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Non-stationarity Removal Techniques in MEG Data: A Review

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Abstract

Brain Computer Interface (BCI) enables communication solely through mental activity. For patients who have lost complete voluntary muscle control, it serves as a potential communication and rehabilitation channel. In a number of recent investigations, BCl based on electroencephalography (EEG) has demonstrated increased reaction in nonresponsive people to interact with others. Despite the method's effectiveness, patient interaction takes way too long. However, magnetoencephalography (MEG) may shorten the training period, improving BCI reliability in the process. One of the major technological difficulties confronting MEG data collection and interpretation is that the strength of neuromagnetic fields recorded externally is considerably lower than interfering signals. There hasn't been much substantial progress on an effective MEG-BCI system because there is no large enough MEG dataset. Despite their huge potential, MEG-based BCI systems still need a lot of work in terms of signal processing algorithms that are both reliable and efficient. Unexpected head movements and changing orientation between sessions may be the cause of non-stationarity in the MEG data that was captured, changing the most effective channel selection between sessions and participants. Not only the head movement, but also non-stationarity in data can be caused by a variety of factors like user weariness, mood changes, or external noise interfering with the MEG system. This paper discusses the many types of data acquisition artifacts and review the techniques to minimize the artifacts to increase the signal-to-noise ratio.

Keywords: Brain-computer interface; Magnetoencephalography; Data acquisition; Artifacts

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1. Introduction

The brain-computer interface (BCI) is a form of communication system that relies on the utilization of brain impulses rather than peripheral muscle movement to enable interaction with other assistive devices. People with a variety of disabilities in their movement except eyes or locked-in syndrome, may rely on such interfaces as their only mode of communication. Electrophysiological signal acquisition techniques are the key criteria used to categorize BCIs. For mapping brain responses, current BCI systems may use magnetoencephalography (MEG), electroencephalography (EEG), functional magnetic resonance imaging (fMRI), or electrocorticography. Among these, MEG is an effective non-invasive method for studying brain activity especially its high temporal and moderate spatial resolutions. BCIs can recognize and interpret the cognitive processing observed with the use of MEG into actions and act as a possible means of interaction and therapy for those with severe neuromuscular impairment. MEG-based BCI, though not portable, is having reasonably high resolution makes it relevant for rehabilitation therapies [1]. With the utilization of MEG data, many areas of the medical industry, including clinical research and cognitive science, have experienced considerable success.

The absence of open-source MEG-BCI datasets is a major roadblock for developing new algorithms or testing existing BCI signal processing pipelines. Apart from the dataset provided in [1], there are any other large datasets currently available. They provide a MEG-based BCI dataset that was recorded using a traditional BCI paradigm that included motor imagery (MI) and cognitive imagery (CI) activities. The dataset contains 1134 minutes of MEG recordings from 17 healthy people during 34 recording sessions. The absence of open-source MEG-BCI datasets due to quality difficulties is one of the main reasons why current MEG-BCI systems still underperform [2]. In a non-invasive neuroimaging procedure called MEG, tiny magnetic fields that are generated by current flows in the brain are measured outside the head. Recording brain activity using MEG technology allows for improved temporal and spatial resolution because the entire scalp is used. In BCI studies, there are a variety of signal modulation sources that need to be properly controlled for and tracked which need not be considered during investigation [4]. For the MEG data to work well, these undesirable signals must be eliminated. The various methods for removing artifacts will be discussed in this study.

2. MEG- based BCI

The MEG is a non-invasive method of recording electrical brain activity. In this, the magnetic field is recorded from the electrical impulses generated by cortical neurons [3]. MEG systems consist of a large number of channels e.g. 306 for Elekta Neuromag Triux system, which must be operated at liquid helium temperature results in higher spatial resolutions. The MEG delivers full-head views, excellent spatiotemporal resolution, and signal spatial distribution that is resistant to altering masses inside the skull structure. MEG signals are measures of brain current-induced minute magnetic fields. Pick up coils, which are affixed to Superconducting QUantum Interference Device (SQUID) sensors, are used to find the minute magnetic fields. The two most popular kinds of pick-up coils are gradiometers and magnetometers [4]. Gradiometers measure the differential value that provides rejection against distant noise sources whose fields are spatially homogeneous, whereas magnetometers detect a specific component of the magnetic field directly.

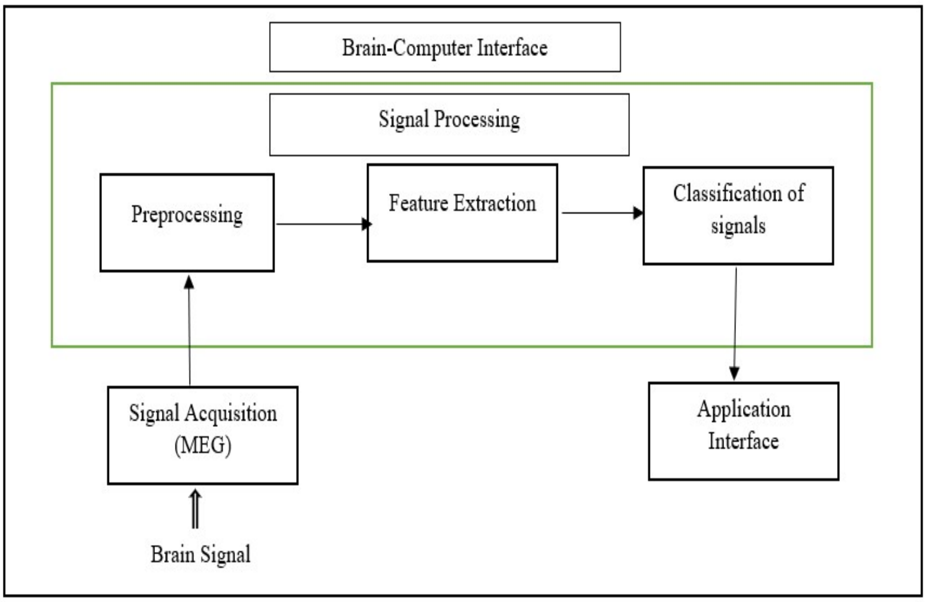

Fig. 1. Block Diagram of MEG signal pre-processing and BCI

2.1. Signal acquisition and pre-processing

The initial step in the MEG signal processing pipeline is the accurate detection of neural magnetic fields. The MEG signals are obtained using a multichannel MEG amplifier. Physiological artifacts, such as eye movements, muscular activity, heart signals, abrupt high-amplitude shifts, system noise and external noise, could affect the measurement while it was being recorded [5]. Typically, noise with biological or technical roots hides cerebral processes by themselves. The noises during signal recording should be removed and the signal-to-noise ratio is improved using a pre-processing phase. In BCI, the pre-processing techniques involve data gathering of brain signals in order to assess signal strength without missing the vital data. To obtain relevant information embedded in the signal, the captured signals are cleaned and noise is removed.

2.2. Feature extraction

The feature extraction is the process of extracting traits that have been chosen in advance from MEG signals to feed into a processing scheme (such as a classifier) in order to enhance the effectiveness of a MEG-based control system. To make the types of cognitive skills needed to operate the BCI more separable, characteristics that are likely to create distinctively recognized patterns are extracted from the pre-processed signal [2]. Regardless of the quality of a brain signal, the fundamental goal of feature extraction is to obtain features relevant to mental tasks. Some of the elements that can be extracted are statistical characteristics, harmonic elements, wavelet domain components, and power spectrum features. Separability is significant in BCI applications as it may influence classification accuracy, if a feature or group of features recovered does not give higher separability. Thus, the output of the feature extraction stage has a significant impact on the subsequent feature classification stage's performance [6].

Recent works have used feature selection approaches based on mutual information, fisher score, and L1-norm regularization to enhance the accuracy of MI task classification by employing features created after spectral and spatial filtering [7]. The relevant features were selected using an algorithm in order to achieve the objectives of a significant decrease in the problem's dimensionality and performance optimization. Sliding window design, a feature extraction technique, aids in determining the ideal window size for the most precise activity classification. Though a sliding time window boosts classification accuracy, it also makes the model more complex and increases the time it takes to solve it. The suggested optimization technique can even be improved by automatically choosing the appropriate time window, even though it has only been proven to maximize spectral-spatial features.

2.3. Feature Classification

The use of suitably detected MEG signals is common in order to identify neurological conditions or disorders as well as to learn more about the different cognitive processes. In the classification step, a pattern classifier is employed to accurately classify the specific features retrieved in the feature extraction stage. It has been determined that the outcomes of a variety of linear and nonlinear classification techniques, including support vector machines, multilayer perceptrons, type-2 fuzzy logic, and linear discriminant analysis (LDA), differ [8]. One of the most common classification algorithms used in BCIs is a variant of LDA. The semi-stationarity of the brain signals utilized in BCI design is one of the main reasons why complicated classification algorithms function inconsistently [9]. The neural network models are also used for subject classification of signals for high accuracy and interpretability. There are still improvements to be made in accuracy, generalizability, and learning time of the present classification methods.

3. Non stationarity removal in recorded signal

The quality of the signal that is recorded is significantly diminished by the presence of artifacts. In turn, this will result in the signal's non-stationarity, a major factor for low accuracy in the event signal. The existence of both physiological and non-physiological artifacts is what causes the signal's non-stationarity. In order to separate and remove artifacts, a variety of general strategies are employed. Non-stationarity can also be caused by head movements in the MEG, which shift the producing brain areas under a different sensor, or by changes in the subject's mental state over time (such as growing tired or losing focus). When transmitting data from one session to another or across time, this non-stationarity can substantially lower the BCI's performance. To minimize the non-stationarity of the recorded signal, various techniques are being used.

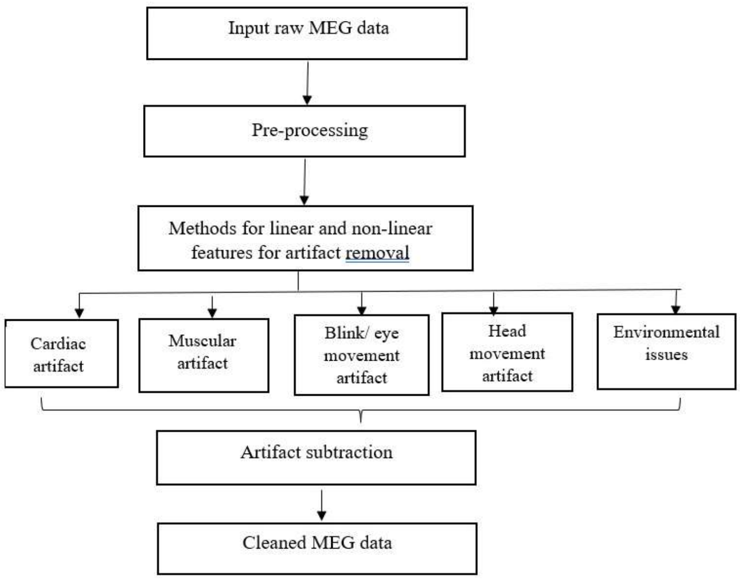

Fig. 2. Flow Diagram of processing of MEG data from artifacts

3.1. Non-physiological artifacts reduction techniques

The most widely used method of noise reduction is shielding, which encloses the system and subject in a chamber walled with layers of mu-metal and aluminium [3]. A superconducting shield soaked in liquid helium surrounds the head and sensors in [10]. However, the high cost and size of shielding prevents MEG from being widely used in scientific and medical applications. Recent developments include improvements in MEG technology (e.g., the non-cryogenic system [11]) and brain-machine interfaces (BMI), make shield less systems desirable. Slowly fluctuating fields from elevators, cars, and other sources of environmental noise, as well as power line components, can be reduced by hardware filters [12]. To reduce noise and/or increase brain activity, linear combinations of sensor signals are created, for instance, Synthetic gradiometers, the Laplacian [13], Principal Component Analysis (PCA) [14], Independent Component Analysis (ICA) [15][16], Signal Space Projection (SSP) [17], Signal Space Separation (SSS) [18], and other linear approaches [19]. Denoising MEG signals via reference channels that pick-up noise from the surroundings, the time-shift PCA (TSPCA) method [20] is effective. The time-shifted reference signals span a subspace that the sensor channels are projected on.

System-related artifacts like noisy sensors are eliminated by ignoring flat and extremely noisy channels and minimizing line noise with notch filters at the relevant frequencies. The technique for managing environmental noise relies on the manufacturer. For instance, in Elekta scanners, with the help of two techniques, namely Signal Space Separation (SSS) [21] and temporal Signal Space Separation (tSSS) [22] , the signal is split into components coming from inside and outside the head, with the latter being eliminated.

3.2. Physiological artifacts reduction techniques

Electrooculographic (EOG) artifacts are produced in the recorded MEG data as a result of the significant electrical impulses produced by eye movement or blinks. Due to their frequency and temporal domain overlap with MEG signals, these artifacts are challenging to eliminate. Despite independent component analysis (ICA)-based methods have shown promising results for removing EOG artifacts, ocular sources and brain sources are not completely segregated, which makes the whole component rejection method less than ideal [5]. For the purpose of removing artifacts while preserving the original neuronal information present in the data, more advanced ICA-based algorithms have been developed [15][23]. The methods for removing EOG artifacts based on linear regression have been widely studied which also need EOG electrode during recording.

In [24], instead of using traditional approaches that require finding the blink artifact from electrooculograms, a novel algorithm based on machine learning—specifically, the artificial neural network (ANN)—is proposed for automatically and on-the-fly identifying the blink artifacts from the original detected MEG data. The main disadvantage is that training the ANN to increase accuracy requires large amounts of calibrated data. Various sorts of artifacts are required to train the ANN in order to apply this technology to real-world issues, but they are not included in this work. The effectiveness of the artifact removal techniques can be negatively impacted by the non-stationarity of the cardiac artifacts. Both spatial patterns in multichannel data and time-domain templates for specific channels are the foundations of the most prominent ways to remove these distortions from MEG data [25].

The myographic artifacts and head motions are potential sources of signal modulation in BCI experiments that should be strictly regulated and monitored. The spatial source pattern, unlike a muscle on the head, reveals a dipolar source instead of a spatially spread source. With persistent BCI training, meticulous geographical and spectral research, and appropriate participant information, contamination has been shown to disappear over time. Head localization coils are used for continuous head location monitoring in order to limit how head motions affect the regulation of brain signals [23]. Reconstructing a participant's head position in this system was only feasible up to a rather high variance, or about one MEG sensor distance.

The study [26] examined online and offline strategies for correcting MEG information for head orientation using a statistical technology similar to that employed in most cognitive research investigations. Source localization errors are generated as a result of spatial blurring of the observations at the sensor level due to head movement during recording. Within-session head motions created confounding variation, which was minimized through regression analyses, i.e. the offline integration of the head position time-series into a general linear model (GLM). GLM is frequently employed in functional magnetic resonance imaging research to eliminate distracting head motion, and is also used during MEG recordings. The substantial increase in statistical sensitivity, on the other hand, indicates that the new studies using the GLM technique will be able to use smaller subject groups or, alternatively, smaller effect sizes.

Table 1. Types of physiological artifacts in MEG data.

Physiological artifacts	Description
Eye blink or eye movement	Large electrical potentials which overlap with MEG signals in frequency and temporal domains.
Cardiographic activity	The magnetic field produced by the heart's electrical activity, which frequently exceeds the corresponding brain signals by more than an order of magnitude.
Myographic activity	The primary components are the muscles of the face and neck, that are reflected in strong signals over a broad range of frequencies.
Head movement	Source localization errors are generated as a result of spatial blurring of the observations at the sensor level due to head movement during recording.
Hand/feet movements	Artifacts are not directly caused by actual hand or foot movements, but they could be required to create the input which operates the cursor.[42]

3.3. Overview of artifact removal methods

Due to the increased clinical use of the recorded physiological signals over the past few decades, there has been an increase in the demand for algorithms that can remove unwanted artifacts. The most widely used artifact removal methods currently in use have been examined in this paper.

A linear mapping called the Principal Component Analysis (PCA) transforms a number of potentially correlated variables into fewer, principal component-style, uncorrelated variables [20]. The method is difficult when the artefacts are unrelated to the data, which is a big downside. A blind source method in which recorded, multi-channel data are split into their independent constituent components or sources using the spatial technique known as independent component analysis (ICA) [41]. Compared to some other parametric algorithms, such as adaptive filtering, ICA has the significant benefit that no a priori knowledge is necessary for the method to work. As a result, no reference signals are needed, and the method is very effective at detecting physiological artifacts like the cardiac, eye blinks, eye movements, and muscular activity. The fundamental drawback of ICA is the requirement for a manual artifact identification step which significantly lengthen data pre-processing. Another BSS technique for decoupling a variety of mixed data is canonical correlation analysis (CCA) and by maximizing the sources' autocorrelation and uncorrelation, CCA resolves the issue [39]. Temporal correlations are not taken into account by ICA, however CCA consider uncorrelated components that also have the highest possible spatial or temporal correlation within each component. The method of morphological component analysis (MCA) involves breaking down the recorded signal into components with various morphological properties [31]. The term "atoms" refers to each component of the signal and can be used to refer to the several underlying signals. As a result, the total signal is simply the sum of these individual atoms times their coefficient vectors. The benefit of BSS algorithms is that head propagation model faults do not influence them. The drawback is that there is no assurance that any given BSS approach will be able to collect all of the individual signals that make up each component signal.

Signal Space Separation (SSS) is a spatial model for representing the multichannel MEG data. The most significant aspect of this method is that the signals generated inside the sensor array and the signals generated by the environment around the sensor array have independent basis functions. No specified reference channels are required because the breakdown is based on the signal channels. SSS cannot distinguish sources that are very close to the sensors, but by extracting temporal components they can be identified [22]. With improved localization accuracy and decreased noise, Spatiotemporal signal space separation (tSSS) is able to attenuate noise coming from sources immediately adjacent to the sensors. However, it cannot be done for a single time point alone and needs a certain time window [28]. In order to improve the accuracy of the interference basis, the SSS technique has been developed to take into account the statistical properties of the data. The Extended SSS (eSSS) approach lessens sensitivity to geometry- and calibration problems while maintaining the universality of SSS. eSSS produces high shielding factors with "actual" data and appears to work similarly well even with measured and simulated data [27]. Another common technique for multichannel MEG interference suppression is signal-space projection (SSP). The number of major components for interference suppression may also need to be chosen for the SSP approach. The main drawback of the SSP method is the assumption that interference conditions will not change between the empty recording and the actual measurements, which is how it is determined. The SSP approach is insensitive to sensor factors like calibration, location, and orientation, given that these parameters remain constant, as it is based on a statistical rather than physical description of the data [27]. As observed in [29], tSSS produced superior artifact suppression from nearby and external noise sources compared to SSS approach. The components of the decomposed data could not be statistically independent and thus SSP technique eliminated some of the signal of interest along with the artifacts, while the signal amplitude is similar before and after the artifact reduction based on ICA.

The various techniques for non-stationarity removal or interference suppression in the MEG data that are reviewed in this work are summarized in the taxonomical representation shown below.

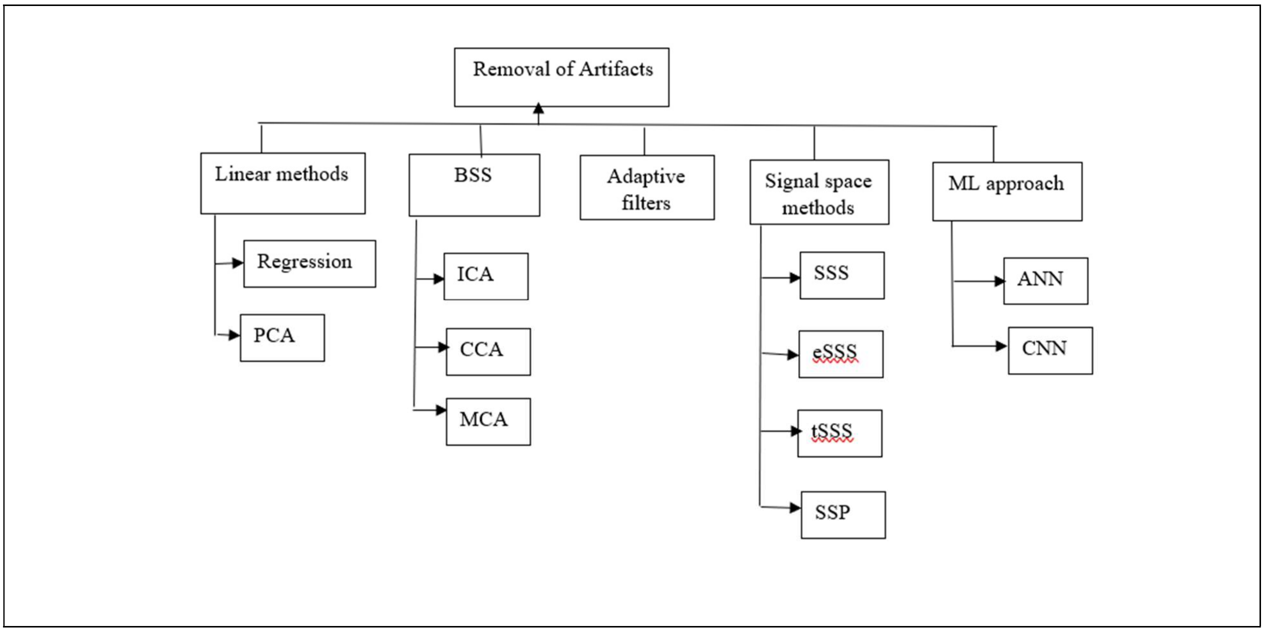

Fig. 3. Taxonomy of various methods in preprocessing of raw MEG data

Table 2. Techniques for MEG interference suppression

Methods	Description	Limitations
Signal-space projection (SSP) [27]	A recording made without a subject is used to determine the spatial model. Principal component analysis (PCA) is used to determine the directions of the main interference signal in space	The method lacks sensitivity since it relies on a statistical model of the data rather than a physical one.
Signal space separation (SSS) [21]	using spatial methods, electromagnetic multichannel data can be broken down into uncorrelated fundamental components	less accuracy due to truncation error and the MEG sensor array's calibration errors
Spatiotemporal signal space separation (tSSS) [22][28][39]	able to attenuate noise from sources right next to the sensors. enhanced localization accuracy and reduced the noise.	requires certain time window and cannot be performed for a single time point only

Extended Signal space separation (eSSS) [27]	retains SSS's generality but lessens its susceptibility to calibration- and geometry-related issues	reduced performance in case of unknown external interference
Principal Component Analysis (PCA) [20]	employs an orthogonal transformation to convert a set of potentially correlated variables into a set of completely uncorrelated variables.	Process is challenging when the artifacts are unrelated to the data
Independent Component Analysis (ICA) [30]	belongs to the category of generic linear models and distinguishes independent sources from linearly mixed data.	a non-Gaussian distribution must be met by the independent sources
Canonical Correlation Analysis (CCA) [30][31]	employs second order statistics (SOS) to produce components based on the fact that the data are uncorrelated	need to be aware of the facts beforehand
Morphological Component Analysis (MCA) [31]	method for disintegrating a signal into segments with various morphological properties.	considers a signal to be a mix of features that are sparsely represented in various dictionaries and creates a sparse representation of the signal.
Empirical Mode Decomposition (EMD) [32]	The methodology is data-dependent and adaptable; breaks down a signal into a finite number of IMFs, which are symmetric and band-limited functions.	The amplitude-frequency relationship of a mixed signal leads to mode-mixing which affects univariate EMD.

Table 3 discussed about different techniques adopted for removing various physiological artifacts to increase the signal quality for better BCI performance.

Table 3. Comprehensive review on techniques for removing artifacts to improve signal quality

Author	Year	Method	Artifact type
Uutela K, Taulu S, Hämäläinen M. [33]	2001	MNE-SSP	Head movement
Medvedovsky M, Taulu S, Bikmullina R, Paetau R.[34]	2007	tSSS MC	Head movement
Wehner, D. T., Hämäläinen, M. S., Mody, M., & Ahlfors, S. P. [35]	2008	SSS	Head movement
S. Taulu and R. Hari [36]	2009	tSSS	Ocular
Nenonen J, Nurminen J, Kičić D, Bikmullina R, Lioumis P, Jousmäki V, Taulu S, Parkkonen L, Putaala M, Kähkönen S. [37]	2012	tSSS	Head movement
Sun, L., Ahlfors, S. P., & Hinrichs, H.[25]	2016	RMAS	Cardiac
Niels Trusbak Haumann, Lauri Parkkonen, Marina Kliuchko, Peter Vuust, Elvira Brattico [29]	2016	ICA	Ocular and cardiac
Abbasi, O., Hirschmann, J., Schmitz, G., Schnitzler, A., and Butz, M. [38]	2016	ICA	All
Qingze Liu, Aiping Liu, Xu Zhang, Xiang Chen, Ruobing Qian, Xun Chen [39]	2019	SSA-CCA	Myographic
Abbasi O, Steingräber N, Gross J. [40]	2021	Coherence, time-frequency, statistical analysis	speech-related artifacts, focusing on head movements

4. Conclusion

Recently, MEG-based BCIs have shown a lot of potential. In this research, we looked at the various causes of non-stationarity in data, physiological and non-physiological factors like head movement, user tiredness, mood changes, or external noise interfering with the MEG system, as well as some of the techniques to mitigate it. To sum up, artifact reduction is a crucial step when researching brain dynamics in a real-world situation or when executing difficult motor tasks. While there are various methods for minimizing the impact of artifacts originating from various sources, a reliable and effective signal processing algorithm is still required to produce high-quality data for MEG-based BCI systems. Furthermore, BCI ideas and appropriate features, as well as the most often used classification techniques, are discussed. It should be mentioned that the research provided in this publication is still ongoing. New features and classifiers will be added in the future.

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