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TOPICAL REVIEW

Removal of movement-induced EEG artifacts: current state of the art and guidelines

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Abstract

Objective: Electroencephalography (EEG) is a non-invasive technique used to record cortical neurons' electrical activity using electrodes placed on the scalp. It has become a promising avenue for research beyond state-of-the-art EEG research that is conducted under static conditions. EEG signals are always contaminated by artifacts and other physiological signals. Artifact contamination increases with the intensity of movement. *Approach:* In the last decade (since 2010), researchers have started to implement EEG measurements in dynamic setups to increase the overall ecological validity of the studies. Many different methods are used to remove non-brain activity from the EEG signal, and there are no clear guidelines on which method should be used in dynamic setups and for specific movement intensities. *Main results:* Currently, the most common methods for removing artifacts in movement studies are methods based on independent component analysis. However, the choice of method for artifact removal depends on the type and intensity of movement, which affects the characteristics of the artifacts and the EEG parameters of interest. When dealing with EEG under non-static conditions, special care must be taken already in the designing period of an experiment. Software and hardware solutions must be combined to achieve sufficient removal of unwanted signals from EEG measurements. *Significance:* We have provided recommendations for the use of each method depending on the intensity of the movement and highlighted the advantages and disadvantages of the methods. However, due to the current gap in the literature, further development and evaluation of methods for artifact removal in EEG data during locomotion is needed.

List of abbreviations

AMICA	adaptive mixture independent component analysis
ASR	artifact subspace separation
BCI	brain–computer interface
BSS	blind source separation
CCA	canonical correlation analysis
EEG	electroencephalography
EEMD	ensemble empirical mode decomposition
ICA	independent component analysis
MoBI	mobile brain/body imaging
ORICA	online recursive independent component analysis
PCA	principal component analysis
RELICA	reliable independent component analysis

1. Introduction

EEG is a non-invasive technique used to record the electrical activity of cortical neurons with electrodes placed on the scalp [1]. EEG amplifiers can be lightweight and portable while providing high temporal resolution of the recorded signal rendering EEG the most suitable brain imaging device to measure human brain activity during locomotion [2]. However, EEG signals are highly susceptible to artifact contamination due to their electrical properties [3]. Artifacts can be of mechanical or electrical origin, such as cable or electrode movements, or the presence of other electromagnetic devices. Besides that, the EEG signal is also affected by other physiological signals, such as eye movements or muscle activity. In traditional EEG research, these non-brain physiological contributions to the recorded EEG signal are considered artifactual as they distort the signal of interest due to volume and capacitive conduction. Nonetheless, eye movement and muscle activity provide additional information about cognitive processes if analyzed separately and thus should not be considered artifacts [4]. These physiological signals originate mainly from muscle activity, eye movements, and cardiac activity of the participant which increase with movement in general and with the intensity of movement specifically. Recording EEG in stationary positions and a controlled laboratory environment can result in very clean signals, however, these kinds of experiments do not lead to a good understanding of brain dynamics in real-life situations [5]. On the other hand, movement as part of realistic and natural behavior increases the occurrence of unwanted signals in the EEG signal [6]. MoBI [4, 7, 8] overcomes these restrictions by combining EEG with motion tracking and potentially other physiological signals combined with data-driven analyses techniques to dissociate brain from non-brain activity. MoBI is thus a promising approach to investigate human brain dynamics in actively locomoting humans.

Walking, along with standing and sitting, is the most important activity of daily living and has recently been extensively studied with EEG [9–14]. The better understanding of the brain dynamics and motor control of gait might aid in the control of lower limb exoskeletons [14], the understanding of the effect of cognition on gait, or the association of the neural correlates of altered gait patterns with pathologies [15]. Measuring EEG during gait is challenging due to its susceptibility to artifacts [3]. A study comparing EEG to accelerometer data during treadmill walking [16] found that EEG and accelerometer signals have similar time-frequency properties up to 150 Hz. In addition, they found that movement artifacts phase-coupled with the stepping frequency produce a signal contaminated with up to 15 harmonics. The number of harmonics depends on the walking speed and location of the electrode. These results show that gait-related artifacts are complex, difficult to detect and remove, and that simple solutions such as band-pass filters are not sufficient [17].

The characteristics of gait-related artifacts are closely related to the biomechanics and the type of gait. The gait cycle consists of two main phases: swing phase and stance phase. The stance phase begins with heel strike and ends with toe-off, the first and last contact of the foot with the ground, respectively. In normal gait, the sequence is usually as follows: right heel strike, left toe-off, left heel strike, right toe-off. Between right/left heel strike and left/right toe-off is a double support phase and the rest is a single support phase [15]. A recent study [18] combined seven features from various data dimensions to thoroughly characterize gait-related artifacts as a seven-dimensional footprint. This footprint includes features of time, time-frequency, spatial, and source domains. This gait-related artifact characterization could be used to optimize future preprocessing and artifact removal pipelines or to compare different artifact removal methods for EEG data during walking [18]. An earlier study by Kline *et al* examined the characteristics of movement artifacts recorded with EEG at different walking speeds and they found that with walking speed increased movement artifact frequency spectra amplitudes and maximal frequency at which the movement artifact occurred [17]. Additionally, they found that the head accelerometer data had poor correlation with the movement artifact on the EEG electrodes. In general, artifacts are more pronounced in the EEG signal during movement, have specific characteristics depending on the type and intensity of movement, and they interfere with the EEG signal, making it difficult to distinguish them from brain signals. Some studies raised doubts about the cortical origin of time-frequency results during walking due to insufficient artifact removal [16, 17].

The most commonly used methods for artifact removal in movement studies are mainly techniques based on ICA [19], ASR [20], and CCA [21]. There are many types of improved versions or combinations of these methods (e.g. AMICA [22] or RELICA [23] in the case of ICA), and new methods for artifact removal in the EEG domain are constantly being developed or evaluated. To date, there are no clear guidelines as to which artifact removal methods are suitable for specific movement studies. The current paper bridges this gap in the literature and reviews the methods currently used in EEG studies involving human movement.

Since the publication of the first studies using EEG signals recorded during whole body movement [2, 24], many studies have been conducted investigating walking [12, 25, 26], cycling [27–29], and some other types of whole body movement such as jumping and squatting [30, 31]. In the current study, we focus on walking and cycling, as these are the most frequently studied. Only a few studies have

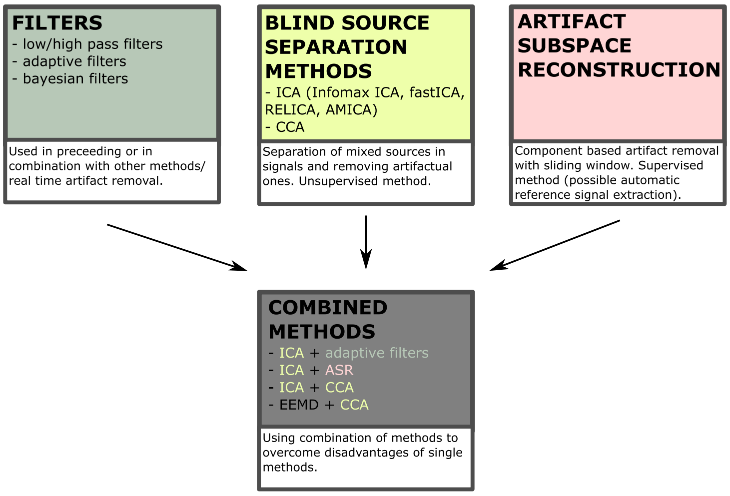

Figure 1. Diagram of artifact removal methods used in movement studies described in this section.

investigated EEG during running [2, 32, 33], and although the feasibility of measuring the signal during running was confirmed [2], sometimes researchers are unable to use the signal due to artifact contamination [33] or most electrodes and parts of the data had to be removed [32]. To avoid such cases, it is important to have appropriate hardware, follow recommendations to minimize artifacts during measurement (i.e. appropriate size of electrode cap, preparation of electrodes, testing of signal, removal of all possible sources of artifacts from the environment), and use effective methods for artifact removal after the data have been measured. The lack of EEG studies during intense movement implies the need to improve EEG systems to further avoid artifacts and to develop more efficient methods for artifact removal and to evaluate existing methods for specific types and intensities of movement.

This manuscript provides an overview of artifact removal methods used in walking and cycling studies. We discuss the most commonly used filtering techniques, BSS methods, and ASR as well as the development of new combinations of methods evaluated for EEG signals during locomotion (figure 1). We summarize these evaluated practices to improve the efficiency of each method on locomotion EEG data. The goal is to provide recommendations on suitable artifact rejection methods for use in EEG studies with locomotion of participants, possibly depending on the intensity of the movement itself.

2. Artifact removal methods used in movement studies

2.1. Filters

2.1.1. Low and high-pass filters

Low-pass and high-pass filters are commonly used preceding other artifact removal methods. This type of filter alone is sufficient only if the frequency bands of artifacts and signals do not overlap, which is not the case in studies involving movement [16]. Usually, high-pass filters with cut-off frequencies of 0.1–1 Hz are used in EEG studies, but higher cut-off frequencies might be indicated in studies involving fast movements [5, 34]. Before performing ICA, it is recommended to use a high-pass filter to improve decomposition rather than a low-pass filter. Especially for higher intensities of movement (e.g. higher speed of walking), the cut-off frequency can be higher, up to 2 Hz or even more, as the signals are more contaminated with artifacts [5]. Similarly, in adaptive filtering, a high-pass filter with a cut-off frequency of 2 Hz is found to give better results [34]. When using these filters, it is important to know which frequency range is of interest, as applying a higher high-pass filter will also remove information in delta and theta frequencies bands that originate from the brain.

2.1.2. Adaptive filters

Adaptive filters can adapt to the changing characteristics of the artifacts by adjusting filter weights or coefficients from one to the next time point according to the reference signal with an optimization algorithm. These filters use external sensors as a reference for artifacts. One of the first adaptive filters were the least mean squares algorithms which are used to find the filter coefficients that produce the least mean square of the error signal (difference between the reference and the output signal). The goal of these filters is to find the relationship between the input signal and the reference signal. Linear mapping of the reference signal (artifact signal) to the contaminated EEG signal is insufficient because of the complexity and dynamics of the signal. Therefore, non-linear filters are recommended in EEG studies involving movement. Non-linear adaptive filters such as Volterra [35], bilinear filter classes, cuckoo's optimization algorithm or alternative approaches can be used [36].

The advantage of using adaptive filters for artifact removal in EEG signals is that they can be used in real-time, which is crucial in the case of BCI studies, and the fast computation can also be beneficial for offline analysis. The disadvantage of such adaptive filter approaches is that a good reference signal is necessary to identify artifacts in the EEG signal. Therefore, an appropriate selection of the reference signal is important and significantly impacts the outcome of the adaptive filter. In [35] three-axis head acceleration values was used as a reference signal, which worked well for removing movement artifacts from EEG signals during walking. In [34] a subset of electrode-tissue impedance components such as magnitude, in-phase, and quadrature per EEG channel was used for removing movement artifacts during head shaking and nodding.

Adaptive filtering can be sufficient for artifact removal in movement EEG studies, but the selection of the reference signal, the non-linear relationship between the EEG signal and the artifact signal, and optimal algorithm for parameter adaptation process need to be considered. In [35] it was found that their algorithm can clean EEG data from 60 electrodes in real-time during walking at a different speed, but they used it only on signals filtered between 0.3 and 15 Hz. In [34] it was found that band-pass filter and adaptive filtering can substantially reduce movement artifacts produced by head movement, but they did not evaluate the extent to which movement artifacts are still present in the cleaned signal. Adaptive filters in EEG studies involving movement are also commonly used in combination with other artifact removal methods such as ICA and ASR only to remove ocular artifacts [14, 37]. Most critically, the described studies do not investigate whether adaptive filters attenuate functional neural correlates underlying cognitive processes during active behaviors.

2.1.3. Bayesian filters

Bayesian filters use the recorded signal to estimate the EEG state based on the probability. Thus, if the originally recorded data includes artifacts, they will be part of the probability distribution. Bayesian filters then use a prediction-correction technique with two models. The time update model describes how the state updates from one time point to another. The measurement model describes how the recorded data relates to the internal state of the brain. This means that the algorithm first estimates the state at one time point and then obtains the feedback as a noisy measurement, which is used to predict a new *a priori* estimate. These filters work without a reference signal and can be used online [38]. In EEG studies involving movement, the Kalman filter is the most commonly used Bayesian filter, especially for BCI, as the possibility of real-time application and no additional sensors for the reference signal are vital for this type of studies. The main assumption of the Kalman filter is that the initial uncertainty is Gaussian and that the relationship between the recorded data and the state is linear. These assumptions prevent the method to capture the complex relationship between brain and artifactual activity during dynamic movements. Therefore, an improved version of the Kalman filter with nonlinear estimation was developed, called the unscented Kalman filter. The latter filter was found to be effective for BCI applications in movement studies [12, 37].

2.2. BSS methods

BSS methods solve the problem of reconstructing statistically independent sources from a linear mixture without the reference signal or any other prior knowledge. Due to volume and capacitive conduction, many different sources are mixed before being recorded with EEG. Thus, BSS methods have gained popularity as they estimate the sources from the linear mixtures measured at the scalp providing insights into different underlying brain or non-brain generators. In general, these methods try to find the mixing matrix of different sources and estimate the source signal only by learning from the data, making different assumptions. Usually, it is assumed that the number of sources is equal to the number of signals, that the sources are statistically independent and that the columns in the mixing matrix are linearly independent [39].

2.2.1. ICA

In recent years, the most popular method for artifact removal in EEG studies, especially in EEG studies involving movement, has been ICA and other improved variants based on this method. It is also the most investigated method in the case of data preprocessing and comparing its performance on different types of data [40]. Many variations of ICA-based methods are used in movement studies, such as InfoMax ICA, fastICA, RELICA, and AMICA [24, 41–44].

The ICA method is solving the BSS problem by assuming that the signals are a linear mixture of statistically independent sources associated with different physiological activities and artifacts. ICA decomposes the observed signals into independent components and after removing the unwanted components, the clean signal is reconstructed from the remaining independent components. It separates the signal with a contrast function based on maximizing the non-Gaussian similarity and minimizing the mutual information. Infomax ICA is a variation of the method using the Infomax algorithm that works as a line iteration learning algorithm with the contrast function on the principle of information maximization [39]. FastICA is a fast iteration algorithm with an increased convergence speed. ORICA can estimate the solution of BSS problem in almost real-time and therefore is useful for BCI experiments [45]. REL-ICA or reliable ICA characterizes statistical reliability within a dataset of independent components. AMICA is an asymptotic Newton algorithm used to calculate the maximum likelihood estimate for a mixed model of independent components. It is a combination of Infomax and multiple mixture methods [22]. ICA-based algorithms usually provide similar results, but AMICA generally achieves a more accurate ICA decomposition, which has been tested on EEG data from static tasks [19, 46]. Additionally, Infomax ICA and AMICA were tested on EEG datasets during different exercises (isometric contractions, treadmill running and ergometer cycling), and AMICA always performed better or equally well as the Infomax ICA [47]. AMICA requires more computational power and time because it learns a more complex model than other ICA algorithms. The removal of independent components that reflect non-brain activity (e.g. physiological activity or mechanical artifacts) is not part of the ICA method. Traditionally, unwanted independent components are manually removed by an expert in the field. Since automatized removal is more transparent and less subjective, classifiers are used to identify and reject artifactual components. Classifiers are usually pre-trained and do not adapt to the dataset [48, 49]. Thus, if the classifier has not been trained on data similar to the data being classified, it may not produce as good results as manual classification by an expert. Some classifiers also require pre-recorded artifact sections [50].

ICA algorithms tested at different walking speeds showed that EEG data recorded at a faster walking speed are more difficult to clean, to the extent that it might not be sufficient for faster walking and running [46]. Additionally, ICA algorithms perform worse when walking overground in comparison to treadmill walking because of higher ground-reaction forces and inconsistency of stepping frequency when walking overground, resulting in a quasi-periodic signal that is more complicated to decompose using the ICA method [40].

Preparation of the data before using ICA algorithms is as important or maybe even more important than the algorithm itself. High-pass filtering of the data before using this method greatly improves the quality of artifact separation [5, 51]. In [51] high-pass filtering was suggested where the cut-off frequency is just below the frequency band of interest while simultaneously using a low-pass filter. In [5] it was shown that for movement studies, a high-pass filter with a cut-off frequency of at least 1.5 or even 2 Hz should be used before ICA is employed, depending on the intensity of the movement and the amount of noise in the signal. However, in contrast to [51], the authors found no improvement when using a much higher high-pass frequency. This might be due to the difference in the low-pass filter settings in the two studies with no low-pass filter in [5]. The quality of the ICA decomposition is also affected by the number of channels used. In [33] it was found that 35 electrodes could be sufficient to record the two most dominant electrocortical sources during walking with a concurrent cognitive task, but they also found that additional electrodes at least up to 125 improve ICA decomposition. Generally, it is recommended to use 64 channels or more, and in movement studies, it is good to increase the number of channels with increasing movement intensity [5] to provide higher degrees of freedom for ICA to explain the increasing numbers of potential artifactual sources. Another method found to improve ICA decomposition is first cleaning the data with ASR [52], which we discuss below.

2.2.2. CCA

CCA is another technique that can solve the problem of BSS. It has been shown to successfully remove muscle activity and gradient artifact from the brain signal and to improve the signal-to-noise ratio in EEG studies [21, 53, 54]. The occurrence of muscle activity and gradient artifact in brain signals is more frequent when the subject is moving, therefore CCA can be useful in movement studies [54, 55].

CCA decomposes the sources of signals in a way that the source components are maximally autocorrelated and mutually uncorrelated. It is a multivariate statistical method that maximizes the underlying correlation between two multivariate signals. The first dataset is the recorded EEG signal and the second dataset is a time-delayed versions of the same signal. CCA seeks two vectors of weights that project the input signals onto two canonical variables in a way that the canonical correlation is maximized. Since muscle signals, unlike EEG signals, do not have high autocorrelation, muscle activity is removed by setting several of the least autocorrelated source components to zero before reconstructing the signals. CCA uses second-order statistics, resulting in lower computational complexity compared to ICA, which uses higher-order statistics [56, 57]. CCA has shown to perform better or comparable to ICA in removing muscle activity [53, 54].

There are some improved variants of this method. For example, multiset CCA extends CCA to more than two datasets. Instead of maximizing the canonical correlation between two datasets, it attempts to maximize the overall correlation of several canonical variables with the intention of extracting source components that are uncorrelated in each dataset but well correlated across multiple datasets [58]. In [53] it was shown that CCA increases performance when followed by rejection of spectral slope of its components. They also found that CCA usage is limited to artifact removal since its components are still mixtures from different sources. In [54] authors proposed a CCA-based framework that was evaluated on walking data and found to be efficient for movement studies. It is recommended to use CCA in combination with other methods for higher efficiency. The combination with ICA could be beneficial since then both Gaussian and non-Gaussian temporally correlated sources could be separated [53]. Other combinations of CCA has also been shown to be effective, such as EEMD-CCA [59], singular spectrum analysis (SSA) [60], or Gaussian mixture models (GMMs) [61].

2.3. ASR

Another method used in movement studies is ASR [12, 62, 63]. The ASR method has several advantages including the automated removal of artifactual components, its usability for online applications, and the ability to remove transient or large-amplitude artifacts that the ICA method struggles with [52]. This method is relatively new, and its application to movement EEG data is currently poorly evaluated.

ASR is an automatic non-stationary component-based artifact removal method for removing artifacts from multi-channel EEG data. It uses a sliding window on the EEG data and performs PCA decomposition on each window. First, the ASR method automatically extracts reference data from the raw data based on the distribution of signal variance. Then, it determines thresholds for artifact component identification based on the standard deviation across the principal component space of all windows multiplied by the cut-off parameter k, which must be defined by the user. This means that a larger k parameter leads to no ASR correction; for example, when k is more than 100, less than 3% of the data is modified and when k is between 5 and 7, 90% of data can be modified. In the end, the ASR method rejects the artifact components in each time window if the principal component is larger than the rejection threshold. Subsequently, the final reconstruction of the cleaned signals from the remaining data was computed [20, 52]. Reimannian ASR is an improved version of the ASR method that uses Reimannian methods for covariance matrices computation, which has been shown to be beneficial for artifact removal [64].

In a case study with motor imagery EEG data [20] it was found that the ASR method with default parameters is more efficient in artifact removal compared to ICA and PCA methods. In [52] it was found that for optimal results of the ASR method, a cut-off parameter between 20 and 30 should be used instead of default values of 5–7 as previously recommended. They found that the parameter 5–7 is too aggressive, which means that brain activity is greatly removed along with artifacts. When the parameter is less than 20, more brain components than artifact components were affected by this method [52]. This could explain the impressive results of ASR in [20]. In [65] it was found that the quality of independent components calculated after ASR is best with a cut-off parameter of 10 or higher which is lower than that in [52], possibly due to different motor tasks [65]. In [52] authors demonstrated that ASR is an effective automatic method for artifact removal in EEG data from attention tasks in a driving simulator, while in [65] ASR was used with fast walking and single leg stance EEG data. Further, in [65] it was found that ASR performed better in motor tasks with more artifact contamination compared to non-motor tasks. The drawback of the ASR method is that without aggressive cut-off parameters, it might not be as effective at removing artifacts such as eye blinks that regularly occur, and it might not remove movement artifacts if they are present in the reference data. ASR can be used in online applications, however, especially for movement studies that typically use a large number of channels, one should consider that the computation time grows quadratically or faster with the number of channels and one needs to use a longer time window to compensate for this. In addition, user-defined reference data is needed to use the method in real-time [52].

2.4. Combined methods

We have mentioned only the most commonly used and evaluated methods for artifact removal in movement studies, although there are many other possible techniques. All have their advantages and disadvantages, and to avoid some of the downsides, combinations of several methods have been proposed. In most studies, artifact removal has been found to be more effective when a combination of methods is used than when only one method is used [60, 61, 66].

Many combinations with BSS techniques ICA and CCA with other methods have been evaluated for different purposes. It was found that ICA combined with spatial filtering as a preprocessing method (e.g. Laplacian filter, common average rejection filter) effectively suppresses artifacts even in very small sets with only three EEG channels [67]. ICA has also been combined with ASR to improve the quality of the signal at different walking speeds [68] and to improve ICA decomposition [52], with ASR as a preprocessing method for ICA. ICA and CCA methods are combined into a method called independent vector analysis. Their complementary exploited statistical information benefits the removal of artifacts [66].

CCA has also been combined with EEMD, which can be applied to individual channels. First, the EEMD method is used to decompose a single-channel signal into a multi-dimensional signal. Then, CCA isolates the artifact components from the underlying signal [56, 69]. In [70] authors used their version of EEMD-CCA to remove artifacts in movement studies with perturbations. A combination of methods that has been shown to be even more powerful than EEMD-CCA with multichannel data is CCA and SSA, with SSA being conducted before CCA. The recommended window length parameter for SSA method is between 50 and 100. It can take advantage of the multivariate statistics that SSA is based on, as well as the cross-channel information [60]. Another CCA combination with GMMs was evaluated using GMM after CCA decomposition to cluster extracted features into groups to recognize and remove artifacts [61].

3. Summary and guidelines

Based on the reviewed literature on artifact removal methods in EEG studies involving movement, we cannot unambiguously conclude which method is the most appropriate for removing artifacts from locomotion EEG data, however some guidelines on which method to choose in specific movement cases can already be presented. We provide some general recommendations based on studies that have investigated methods to remove artifacts from EEG data related to locomotion, which are discussed in this paper. We summarized the guidelines on how to use each method depending on the intensity of locomotion in table 1.

First, it is important to acknowledge that characteristics of artifacts depend on the type and intensity of movement. The most studied features of artifacts are those in EEG data that involve gait [17, 18]. These studies found that increased speed of walking enhances the occurrence of artifacts and increases specific frequency parameters of artifacts. This shows that artifact characteristics (e.g. timing and location) depend on certain events in gait cycle. Artifact characteristics of EEG data involving other types of movement are poorly evaluated, therefore we cannot provide recommendations depending on the type of movement (e.g. walking vs cycling).

In locomotion EEG measurements, especially in high-intensity locomotion, such as fast walking and running, artifacts and other physiological signals are more pronounced. Therefore, when recording and analyzing locomotion EEG data, special attention must be directed to artifacts starting with the setup of the experiment. First, the risk of artifacts can be reduced with good preparation of the participant, electrodes, and environment. Next to standard procedures performed in static EEG measurements [71, 72], it is recommended to set-up the artifact removal methods preceding data recording because some methods (e.g. adaptive filters, ASR) require additional signals of artifacts or baseline periods that are as clean as possible. The choice of the artifact removal method depends on the type and intensity of the movement, which affects the characteristics of artifacts and EEG parameters of interest [46].

The most common methods for artifact removal in movement studies are methods based on ICA. To date, AMICA was found to be the best in stationary tasks and at least as good as Infomax ICA or better in treadmill running and ergometer cycling [19, 47]. However, not all existing ICA-based methods were compared to each other, not allowing for a generalized conclusion. In low intensity locomotion defined as slow to normal walking it is recommended to use a high pass filter with a cut-off frequency around 1.5 Hz and no low-pass filter, while for higher intensities (fast walking or running movement) this frequency can be 2 Hz or more [5]. It is recommended to use at least 35 electrodes; however, the decomposition improves at least up to 125 electrodes, therefore for higher intensity locomotion more than 64 electrodes are recommended [5, 33]. For ASR it is recommended to use cut-off parameter *k* from 10 to 30 for low-intensity locomotion, and around 10 for high-intensity locomotion [52, 65]. CCA is a promising method to remove muscle artifacts, but it is recommended to be used in combination with other methods (e.g. ICA, SSA, EEMD) to remove artifacts more thoroughly. All the methods reviewed are commonly used in combination with each other, which helps to overcome some disadvantages of the same methods used alone. Therefore, it is recommended to use the proposed combined methods when appropriate. Parameter tuning in combined methods should be the subject of future studies, as this topic has been poorly investigated.

Another limitation in evaluating different methods for artifact removal is the lack of an objective measure to compare the efficiency of the methods, since the true value of brain activity is unknown. One way to bypass this problem is to evaluate methods on simulated data with known true brain activity, where we can use standard measures such as the signal-to-noise ratio [73, 74]. Simulations of EEG signals have been improved by using 3D head models, which allow linear mixing and spatial dependence of signals. However, some characteristics of the EEG signal are still difficult to simulate, so evaluation using real data is also important. On real data, estimation of true brain activity is used, e.g. by baseline EEG measurements with minimized artifacts (without movements, eyes closed…) [47] or by ICA and automatic classification of independent components is used to evaluate how many artifactual components are in the signals before and after artifact removal [52]. Further research is needed to improve simulation of EEG signals and to evaluate different objective measures for comparing artifact removal methods on real data.

To sufficiently remove artifacts, especially in EEG studies involving high-intensity locomotion, and to clarify the problem of choosing the artifact removal method depending on the type and intensity of movement, different combinations of artifact removing methods applied to different types of movement data should be further evaluated. Review studies similar to the current one would guide researchers through different methods and would help to transparently compare results of different artifact removing methods and to create pipelines for EEG data processing. We focused mainly on the algorithms to remove artifacts in the recorded signals, however joint hardware and software solution improvements and

Table 1. Recommendations for the application of the individual methods for artifact removal depending on the movement intensity (e.g. static: standing, low intensity: slow and normal walking, high intensity: fast walking and running).

Artifact removal methods		Cyclic movement task: Static	Cyclic movement task: Low intensity	Cyclic movement task: High intensity
Low and high pass filters	Application guidelines	In combination with other methods or when frequency range of interest is small and not much contaminated with artifacts (high-pass filter cut-off frequency: 0.1–1 Hz)	In combination with other methods (high-pass filter cut-off frequency: >1 Hz/2 Hz or higher as preprocessing for ICA or spatial filtering)	
	Necessary electrodes	Can be used on single channel		
	Real-time compatibility	YES		
Adaptive filters	Application guidelines	Needs reference artifacts signal (depends on which artifacts you want to remove)	Needs reference artifacts signal (e.g. three-axis head acceleration) Non-linear filters (e.g. Volterra, cuckoo's optimization algorithm) are recommended	Needs reference artifacts signal (e.g. three-axis head acceleration), Non-linear filters (e.g. Volterra, cuckoo's optimization algorithm) are recommended Better in combination with other methods (e.g. ICA, ASR)
	Necessary electrodes	Can be used on single channel		
	Real-time compatibility	YES		
Bayesian filters	Application guidelines	Kalman filter is recommended	Kalman filter/unscented Kalman filter is recommended	Unscented Kalman filter is recommended
	Necessary electrodes	Can be used on single channel		
	Real-time compatibility	YES		
Infomax ICA	Application guidelines	Pre-processing with high-pass filter (1.5 Hz cut-off frequency)		Pre-processing with high pass filter (>1.5–2 Hz cut-off frequency)
	Necessary electrodes	⩾35 electrodes		⩾64 electrodes
	Real-time compatibility	NO/some versions of ICA can be used real-time (e.g. ORICA)		
AMICA	Application guidelines	Pre-processing with high pass filter (1.5 Hz cut-off frequency)		Pre-processing with high pass filter (>1.5–2 Hz cut-off frequency)
	Necessary electrodes	⩾35 electrodes		⩾64 electrodes
	Real-time compatibility	NO		

(Continued.)

Table 1. (Continued.)

Artifact removal methods		Cyclic movement task		
		Static	Low intensity	High intensity
CCA	Application guidelines	Good for muscle artifact removal	Good for muscle artifact removal Better in combination with e.g. ICA, SSA, EEMD	
	Necessary electrodes	Multiple (e.g. 19)/poorly investigated		
	Real-time compatibility	NO		
ASR	Application guidelines	k parameter: 10–30	k parameter: 10–30 Better with reference signal Good in combination with ICA, AMICA	k parameter: 10 Better with reference signal Good in combination with ICA, AMICA
	Necessary electrodes	Multiple (e.g. 32)/poorly investigated		
	Real-time compatibility	YES with reference signal recorded before measurement		

implementations are the key to the advancement of artifact removal in complex high intensity movement EEG data. Currently, the state-of-the-art hardware solution is probably a double-layer electrode system, which includes electrodes recording only movement artifacts and then removing them from EEG measurements [75]. However, this solution is for now unavailable on the market and is therefore not commonly used.

In conclusion, artifact removal is a crucial process to study brain dynamics in a natural everyday environment or during high-intensity motor activities. Although the field of artifact removal methods is rapidly advancing, further evaluation of methods on locomotion EEG data is needed. Bottom-up recommendations for adjusting the parameters of various methods as a function of movement intensity are formulated. Although we have focused on software methods to remove artifacts, software and hardware solutions must be combined to achieve sufficient removal of unwanted signals from EEG measurements in locomotion or other non-stationary EEG experimental setups.

Data availability statement

No new data were created or analyzed in this study.

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Consent for publication

This study is permitted to be submitted and published in the Journal of Neural Engineering.

Availability of data and materials

Not applicable.

Conflict of interest

None.

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References

[1] Kaiser D A 2005 Basic principles of quantitative EEG *J. Adult Dev.* **12** 99–104

[2] Gwin J T, Gramann K, Makeig S and Ferris D P 2010 Removal of movement artifact from high-density EEG recorded during walking and running *J. Neurophysiol.* **103** 3526–34

[3] Tandle A, Jog N, D'cunha P and Chheta M 2016 Classification of artefacts in EEG signal recordings and EOG artefact removal using EOG subtraction *Commun. Appl. Electron.* **4** 12–19

[4] Gramann K, Ferris D P, Gwin J T and Makeig S 2014 Imaging natural cognition in action *Int. J. Psychophysiol.* **91** 22–29

[5] Klug M and Gramann K 2020 Identifying key factors for improving ICA-based decomposition of EEG data in mobile and stationary experiments *Eur. J. Neurosci.* **54** 8406–20

[6] Jungnickel E, Gehrke L, Klug M and Gramann K 2019 *MoBI-Mobile Brain/Body Imaging* (Amsterdam: Elsevier)

[7] Makeig S, Gramann K, Jung T P, Sejnowski T J and Poizner H 2009 Linking brain, mind and behavior scott *Int. J. Psychophysiol.* **73** 95–100

[8] Gramann K, Gwin J T, Ferris D P, Oie K, Jung T P, Lin C T, De L L and Makeig S 2011 Cognition in action: imaging brain/body dynamics in mobile humans *Rev. Neurosci.* **22** 593–608

[9] Gwin J T, Gramann K, Makeig S and Ferris D P 2011 Electrocortical activity is coupled to gait cycle phase during treadmill walking *NeuroImage* **54** 1289–96

[10] Nordin A D, Hairston W D and Ferris D P 2019 Human electrocortical dynamics while stepping over obstacles *Sci. Rep.* **9** 1–12

[11] Seeber M, Scherer R, Wagner J, Solis-Escalante T and Müller-Putz G R 2014 EEG beta suppression and low gamma modulation are different elements of human upright walking *Front. Hum. Neurosci.* **8** 1–9

[12] Brantley J A, Luu T P, Ozdemir R, Zhu F, Winslow A T, Huang H and Contreras-Vidal J L 2016 Noninvasive EEG correlates of overground and stair walking *Proc. Annual Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC) (October 2016)* pp 5729–32

[13] Salazar-Varas R, Costa Á, Iáñez E, Úbeda A, Hortal E and Azorín J M 2015 Analyzing EEG signals to detect unexpected obstacles during walking *J. Neuroeng. Rehabil.* **12** 1–15

[14] Li J, Dimitrakopoulos G N, Thangavel P, Chen G, Sun Y, Guo Z, Yu H, Thakor N and Bezerianos A 2019 What are spectral and spatial distributions of EEG-EMG correlations in overground walking? An exploratory study *IEEE Access* **7** 143935–46

[15] Lim M R, Huang R C, Wu A, Girardi F P and Cammisa F P 2007 Evaluation of the elderly patient with an abnormal gait *J. Am. Acad. Orthop. Surg.* **15** 107–17

[16] Castermans T, Duvinage M, Cheron G and Dutoit T 2014 About the cortical origin of the low-delta and high-gamma rhythms observed in EEG signals during treadmill walking *Neurosci. Lett.* **561** 166–70

[17] Kline J E, Huang H J, Snyder K L and Ferris D P 2015 Isolating gait-related movement artifacts in electroencephalography during human walking *J. Neural Eng.* **12** 046022

[18] Jacobsen N S J, Blum S, Witt K and Debener S 2020 A walk in the park? Characterizing gait-related artifacts in mobile EEG recordings *Eur. J. Neurosci.* **54** 8421–40

[19] Delorme A, Palmer J, Onton J, Oostenveld R and Makeig S 2012 Independent EEG sources are dipolar *PLoS One* **7** e30135

[20] Plechawska-Wojcik M, Kaczorowska M and Zapala D 2019 The artifact subspace reconstruction (ASR) for EEG signal correction. A comparative study *Information Systems Architecture and Technology: Proceedings of 39th International Conference on Information Systems Architecture and Technology – ISAT 2018* vol 853 (Switzerland: Springer International Publishing) pp 125–35

[21] de Clercq W, Vergult A, Vanrumste B, van Paesschen W and van Huffel S 2006 Canonical correlation analysis applied to remove muscle artifacts from the electroencephalogram *IEEE Trans. Biomed. Eng.* **53** 2583–7

[22] Palmer J, Kreutz-Delgado K and Makeig S 2011 AMICA: an adaptive mixture of independent component analyzers with

shared components *Tech. Report, Swart. Cent. Comput. Neurosci.* (San Diego, CA) pp 1–15

[23] Artoni F, Menicucci D, Delorme A, Makeig S and Micera S 2014 RELICA: a method for estimating the reliability of independent components *NeuroImage* **103** 391–400

[24] Gramann K, Gwin J T, Bigdely-Shamlo N, Ferris D P and Makeig S 2010 Visual evoked responses during standing and walking *Front. Hum. Neurosci.* **4** 1–12

[25] Nordin A D, Hairston W D and Ferris D P 2020 Faster gait speeds reduce alpha and beta EEG spectral power from human sensorimotor cortex *IEEE Trans. Biomed. Eng.* **67** 842–53

[26] Cevallos C, Zarka D, Hoellinger T, Leroy A, Dan B and Cheron G 2015 Oscillations in the human brain during walking execution, imagination and observation *Neuropsychologia* **79** 223–32

[27] Zink R, Hunyadi B, van Huffel S and de Vos M 2016 Mobile EEG on the bike: disentangling attentional and physical contributions to auditory attention tasks *J. Neural Eng.* **13** 046017

[28] Jain S, Gourab K, Schindler-Ivens S and Schmit B D 2013 EEG during pedaling: evidence for cortical control of locomotor tasks *Clin. Neurophysiol.* **124** 379–90

[29] Enders H, Cortese F, Maurer C, Baltich J, Protzner A B and Nigg B M 2016 Changes in cortical activity measured with EEG during a high-intensity cycling exercise *J. Neurophysiol.* **115** 379–88

[30] Butkeviciute E, Bikulciene L, Sidekerskiene T, Blazauskas T, Maskeliunas R, Damasevicius R and Wei W 2019 Removal of movement artefact for mobile EEG analysis in sports exercises *IEEE Access* **7** 7206–17

[31] Baumeister J, von Detten S, van Niekerk S M, Schubert M, Ageberg E and Louw Q A 2013 Brain activity in predictive sensorimotor control for landings: an EEG pilot study *Int. J. Sports Med.* **34** 1106–11

[32] Doppelmayr M, Sauseng P, Doppelmayr H and Mausz I 2012 Changes in EEG during ultralong running *J. Hum. Perform. Extrem. Environ.* **10** 4

[33] Lau T M, Gwin J T and Ferris D P 2012 How many electrodes are really needed for EEG-based mobile brain imaging? *J. Behav. Brain Sci.* **2012** 387–93

[34] Mihajlovic V, Patki S and Grundlehner B 2014 The impact of head movements on EEG and contact impedance: an adaptive filtering solution for motion artifact reduction *2014 36th Annual Int. Conf. IEEE Engineering in Medicine and Biology Society* pp 5064–7

[35] Kilicarslan A and Contreras Vidal J L 2019 Characterization and real-time removal of motion artifacts from EEG signals *J. Neural Eng.* **16** 056027

[36] Ahirwal M K, Kumar A and Singh G K 2013 EEG/ERP adaptive noise canceller design with controlled search space (CSS) approach in cuckoo and other optimization algorithms *IEEE/ACM Trans. Comput. Biol. Bioinform.* **10** 1491–504

[37] Luu T P, Nakagome S, He Y and Contreras-vidal J L 2017 Real-time EEG-based brain–computer interface to a virtual avatar enhances cortical involvement in human treadmill walking *Sci. Rep.* **7** 8895–906

[38] Sweeney K T, Kelly D, Ward T E and McLoone S F 2011 A review of the state of the art in artifact removal technologies as used in an assisted living domain *IET Semin. Dig.* **2011**

[39] Jain S N 2012 Blind source separation and ICA techniques: a review *Int. J. Eng. Sci. Technol.* **4** 1490–503

[40] Arad E, Bartsch R P, Kantelhardt J W and Plotnik M 2018 Performance-based approach for movement artifact removal from electroencephalographic data recorded during locomotion *PLoS One* **13** e0197153

[41] Wagner J, Solis-Escalante T, Grieshofer P, Neuper C, Müller-Putz G and Scherer R 2012 Level of participation in robotic-assisted treadmill walking modulates midline sensorimotor EEG rhythms in able-bodied subjects *NeuroImage* **63** 1203–11

[42] Tortora S, Ghidoni S, Chisari C, Micera S and Artoni F 2020 Deep learning-based BCI for gait decoding from EEG with LSTM recurrent neural network *J. Neural Eng.* **17** 4

[43] Weersink J B, Maurits N M and de Jong B M 2019 EEG time-frequency analysis provides arguments for arm swing support in human gait control *Gait Posture* **70** 71–78

[44] Sburlea A I, Montesano L, Cano-de la Cuerda R, Alguacil Diego I M, Miangolarra-Page J C and Minguez J 2015 Detecting intention to walk in stroke patients from pre-movement EEG correlates *J. Neuroeng. Rehabil.* **12** 1–12

[45] Pion-Tonachini L, Hsu S H, Makeig S, Jung T P and Cauwenberghs G 2015 Real-time EEG source-mapping toolbox (REST): online ICA and source localization *Proc. Annual Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC) (November 2015)* pp 4114–7

[46] Snyder K L, Kline J E, Huang H J and Ferris D P 2015 Independent component analysis of gait-related movement artifact recorded using EEG electrodes during treadmill walking *Front. Hum. Neurosci.* **9** 1–13

[47] Leutheuser H, Gabsteiger F, Hebenstreit F, Reis P, Lochmann M and Eskofier B 2013 Comparison of the AMICA and the InfoMax algorithm for the reduction of electromyogenic artifacts in EEG data *Proc. Annual Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC)* pp 6804–7

[48] Radüntz T, Scouten J, Hochmuth O and Meffert B 2017 Automated EEG artifact elimination by applying machine learning algorithms to ICA-based features *J. Neural Eng.* **14** 046004

[49] Pion-Tonachini L, Kreutz-Delgado K and Makeig S 2019 The ICLabel dataset of electroencephalographic (EEG) independent component (IC) features *Data Br.* **25** 104101

[50] Zhang C, Bu H B, Zeng Y, Jiang J F, Yan B and Li J X 2015 Automatic artifact removal from electroencephalogram data based on *a priori* artifact information *Int. IEEE/EMBS Conf. Neural Engineering NER (July 2015)* pp 1108–11

[51] Frølich L and Dowding I 2018 Removal of muscular artifacts in EEG signals: a comparison of linear decomposition methods *Brain Inf.* **5** 13–22

[52] Chang C Y, Hsu S H, Pion-Tonachini L and Jung T P 2020 Evaluation of artifact subspace reconstruction for automatic artifact components removal in multi-channel EEG recordings *IEEE Trans. Biomed. Eng.* **67** 1114–21

[53] Janani A S, Grummett T S, Lewis T W, Fitzgibbon S P, Whitham E M, DelosAngeles D, Bakhshayesh H, Willoughby J O and Pope K J 2018 Improved artefact removal from EEG using canonical correlation analysis and spectral slope *J. Neurosci. Methods* **298** 1–15

[54] Li J, Chen Y, Taya F, Lim J, Wong K, Sun Y and Bezerianos A 2017 A unified canonical correlation analysis-based framework for removing gradient artifact in concurrent EEG/fMRI recording and motion artifact in walking recording from EEG signal *Med. Biol. Eng. Comput.* **55** 1669–81

[55] Severens M, Nienhuis B, Desain P and Duysens J 2012 Feasibility of measuring event related desynchronization with electroencephalography during walking *Proc. Annual Int. Conf. IEEE Engineering in Medicine and Biology Society EMBS* vol **8** pp 2764–7

[56] Chen X, Xu X, Liu A, Lee S, Chen X, Zhang X, McKeown M J and Wang Z J 2019 Removal of muscle artifacts from the EEG: a review and recommendations *IEEE Sens. J.* **19** 5353–68

[57] Lin Y P, Wang Y and Jung T P 2014 Assessing the feasibility of online SSVEP decoding in human walking using a consumer EEG headset *J. Neuroeng. Rehabil.* **11** 1–8

[58] Li Y O, Adali T, Wang W and Calhoun V D 2009 Joint blind source separation by multiset canonical correlation analysis *IEEE Trans. Signal Process.* **57** 3918–29

[59] Chen X, Chen Q, Zhang Y and Wang Z J 2019 A novel EEMD-CCA approach to removing muscle artifacts for pervasive EEG *IEEE Sens. J.* **19** 8420–31
[60] Liu Q, Liu A, Zhang X, Chen X, Qian R and Chen X 2019 Removal of EMG artifacts from multichannel EEG signals using combined singular spectrum analysis and canonical correlation analysis *J. Healthc. Eng.* **2019** 4159676
[61] Lin C T, Huang C S, Yang W Y, Singh A K, Chuang C H and Wang Y K 2018 Real-time EEG signal enhancement using canonical correlation analysis and Gaussian mixture clustering *J. Healthc. Eng.* **2018** 5081258
[62] Bulea T C, Prasad S, Kilicarslan A and Contreras-Vidal J L 2014 Sitting and standing intention can be decoded from scalp EEG recorded prior to movement execution *Front. Neurosci.* **8** 1–19
[63] Tortora S, Artoni F, Tonin L, Chisari C, Menegatti E and Micera S 2020 Discrimination of walking and standing from entropy of EEG signals and common spatial patterns *IEEE Int. Conf. on Systems, Man and Cybernetics (October 2020)* pp 2008–13
[64] Blum S, Jacobsen N S J, Bleichner M G and Debener S 2019 A Riemannian modification of artifact subspace reconstruction for EEG artifact handling *Front. Hum. Neurosci.* **13** 1–10
[65] Anders P, Müller H, Skjæret-Maroni N, Vereijken B and Baumeister J 2020 The influence of motor tasks and cut-off parameter selection on artifact subspace reconstruction in EEG recordings *Med. Biol. Eng. Comput.* **58** 2673–83
[66] Chen X, Peng H, Yu F and Wang K 2017 Independent vector analysis applied to remove muscle artifacts in EEG data *IEEE Trans. Instrum. Meas.* **66** 1770–9
[67] Divjak M, Zazula D and Holobar A 2011 Assessment of artefact suppression by ICA and spatial filtering on reduced sets of EEG signals *Annual Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBS)* pp 4422–5
[68] Bulea T C, Kim J, Damiano D L, Stanley C J and Park H S 2014 User-driven control increases cortical activity during treadmill walking: an EEG study *2014 36th Annual Int. Conf. IEEE Engineering in Medicine and Biology Society EMBC* pp 2111–4
[69] Sweeney K T, McLoone S F and Ward T E 2013 The use of ensemble empirical mode decomposition with canonical correlation analysis as a novel artifact removal technique *IEEE Trans. Biomed. Eng.* **60** 97–105
[70] Peterson S M, Rios E and Ferris D P 2018 Transient visual perturbations boost short-term balance learning in virtual reality by modulating electrocortical activity *J. Neurophysiol.* **120** 1998–2010
[71] Teplan M 2002 Fundamentals of EEG measurement *Meas. Sci. Rev.* **2** 1–11
[72] Degabriele R and Lagopoulos J 2008 Techniques for effective EEG subject preparation *Acta Neuropsychiatr.* **20** 218–9
[73] Urigüen J A and Garcia-Zapirain B 2015 EEG artifact removal—state-of-the-art and guidelines *J. Neural Eng.* **12** 31001
[74] Fitzgibbon S P, Powers D M W, Pope K J and Clark C R 2007 Removal of EEG noise and artifact using blind source separation *J. Clin. Neurophysiol.* **24** 232–43
[75] Nordin A D, Hariston D W and Ferris D P 2018 Dual-electrode motion artifact cancellation for mobile electroencephalography *J. Neural Eng.* **15** 5