controlled recording environment in which an acquisition protocol can be followed and assuming that the relevant reference channels may be recorded along with the EEG, the steps for validating the EOG correction could be as follows:

(i) Perform a calibration phase with the presentation of stimuli such that participants move their eyes up and down, left or right and blink, separating one task from another in order to have independent information on each of the artifacts. This stage is necessary in the case where a regression algorithm is adopted, since it is used to compute the regression coefficients for each type of artifact independently of the main tasks.

(ii) Conduct a second phase consisting of audio-visual tasks for participants, to produce one of the artifacts that is to be removed and to generate an auditory N100 (event-related potential) time-locked to each artifact.

(iii) Evaluate the absolute difference between N100 corresponding to eye movements of different polarity (up to down or left to right). This is termed the 'peak difference' validation in [17] and is used for eye movements.

(iv) Finally, perform a least square linear regression analysis to determine how well uncorrected EOG reference channels predict the corrected EEG. This is termed 'regression' validation [17] and is intended for blinks as well as eye movements.

It is advisable to generate artifact-free ERP epochs for a reference average N100 to be calculated. EMG correction may then be validated similarly, but instructing the participants to tense or relax facial muscles upon the presentation of stimuli during the task-related phase, time-locking muscle interference to stimuli. Then, the stimuli-locked N100s may be compared to either those for ocular activity (if they have been recorded) or to the average N100 obtained from the stimuli in intervals where no artifacts exist.

ECG removal may be validated by following the procedure proposed in [149, 164], such that QRS waves (the cardiac peaks) before and after artifact removal are detected and their respective means calculated. Then, the peak-to-peak amplitudes and root mean square values are computed and compared between uncorrected and corrected sets, like with the rejection performance ratio of [157, 165]. Alternatively, [150] offers a validation scheme based on comparing the latencies of the cardiac peaks in a reference ECG channel to those of the ECG-related component (for BSS algorithms).

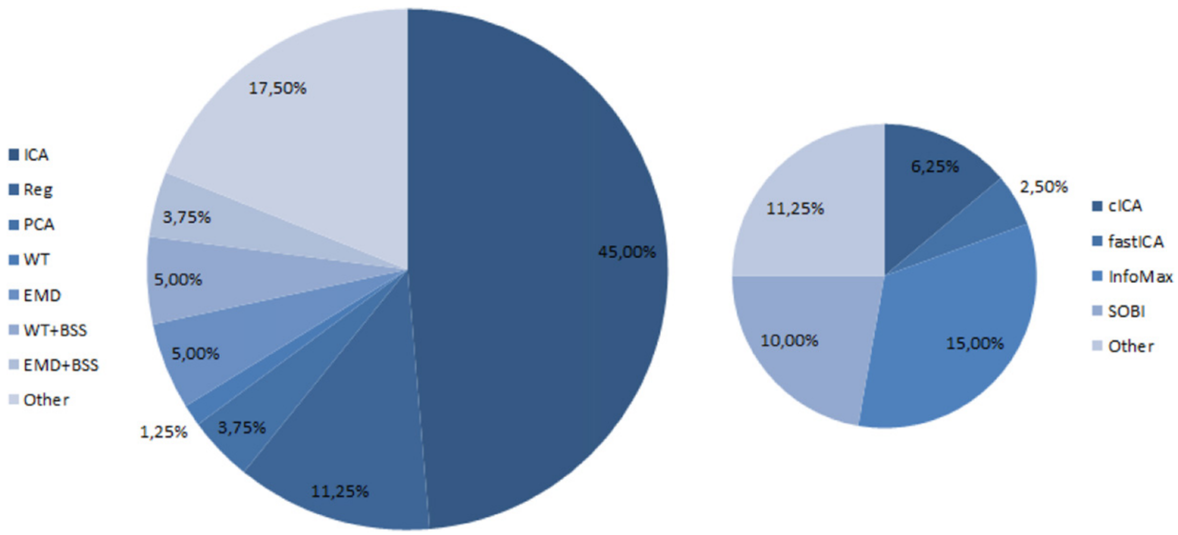

Figure A1. *Percentages of kinds of artifact removal algorithms in our bibliography.* The left chart shows the division of all the techniques that we refer to from the literature, with a single choice for papers that establish comparisons among methods. The right chart shows the division of the ICA algorithms.

5. Conclusions

Over the last 20 years there has been a considerable increase in the number of authors trying to solve the blind source separation problem given by equation (1) in the biomedical context [21], specifically for the removal of artifacts from EEG and MEG signals. However, in more recent years, the interest has been shifting to automating the artifact removal process and to obtaining performance metrics that can objectively validate corrected EEG [15, 16, 34, 55]. Since, as a matter of fact, most algorithms recommended in the literature produce artifact-free EEGs of similar quality [7, 16, 34, 71], researchers in the area are now interested in reproducible experiments and in finding reliable algorithms that do not require human intervention and can be used in the clinical context.

Regression methods were the default choice for correction for artifacts in EEGs up to the mid-1990s, notably for ocular interference for which they still have their place [17, 32]. These algorithms gave way to more elaborate methods based on statistical features of the EEG signal, i.e. blind source separation techniques like principal component analysis and independent component analysis. While PCA has been widely used, it has only been reported to give good results when the contaminant is of substantially bigger amplitude than the signal of interest. The fact that most researchers now agree with the idea that artifacts and brain signals are better modeled as independent rather than orthogonal waveforms justifies the prevalence of ICA techniques for solving the EEG–BSS problem. In addition, more modern algorithms have also been applied in correcting EEG activity, such as the wavelet transform, empirical mode decomposition, nonlinear mode decomposition and their combinations with BSS methods.

To sum up, we recommend using an ICA algorithm based on second-order statistics—to be precise, SOBI, as it has been reported to be successful for all kinds of contaminants and EEG signals. The more recently developed AMICA method is also a promising alternative, especially when various kinds of artifacts occur simultaneously. Once prior knowledge is available, in the form either of a PCA channel (for high amplitude artifacts) or of a certain ICA channel that clearly corresponds to a contaminant, then this should be used to feed a constrained variation of the ICA algorithm of choice to further improve results and to automate the artifact removal process. In order to get a clean reference channel, techniques like low pass filtering [15] or more advanced methods such as WT [55] or regression [134] may be employed. We conclude this review by highlighting that we believe that the optimal method for removing artifacts from EEGs consists in combining various algorithms in cascade to enhance the quality of the signal by using multiple processing stages that eliminate one artifact type at a time, although to the best of our knowledge, this is currently an alternative that remains unexplored (it is only mentioned succinctly in [83]).

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Appendix. The list of references

Our choice of references is based on an exhaustive study of the literature on EEG artifact removal. First of all, we searched for introductory books on EEG signal processing, to learn the background aspects on the subject. Then, we began using Google and Google Scholar to look for review papers on the subject. We included search keywords such as 'comparison', 'overview', 'survey', and 'state of the art', along with 'EEG', 'electroencephalogram' and 'artifact removal'. Interestingly, although this is a very well-researched area, and despite the fact that there exist many publications on improving the quality of EEG measurements, we could not find many reviews on the subject. To be precise, we first found the papers [13, 16]. As a consequence of reading the aforementioned papers and references therein, we expanded our own list of references by including relevant citations. In addition, we identified the leading research groups and authors in the EEG signal processing community, thus increasing the list of references even further.

Within our bibliography, which includes more than 100 journal and conference papers on artifact removal, most from the year 2000 onwards, 45% solve the artifact removal problem via ICA, and of these around 10% use SOBI. We give further details of these statistics in figure A1. Moreover, note that 47% of the papers are focused on background EEG or rhythms, that 45% deal with EOG artifacts and that only 11% automate the algorithms.

Following the advice of the referees who reviewed our manuscript, we have done a more thorough analysis of papers using Scopus (an abstract and citation database of peer-reviewed literature). We decided to limit the searches to titles and abstracts of publications, since when we broadened the search to title, abstract and keywords we obtained too many results that were not meaningful. The basic search that we have based our conclusions on is '`(eeg or electroencephalogram) and (artifact or artifacts or noise) and (removal or removing or cancellation or cancelling)`' (note that the engine is case insensitive), which produces 640 documents registered since 1960. Then, we determined which publications use ICA, PCA, regression, filtering, EMD or WT to remove EEG artifacts, by adding additional restrictions of the form '`(ica or "independent component analysis") and (eeg or electroencephalogram) and (artifact or artifacts or noise) and (removal or removing or cancellation or cancelling)`'. The figures that we obtained were: ICA represents 35.20% of the publications, regression 6.13%, PCA 6.65%, WT 17.69%, EMD 2.28% and other techniques 5.78%. Among ICA works, 3.8% of papers use SOBI, and 2.63% use fastICA and InfoMax respectively. Finally, only 4.01% of the papers explicitly indicate that the algorithm is meant to work automatically.

Thanks to the study of references from Scopus and a more profound revision of the literature, we have increased the number or relevant citations in our work. Note that, according to the analysis of papers found in Scopus, ICA and, more generally, BSS techniques are the methods most widely used for removing artifacts from EEGs. In effect, SOBI and InfoMax are the most commonly used algorithms.

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