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Signal Artifacts and Techniques for Artifacts and Noise Removal

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Chapter 2
Signal Artifacts and Techniques for Artifacts and Noise Removal

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Abstract Biosignals have quite low signal-to-noise ratio and are often corrupted by different types of artifacts and noises originated from both external and internal sources. The presence of such artifacts and noises poses a great challenge in proper analysis of the recorded signals and thus useful information extraction or classification in the subsequent stages becomes erroneous. This eventually results either in a wrong diagnosis of the diseases or misleading the feedback associated with such biosignal-based systems. Brain-Computer Interfaces (BCIs) and neural prostheses are among the popular ones. There have been many signal processing-based algorithms proposed in the literature for reliable identification and removal of such artifacts from the biosignal recordings. The purpose of this chapter is to introduce different sources of artifacts and noises present in biosignal recordings, such as EEG, ECG, and EMG, describe how the artifact characteristics are different from signal-of-interest, and systematically analyze the state-of-the-art signal processing techniques for reliable identification of these offending artifacts and finally removing them from the raw recordings without distorting the signal-of-interest. The analysis of the biosignal recordings in time, frequency and tensor domains is of major interest. In addition, the impact of artifact and noise removal is examined for BCI and clinical diagnostic applications. Since most biosignals are recorded in low sampling rate, the noise removal algorithms can be often applied in real time. In the case of tensor domain systems, more care has to be taken to comply with real time applications. Therefore, in the final part of this chapter, both quantitative and qualitative measures

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are demonstrated in tables and the algorithms are assessed in terms of their computational complexity and cost. It is also shown that availability of some a priori clinical or statistical information can boost the algorithm performance in many cases.

Keywords Artifact · Biosignal · ECG · EEG · Neural signal · Noise, etc.

2.1 Introduction

2.1.1 Background and Motivation

Human body is composed of several complex systems including nervous, cardiovascular and musculoskeletal systems. Each system has a particular structure and carries its own physiological, functional and pathological processes. These complex biological systems are dependent on each other and the processes involved are often considered as non-linear, nonstationary, and stochastic process. The resultant biosignals generated from these complex biological processes can be recorded in both invasive and non-invasive ways. The signals recorded by non-invasive electrodes often have extremely low amplitudes (ranging from μV to mV) due to the attenuation by various body tissues. In addition, due to the non-invasive nature, the recordings are more prone to many external noise sources such as artifacts and interferences resulting in low signal-to-noise ratios (SNRs). Thus, the acquired biosignals and their associated important clinical/biological events are often submerged under noise and required to be processed properly by removing such artifacts and interferences before any further analysis and decision can be made. However, often traditional signal processing techniques, e.g., digital filtering, are not suitable enough to effectively remove such artifacts. Therefore, advanced signal processing techniques have been proposed in the literature for this purpose. Figure 2.1 illustrates the general steps involved in a typical biosignal processing system from signal acquisition until classification.

2.1.2 Objectives

The objectives of this chapter are as follows:

Fig. 2.1 Typical process flow of a biosignal processing system. Only artifact detection and removal is covered in this chapter

- Identify biosignal characteristics and their applications,
- Identify artifact sources and their characteristics,
- Compare and identify suitable signal analysis and processing techniques for artifact detection and removal,
- Demonstrate the influence of reliable artifact detection and removal on the later-stage detection or classification of clinically significant biological events.

2.2 Biosignals and Artifact/Noise Modeling and Characterization

2.2.1 Different Types of Biosignals

Four major types of biosignals including their properties is shown in Fig. 2.2.

2.2.1.1 Biosignals Generated by Cardiac Activity

Electrocardiography

Electrocardiography (ECG aka EKG), shows the electrical activity of heart over a period of time. ECG is recorded via the electrodes that are placed on the chest. Small changes in electrical potentials are picked up by these electrodes due to the cardiac muscle's electrophysiological pattern of depolarizing and repolarizing during each heartbeat. It generally is composed of QRS complexes, P waves and T waves. Figure 2.3 shows an ECG signal of a heart in normal sinus or regular rhythm, at a heart rate of 60–100 beats per minutes.

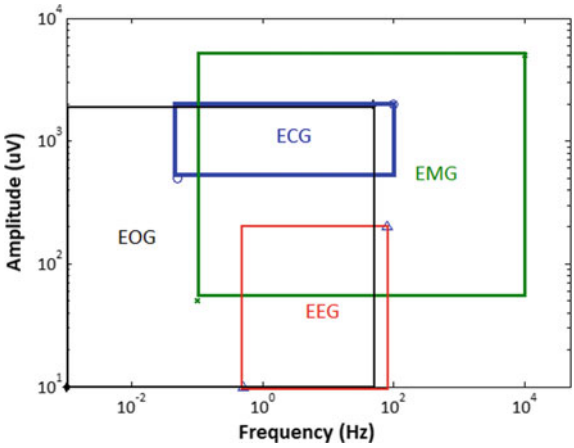

Fig. 2.2 Typical characteristics of some commonly used biosignals in terms of amplitude and frequency range

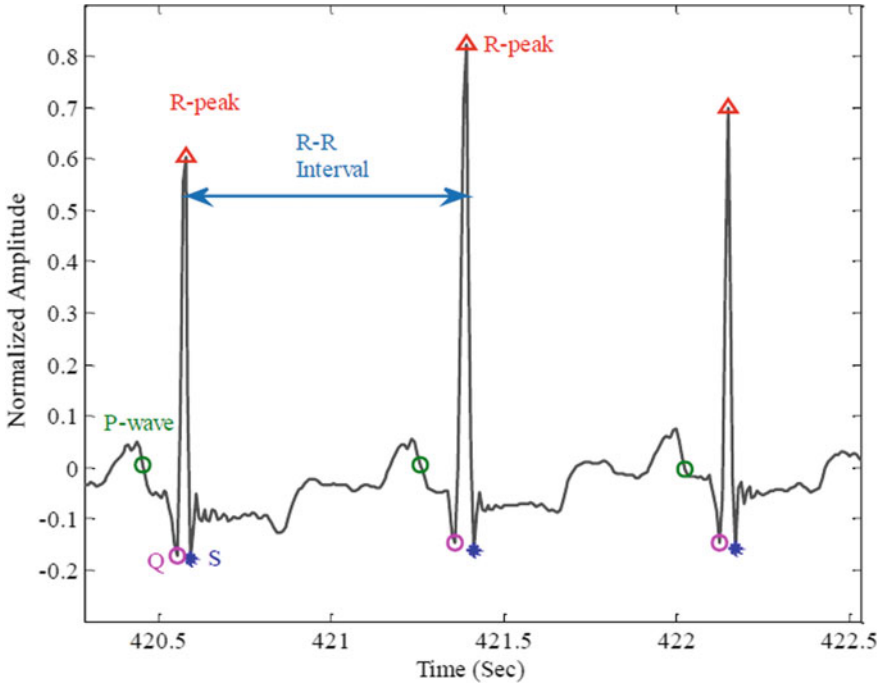

Fig. 2.3 A sample ECG recording with its characteristics points (P-wave, QRS complex) during a cardiac cycle of a normal sinus rhythm

Seismocardiography

Seismocardiography (SCG) is the non-intrusive estimation of cardiovascular vibrations transmitted to the chest divider by the heart and usually recorded by an accelerometer. SCG can provide information of all the activities during cardiac cycle which may not be found only from ECG recordings. Simultaneous recordings of both ECG and SCG may reveal a lot more diagnostic information related to heart diseases. An example SCG recording is given in Fig. 2.4.

2.2.1.2 Biosignals Generated by Muscle Activity

EMG

Electromyography (EMG) is the process of recording electrical potential generated from muscle cells during contraction. Electromyogram is the combined action potentials of the muscle cells of muscle tissue. The amplitude of an EMG signal lies between 0.01 and 1 mV, and its frequency range is 20–1000 Hz. If this signal is

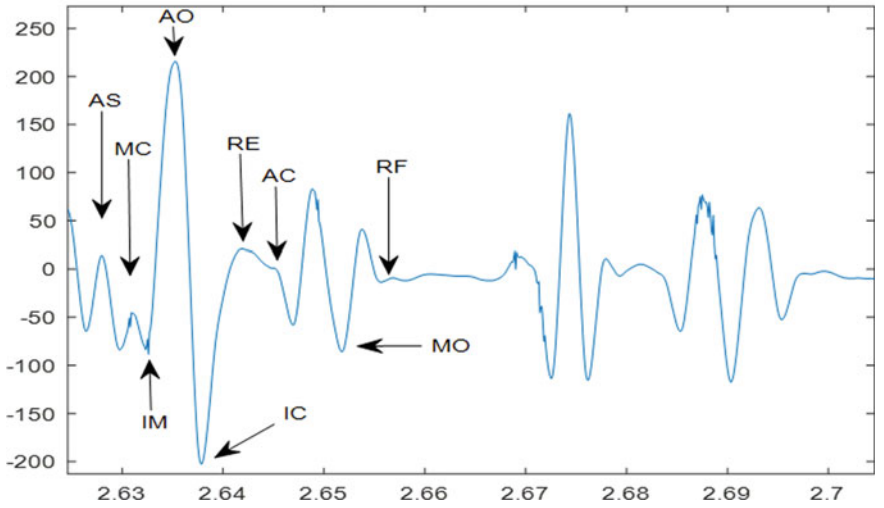

Fig. 2.4 An example of SCG recording during one complete cardiac cycle with annotation proposed by Salerno [1]. Where AS, MC, IM, AO, IC, RE, AC, MO, RF refer to atrial systole, mitral value closure, isovolumic movement, aortic valve opening, isovolumic contraction, rapid systolic ejection, aortic valve closure, mitral valve opening and rapid diastolic filling respectively. X-axis and Y-axis referring to the signal amplitude (in mV) and time (in second) respectively

detected from the surface of the skin, it will be the superposition of messages from all the muscles underneath. A sample raw EMG recording is given in Fig. 2.5.

2.2.1.3 Biosignals Generated by Ocular Activity

Electrooculography

Electrooculogram (EOG) signal is generated due to the potential difference between retina and cornea of the eye which is modeled as an electrical dipole that moves with eyeball movement. The dynamic range of EOG signal is typically 0.05–3.5 mV (peak to peak). The bandwidth of EOG is between 0 and 1000 Hz; however, maximum usable energy of EOG signal lies between 0.1 and 40 Hz [2]. A sample raw EOG recording consisting of both horizontal and vertical eye movements is illustrated in Fig. 2.6.

Eye Blinks

Eye blinks are common ocular artifacts that are found in EEG signals which is due to the blinking of eyes (both voluntary and involuntary). During eye blinks, movement

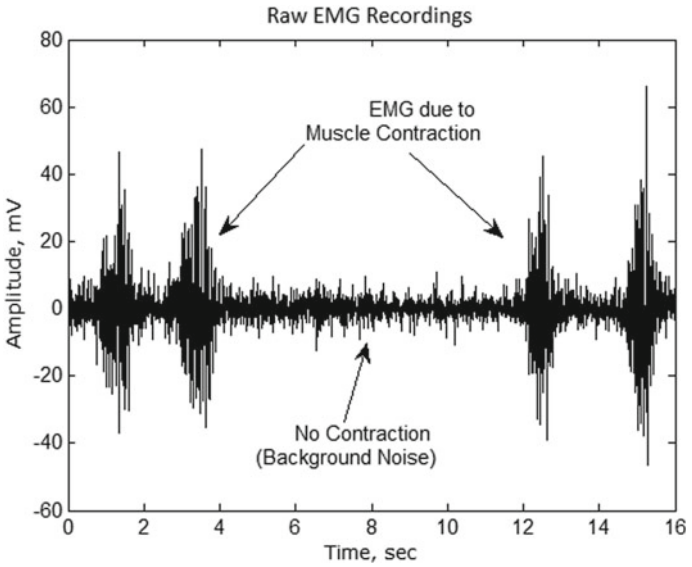

Fig. 2.5 Sample raw EMG signal recorded from arm (after analog amplification) using Ag-AgCl disposable electrodes

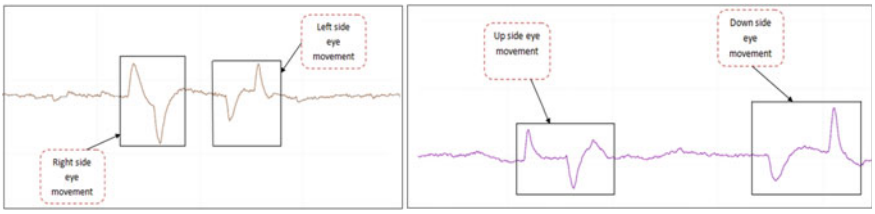

Fig. 2.6 Sample EOG signal recording with disposable electrodes during horizontal (left plot) and vertical (right plot) movement of the eyeball [2]. X-axis and Y-axis referring to the normalized signal amplitude and time (in second) respectively

of eyelid muscles generates such potentials which are counted as artifacts to the neural signal recordings, such as EEG.

2.2.1.4 Biosignals Generated by the Brain

Different biosignals generated due to neural activities in the brain are mainly classified based on their location of recording (i.e. placement of recording electrodes) which is shown in Fig. 2.7 while their characteristics in terms of amplitude and frequency is shown in the Table 2.1.

Table 2.1 Different types of neural signals and their characteristics

Signal type	Frequency range (Hz)	Amplitude range (mV_{pp})
EEG	0.05–128	0.02–0.4
ECoG	0.1–64	0.02–0.1
LFP	0.1–100	0.1–1
EAP	100–10 k	0.04–0.2
IAP	100–10 k	~100

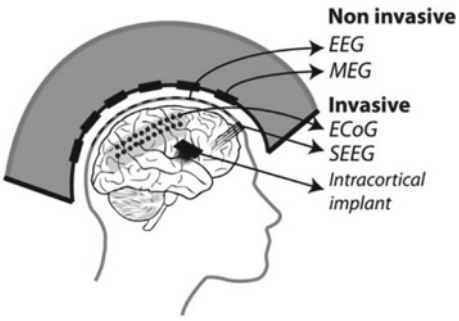

Fig. 2.7 Different types of brain recordings based on the placement of electrodes/sensors. *Courtesy* http://www.frontiersin.org/files/Articles/103134/fnsys-08-00144-HTML/image_t/fnsys-08-00144-g003.gif

Non-invasive Brain Recordings

The most popular non-invasive brain recording technique is Electroencephalography (EEG) that measures the integrated electrical activities produced by billions of neurons in the brain by placing electrodes on the scalp. It is the most commonly used brain recording technique for diagnosis of different neurological disorders along with other applications such as brain-computer interface and basic neuroscience research. The EEG recordings are described in terms of rhythms and transients while the rhythmic activity of EEG is composed of non-overlapping bands of frequency. The most common EEG rhythms are Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz) and Beta (12–30 Hz) waves. Recently a relatively high frequency Gamma wave (>30 Hz) is also considered. On the other hand, artifacts are transient events, although epilepsy seizure events can also be transient but they are more oscillatory than artifacts [3].

To provide a model for recorded raw EEG data, let's denote the clean EEG background activity/rhythm as E_c with weight w_c; Artifact event as A_{T_n} with weight w_{T_n} and time delay τ_{T_n}; where $n = 0, 1, \ldots, N$ denotes the type of artifact. E.g. if it is a Type-1 artifact [4], then denoted by A_{T_1} with weight w_{T_1} and time delay τ_{T_1}. Now the recorded raw EEG signal is usually modeled as the linear combination of these two signal components.

$$E_R(t) = w_c E_c(t) + \sum_{n=1}^{N} w_{T_n} A_{T_n}\left(t - \tau_{T_n}\right) \tag{2.1}$$

Semi-invasive Brain Recordings

Electro-cortiography (ECoG) or intracranial EEG (iEEG) refers to measuring brain signals from the surface of the brain after opening the skull. The temporal resolution of ECoG is better than scalp-EEG but as it requires brain surgery to open up the skull, often it is discouraged in human subject.

Fully Invasive Brain Recordings

Local Field Potentials

Extracellular local field potentials (LFP) are produced by the collective and simultaneous activity of many nearby neurons by synaptic transmission.

Neural Action Potentials (Neural Spikes)

An action potential or neural spike is a short-lasting event (usually 2–3 ms) in which the electrical membrane potential of a neuron rapidly rises (i.e. depolarization) and falls (repolarization), following a consistent trajectory. Such activity gives rise to a specific waveform shape known as action potential. The extracellular action potentials are typically about 100 μV–1 mV), smaller than an intracellular action potential. Microelectrodes (with a tip size of approx. 1 μm) are usually implanted into the brain of a living animal to detect such electrical activity generated by the nearby neurons which is known as 'single-unit' recording. Such recordings of single neurons in living animals can be used to understand the process of information the brain.

2.2.2 Different Sources of Artifacts and Noises

Artifacts can originate from both external and internal sources. Internal sources of artifacts are due to different body activities (both voluntary and involuntary activities). On the other hand, external artifacts arise from coupling due to unwanted external interferences. In addition to that, artifacts in broad sense can be categorized into two classes: 'local' and 'global'. Local artifacts are confined in space, i.e. appear only in a single recording channel while global artifacts are found across multiple channels at the same temporal window. An example of global artifacts found in all recording channels of two different neural recordings is shown in Fig. 2.8.

On the other hand, sometimes an artifact is found once in the whole recording sequence (high entropy) while sometimes can have regular/periodic pattern due to any periodic activities/motions of the subject. An example of such artifacts is shown in Fig. 2.9. Table 2.2 summarizes the artifact classification from different perspectives.

Other noise sources are described below:

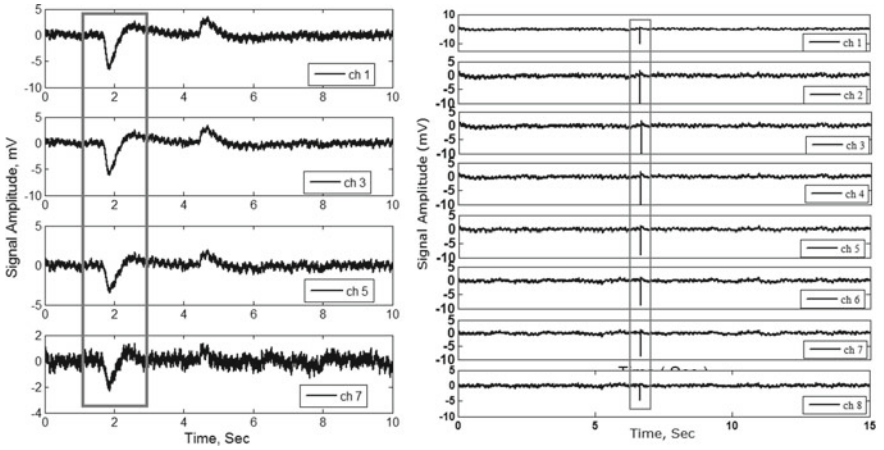

Fig. 2.8 Example of global artifacts from two different datasets of invasive neural signals

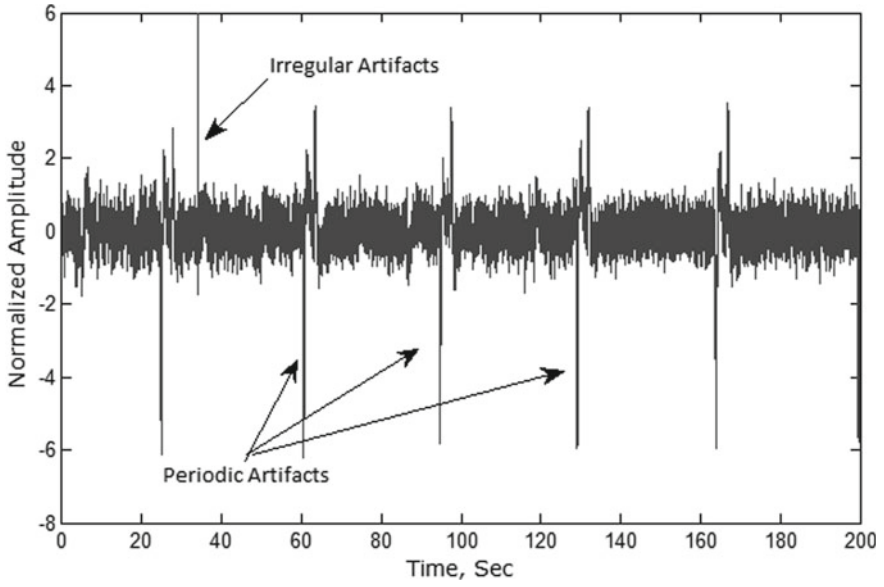

Fig. 2.9 An example of irregular artifact due to electrode pop (left) and periodic artifact due to periodic motion activity of the subject (right) found in invasive neural recordings

Table 2.2 Summary of artifact classification from different perspectives

Perspective	Artifact category	
Repeatability	Irregular/No	Periodic/Regular/Yes
Origin	Internal	External
Appearance	Local	Global

- White Noise: This noise results from thermal electronics noise mainly due to the resistance and follows a flat frequency spectrum. No digital filtering can remove the white noise completely as it has constant noise power over all frequency bands.
- Baseline Wandering: It usually results from respiration and has sub-Hz frequency components.
- $1/f$ Noise: This is a colored noise whose PSD follows reciprocal relation with frequency and thus known as $1/f^{\alpha}$ noise where α varies from 1 to 3.
- Power-line noises (50/60 Hz and its harmonics): Interference resulting from power sources which usually have a very high peak at power line frequency (50/60 Hz) and its harmonics. Proper grounding of electrodes is often required to minimize the effect of such interference.
- Electrode Offset: Skin-electrode interface often is modeled as a DC voltage source known as electrode offset.

2.2.2.1 Different Artifacts in Neural Signals (EEG, ECOG)

Physiological/Internal Artifacts

- Ocular Artifacts: The eyeball acts as an electrical dipole and therefore any movement in eyeball generates large-amplitude artifacts in EEG recordings. Ocular artifacts include eye blink, both horizontal and vertical eye movement, eye flatter, eye movement during REM sleep, eye saccade, etc.
- Muscle Artifacts: One of the most prominent physiological artifacts comes from muscle activity of the subject (EMG). Usually muscle artifacts are of high frequency range (e.g. from 20 to 40 Hz) and are generated from activities like chewing, swallowing, clenching, sniffing, talking, scalp contraction, eyebrows raising, etc.
- Cardiac Artifacts: Cardiac artifacts are due to the electrical activities produced by heart and are of two types: ECG and pulse artifacts. ECG artifacts are rhythmic regular activities while the pulsation sometimes can cause slow waves which might mimic the EEG activity.
- Respiration Artifacts: Respiration artifacts originate from the movement of an electrode with inhalation or exhalation and can take the form of slow, rhythmic EEG activity.
- Sweat Artifacts: Electrodermal or sweat artifacts originate from changes in electrolyte concentration of electrode due to sweat secretion on the scalp and take the shape of a long, slow baseline drift in the spectral band of 0.25–0.5 Hz [5].

Extra-Physiological/External Artifacts

- Motion Artifact: Movement of patient especially in an ambulatory EEG monitoring system [6–8], generates a lot of motion artifacts. This artifact often has

Table 2.3 Different types of artifacts and their sources found in EEG signals

Physiological or internal				Extra-physiological or external		
Ocular	Cardiac	Muscle	Others	Instrumental	Interference	Movement
Eye blink artifacts, eye movement artifacts (both vertical and horizontal EOG), eye flatter, etc.	ECG artifacts; pulse artifacts	Swallowing, chewing, sniffing, clenching, talking, scalp contraction, etc.	Glossokinetic, respiration, skin, etc.	Electrode pop-up or displacement, cable motion, No/poor grounding, etc.	Electrical, sound, optical, magnetic, etc.	Tremor, movements of head, body, and limbs

extremely high amplitude such that it can saturate the recordings. Head movement, body movement, limbs movement, tremor, walking, running, browsing PC, and many other movements in daily activities are responsible for this type of artifact.

- Environmental Artifact
  - Loose electrode: Loose contact between electrode and scalp leads to change of impedance on the tissue-electrode interface and results in prolonged EEG spike-like artifact.
  - Electrode Pop and Movement: Another common source of artifact is due to electrode pop which produces sudden change in impedance in the electrode-tissue interface and results in high amplitude sharp waveform-shaped artifacts. Electrode movement occurs when it moves with respect to the scalp and produces high-amplitude deflection in EEG generally in the low frequency range of 1–10 Hz.
  - EM Interferences: This type of artifacts is due to the interferences coming from the surrounding electrical/electronic devices/machines that produce EM waves. Also any sound or optical interference may also be picked up by the EEG electrodes as artifacts. In addition, one of most common source of artifacts in any biomedical signal acquisition is the 50/60 Hz main voltage and its harmonics. A summary of different artifact types and their sources is provided in Table 2.3.

2.2.2.2 Properties of Artifacts in Neural Recordings

Usually the artifacts have very large magnitude and/or sharper transitions/edges compared to the biosignals of interest. The frequency range for artifacts may vary from very low (e.g. motion artifact) to high frequency (e.g. artifacts due to residue charge on electrodes) range suggesting artifact spectra overlap with biosignal of interest.

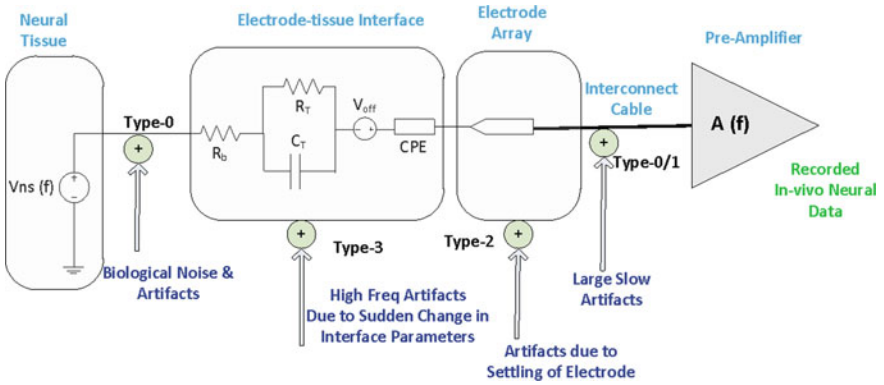

Fig. 2.10 Illustration of origins of different artifact during invasive neural recordings

In order to characterize the spectrum statistics of artifacts as described in [9], different artifact segments have been manually identified and then three artifact templates (Type-1, 2, and 3) were extracted as shown in Fig. 2.11 (a, b, c). Later, artifact spectrum is estimated using windowed Fourier Transform. The results are summarized in Fig. 2.11 (d, e), where it is clearly seen that artifacts tend to display varied spectrum shape and span over broad frequency band of $0 - 6$ kHz. Type-1 and type-2 artifacts are dominating at low frequency range while type-3 has higher

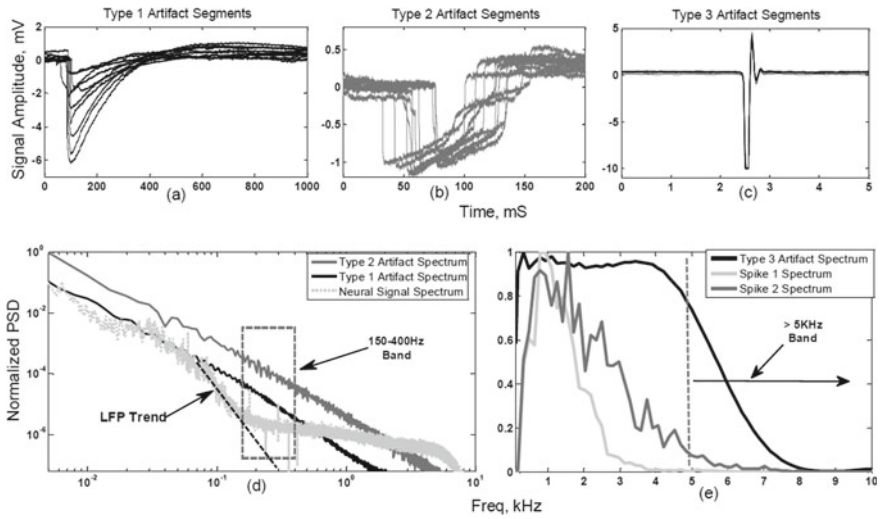

Fig. 2.11 An example of varied artifact characteristics compared with neural signal of interest. **a**, **b**, and **c**: Three different types of artifact templates: type-1, type-2, and type-3, collected from invasive neural recordings. **d**, averaged PSD of type-1 and type-2 artifacts in comparison with LFP. **e**, type-3 artifact spectrum and neural spike (action potentials) spectrum. Spikes are randomly selected from two different templates

frequency bandwidth. Figure 2.10 shows different artifacts' origin during invasive neural recordings.

To estimate power spectrum density of LFP only, data recorded from rat's superficial layer cortex have been analyzed and spectrum are averaged over 8-channels. Figure 2.11d shows that PSD drops to the level of noise floor at frequency over 150 Hz.

To estimate neural spike spectrum, larger grouped spikes are smoothed and averaged to extract different spike templates. As an example, only two spike templates are used to estimate PSD as plotted in Fig. 2.11e, and found that PSD of spikes drops to noise floor at frequency beyond 5 KHz.

2.3 Signal Analysis and Processing Techniques for Handling Artifacts and Noises

Artifact detection and reduction/removal is one of the most faced challenges for EEG and other bio-signal processing applications and is an open research problem. Most of the biosignal recordings are prone to artifacts and interferences. The variety of artifacts and their overlapping with signal of interest in both spectral and temporal domain, even sometimes in spatial domain, makes it difficult for simple signal preprocessing technique such as typical digital filtering or amplitude thresholding to identify them from desired biosignals. Therefore the use of traditional filters often results in poor performance both in terms of signal distortion and artifact removal. Many attempts have been made to develop suitable methods for artifact detection and removal with the help of recent advancement in signal processing techniques/algorithms in the past decade and a half. However, there is no universal complete solution yet and hence still an active area of research. After careful reviewing almost all the major artifact detection and removal techniques found in the literature, in this section we present a comparative analysis among these SPTs considering their brief theoretical background, pros and cons based on their suitability and performance and finally challenges in implementing them in different biosignal applications.

2.3.1 Pre-processing

2.3.1.1 Epoch-by-Epoch Analysis/Segmentation

The recorded sequence of biosignals is often divided to small duration segments known as epoch. The duration of epoch is such that it contains at least one cycle of biological event of interest or such that the signal within the epoch duration can be considered as stationary since most of the biosignals exhibit non-stationary

characteristics. The size of epoch also plays role in determining the computational complexity of the signal processing algorithm in later stage which can be critical in real-time application. The epoch duration is a trade-off between accuracy and real-time computational ability of the SPTs. For EEG, the epoch duration is often decided as one second since within this one second, it can be considered non-stationary whereas EEG is typically a non-stationary signal.

2.3.1.2 Re-Referencing

For multi-channel EEG recordings, re-referencing is often used. Any potential recorded at a particular electrode is with respect to a reference electrode (e.g. in EEG recordings, the mastoid is often chosen as a reference electrode since it is closest to the other electrodes as well as least chance to be influenced by neural potentials). However, still the typical reference electrode may contain some neural information as it also closer to the brain. Therefore, for high density EEG recordings, average activities of all the electrodes may be chosen as reference. This re-referencing can be done offline after the recordings are imported on a software toolbox such as EEGLAB [10].

2.3.1.3 DC Offset Removal

Usually DC signal remains in the biosignal recordings due to electrode-skin interface offset voltage which can be reduced by subtracting the average/mean value of the biosignal from the biosignal itself. If $X(t)$ is a raw biosignal recording and if the mean of $X(t)$ is μ, then the signal after removing DC offset would be $X'(t)$ such that

$$X'(t) = X(t) - \mu \tag{2.2}$$

2.3.1.4 Digital Filtering

Digital filtering, which is nothing but a discrete-time LTI system, is a common part of preprocessing the recorded biosignals to attenuate out-of-band noises and artifacts. Both FIR and IIR filters have been found to be used in such preprocessing stage depending on the application and given specification. The trade-off between FIR and IIR filter is filter-order and stability, respectively. The transfer function of a digital filter can be written as

$$H(z) = \frac{\sum_{l=0}^{M} b_{ml} z^{-l}}{1 + \sum_{k=1}^{N} a_k z^{-k}} \tag{2.3}$$

where $H(z)$ is the z-transform of the impulse response of the LTI system, $h(n)$ knows as system/transfer function while a_k and b_m are the co-efficients of outputs, y(n − k) and inputs, $x(n-l)$ of a Discrete-time LTI system respectively. The difference equation based on which the present output, $y(n)$ is related with the present input, $x(n)$, past inputs, $x(n-l)$ and past outputs, $y(n-k)$ is as follows:

$$y(n) = b_m x(n-l) + a_k y(n-k) \tag{2.4}$$

Low-Pass Filtering

Depending on different biosignals, if desired bandwidth of the recorded signals is known, then a typical FIR low-pass filter is used to cancel out high frequency out-of-band noises and artifacts from the raw recordings. This can be done either in analog domain or in digital domain.

High-Pass Filtering

Sometimes a very steep-slop (IIR or higher order if FIR) high-pass filter with cut-off frequency as low as 0.05–0.1 Hz is used to cancel out electrode (DC) offset including slow-wave artifacts (e.g. motion artifacts).

Notch Filtering

In most of the literatures, a 50 or 60-Hz 3rd or 4th order IIR notch filter is used to remove the 50/60 Hz power line interference (PLI) and its harmonics. Since most of the biosignals have maximum frequency up to 100 Hz (except EMG or invasive neural signals), therefore, often it is good enough to remove the fundamental frequency of the power line interference and removal of higher harmonics (2nd or 3rd harmonic) are not required. However, the problem with notch filtering is that it not only removes the PLI at the fundamental frequency but also removes signal component at that notch frequency. In addition to that, the notch frequency has to be determined in advance to design the notch filter, but in reality, there might be some fluctuations in the notch frequency (e.g. it can be 49.8 or 50.1 Hz instead of exactly 50 Hz). In such cases, the PLI doesn't get removed properly and instead the desired signal component (e.g. Gamma rhythm in EEG recordings) may be removed. In some literatures, researchers proposed the use of adaptive filtering (given that the reference channel can record the power line noise) to remove the PLI without attenuating the signal of interest in that particular (i.e. 50 or 60 Hz) frequency. In [11], a regression approach was proposed to predict the PLI and its harmonics through a mathematical model which doesn't require an extra reference channel and which also doesn't bring any distortion to the signal of interest. An example of application of notch filtering on ECG recordings is illustrated in Fig. 2.12 to remove 50-Hz PLI and its harmonics.

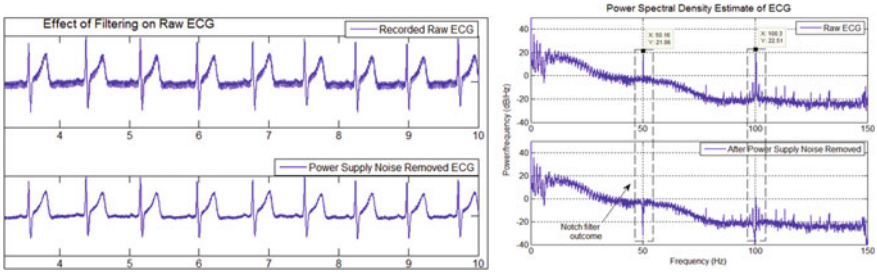

Fig. 2.12 Effect of notch filtering on ECG signals (time domain on left and frequency domain in right) to remove 50-Hz power supply noise and its harmonics

2.3.2 Artifact Avoidance

This is a preventive technique to avoid artifacts or minimize the effect of artifacts by ensuring proper recording environment and protocol such as asking the subject to have least amount of movements or eye-blinks, proper grounding of the recording devices, using enough gel for better connectivity of the wet electrodes, etc. However, artifact avoidance is not the ultimate way of getting rid of artifacts completely, in some applications such as continuous ambulatory monitoring or BCI/HCI applications, subject's movement is inevitable. Moreover, some of the internal or physiological artifacts are involuntary and not possible to avoid, e.g. pulse and eye blink artifacts found in EEG recordings. In addition, the subject may not limit the movement for more than a specific period of time, especially if it is a child. Therefore, these unavoidable artifacts should be removed in the later stage, i.e. digital signal processing (DSP) domain.

2.3.3 Artifact Detection

Reliable identification of artifact contaminated segments of biosignal recording is the most important step for handling artifacts. If any application requires to separate or detect artifacts in real-time, therefore having prior knowledge of characteristics or properties of either the artifact or the signal of interest is really necessary in order to detect them faster. Artifact detection may refer to detection of a specific epoch or an independent component (IC) as artifactual. The detection domain (time or frequency or wavelet) is influenced by the type of artifacts and/or applications. The detection method also varies depending on whether a reference artifact source is available or not, whether the no. of channels is enough, whether artifact removal is required after detection and so on.

2.3.3.1 Simple Amplitude Threshold

Often simple amplitude threshold based approach is taken to detect certain types of artifact or artifactual epoch from artifact-free epoch in time domain. Usually the signal amplitude higher than the set threshold is detected as artifact(s) and lower than the threshold is assumed to be clean epoch. However, due to the non-stationary nature of most biosignals as well as due to variety of artifact types, a pre-defined threshold is not reliable to detect artifact. The following type of threshold value is often seen to be used in the literature for a time series signal, x:

$$Thr = 3 * rms(x) \tag{2.5}$$

2.3.3.2 Machine Learning

Recently machine learning based methods are being used (mostly supervised learning) for artifact separation from useful biosignal of interest by extracting important dominating features. Identified artifactual epochs are either marked as annotator of artifacts for clinicians to make decision (e.g. epileptic onset detection) or rejected before sending for examination to clinician or before sending to automated system [12]. Machine learning techniques are mainly categorized as: supervised (labeled training samples) and unsupervised learning (unlabeled samples). Artificial Neural Network (ANN) [13–17] and Support Vector Machine (SVM) [12, 18–21] are two widely used classifiers among supervised algorithms for separation between artifact and brain signals. While popular unsupervised learning algorithms are k-means clustering and outlier detection in artifact detection applications [12]. A typical process of classifying artifacts from EEG using machine learning is illustrated in Fig. 2.13.

Deep Learning

Deep learning is an advanced version of artificial neural network with representation learning which uses multiple deep layers of neurons to progressively extract higher level features from the raw input and recently has been very popular for separation or identification of artifactual epochs/artifacts from artifact-free epochs [22, 23].

2.3.4 Artifact Rejection

A simple approach to remove the influence of artifacts after detection is to reject/cancel the artifact contaminated epoch or segment. This process not only removes artifact but also removes signal of interest since both overlaps in temporal domain which eventually results in the loss of critical information. This used to

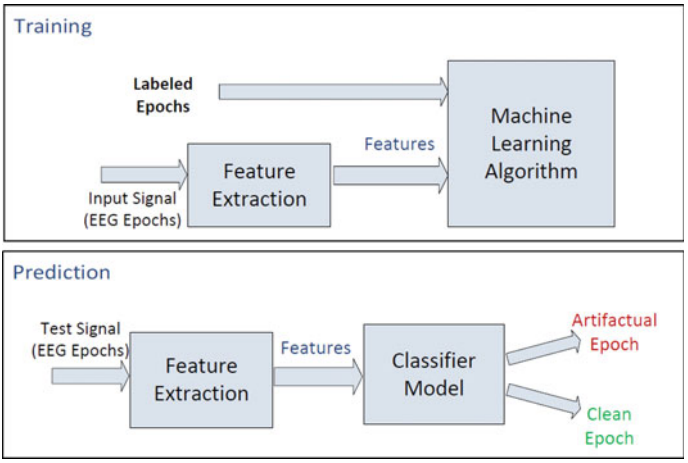

Fig. 2.13 Machine learning approach for classifying artifactual epochs from clean epochs

be traditional way of handling artifacts, but recently with advancement of signal processing techniques, the priority is towards removal or correction of artifactual segments without distorting signal of interest instead of completely rejecting the epoch. However, in some applications, this approach may still be useful, such as offline analysis or training of machine learning classifiers. Artifact rejection can be of following two types:

(a) Full sequence/channel rejection: Bad channels are completely rejected from analysis if found too noisy or artifactual.
(b) Particular Epoch(s) rejection: Only the bad/noisy epochs are rejected from further analysis instead of full channel rejection.

2.3.5 Artifact Removal

Artifact removal refers to cancelling or correcting the artifacts without distorting the underlying biomedical signal of interest. This is mainly performed in two means: (i) by filtering or regression and (ii) by separating or decomposing the biosignal recording to other domains.

2.3.5.1 Regression

In this approach, a multi-modal linear model is assumed between observed artifact-contaminated EEG channel and a reference channel containing artifact source. Then, the samples that do not fit with the model are considered as outliers. Physiological artifacts e.g. ocular and ECG artifacts may be removed using such technique from

EEG recordings. However, if no reference channel is available, then such regression will be able to function. In addition, most biomedical signals originate from non-linear and non-stationary process, which makes the linear regression method not useful for artifact removal from such biosignals.

Single-Variate Autoregressive

In an autoregressive model the current sample of the signal is estimated from its previous samples using a set of prediction coefficients optimally calculated using Yule-Walker equations. Denoting the single biosignal as

$$x(t) = \sum_{i=1}^{p} a_i x(t-i) + e(t) \tag{2.6}$$

where p denotes the prediction order, i.e., the number of previous samples used in prediction of the current sample, and $e(t)$ is the residual signal and needs to be minimized and temporally during the prediction coefficient, a_i, estimation. Smaller values of p result in a smoother estimation of the signal by rejecting more redundancy in the signal considering it as noise. On the other hand, larger p will include more redundancy or noise within the estimated signal. Akaike Criterion [24] was one of the first methods in estimating an acceptable value for p. This criterion however, was improved by the approach proposed by Bengtsson [25] for a more accurate estimation of p.

Multi-variate Autoregressive

This is an extension of single variate (univariate) autoregressive. assuming the main multichannel EEGs are both time and space (channel) correlated, then prediction of one sample from one channel from not only the same channel but samples of other channels, which exploits the correlations between channels, can lead to rejecting noise. This has application in brain connectivity, more robust spectrum estimation, and most importantly denoising.

Variational Bayes

Variational Bayesian methods are some useful techniques to solve the problem of estimating an original signal from degraded observations [26–29]. Unlike the Bayesian methods (such as the Bayesian estimation methods based on Markov Chain Monte Carlo (MCMC) algorithms, in VBA methods the intractable true posterior distribution is approximated using a tractable one from which the posterior mean can be

easily calculated. In addition, VBA methods usefully have a lower computational complexity compared with the sampling-based methods.

2.3.5.2 Blind Source Separation/Subspace Signal Separation

Blind Source Separation (BSS) is known as useful technique for artifact detection from biosignals. Here, the measured biosignals, X are considered as linear mixture of the sources, S along with AWGN vector, N in multi-channel recordings

$$X = AS + N \tag{2.7}$$

In BSS methods, the ultimate goal is to develop an iterative algorithm which estimates the linear mixture matrix, A. Then, the estimated matrix (denoted by W) is used to estimate the source signals, S' by following formula:

$$S' = WX \tag{2.8}$$

In order to use BSS, it is required that the number of sources must be equal or less than the number of observed channels. In addition, the sources should be maximally uncorrelated (for CCA) or independent (for ICA) from each other. A basic BSS based artifact removal technique is illustrated in Fig. 2.14.

Independent Component Analysis

In general, the Independent Component Analysis (ICA) based algorithms require that the source signals are linearly independent and non-Gaussian distributed. In order to apply these algorithms artifact detection and removal, it is also may require manual intervention to reject independent source components (known as ICs) with visually identified artifacts. It may be made automated by combining ICA with another complementary method such as Empirical Mode Decomposition (EMD) or Wavelet Transform (WT). It also may be used with machine learning classifiers such as SVM or even with a help of a reference channel [30]. However, artifactual ICs may also contain few residual neural or biosignals. Therefore, if the artifactual IC is

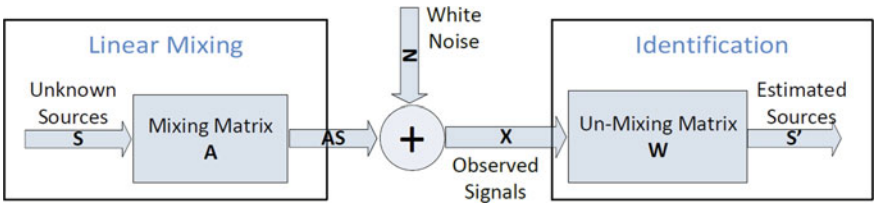

Fig. 2.14 Illustration of a basic blind source separation technique

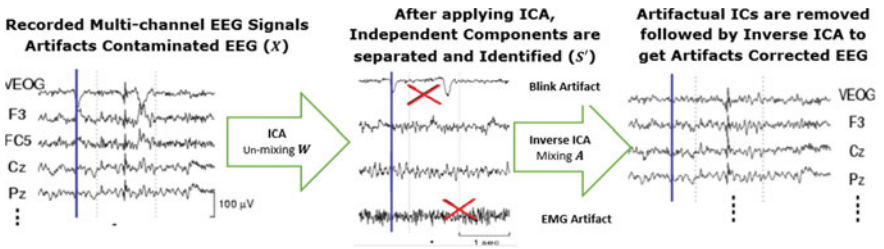

Fig. 2.15 A typical example of application of ICA to identify and remove artifacts (ocular and muscle) that can be separated as an independent sources from multi-channel EEG recordings. Adopted from [40, 41]

completely rejected then distortion to the background neural (or bio) signals occurs. In addition, ICA requires multi-channel recordings to operate which suggests that it cannot be applicable for single (or few channels) recordings. Another challenge that restricts the suitability of ICA for artifact removal (especially in real-time applications) is its high computational complexity. This is because ICA based algorithm usually requires multiple iterations to converge. Considering these factors, ICA may be a suitable choice to remove global artifacts, i.e. ocular artifacts [15, 31–34] or sometimes other physiological artifacts, but not external artifacts. The following works used modified ICA [35] or constrained ICA [36–39] for making it automated artifact detection and removal. An example of ICA based ocular and muscle artifact detection and removal is illustrated in Fig. 2.15.

Canonical Correlation Analysis

A different BSS technique for separating mixed signals is Canonical Correlation Analysis (CCA). In this method, second-order statistics (SOS) is used in order to generate components based on their uncorrelated properties. Considering the uncorrelated components, CCA has weaker criteria than statistical independence used by ICA. CCA addresses temporal correlation unlike ICA, therefore, CCA has maximum temporal or spatial correlation within each component [42].

Morphological Component Analysis

The idea behind the Morphological Component Analysis (MCA) is to decompose the recorded signals into components which have different morphological characteristics and each component is sparsely represented in an over-complete dictionary [43]. It is only applicable to certain artifact types whose waveform shape or morphological characteristics are known in advance and stored in a database. MCA-based method's performance largely depends on the availability of the artifact-template database. An example use of MCA is found in [44] for removing ocular artifacts and few EMG

artifacts originating from muscle activities during swallowing, jaw clenching, and eye-brow raising.

Tensor Decomposition

It is an extension of Singular Value Decomposition (SVD) to multi-dimensional space where in the case of multichannel medical signals can decompose the data into its constituent components in a multi-dimensional (time, frequency, space- which is the channel domain-, trial, subject, and even subject groups) or multi-way space. This method separates the disjoint signals, including noise, and localizes the sources. Tensor decomposition best exploits the diversity in the data and its variation in any possible domain. Therefore, generally it is more effective than any other fusion or decomposition technique such as PCA, ICA, or time-frequency method for detecting and localizing events [45, 46].

Time-Frequency Representation

Time-frequency analysis is often performed for biomedical signals as suitable for non-stationary time-series data such as EEG signals. Time and frequency domain analysis are performed simultaneously since non-stationary biosignals have varied statistical and spectral properties with time. Therefore, any change in the instantaneous frequency of each signal component [e.g. either artifact or seizure [47, 48] can be detected in a particular temporal window. An excellent example of the use of such analysis is found in [49] where it is observed that frequencies up to 181 Hz can be present in a subject's EOG signal for certain tasks after simultaneous time-frequency representation was performed for the recorded ocular artifacts (OA) including saccades and blinks. This result suggests that if EOG recording is used as a reference channel for removing ocular artifact from EEG recordings, then sampling rate of EOG recording must be at least 362 Hz (2×181) to avoid aliasing.

The short-time Fourier Transform (STFT) is a widely used time-frequency representation. In this method a uniform time-frequency resolution is used for all signal spectrum (frequency values). The spectrum of most biomedical signals is around 0.5–100 Hz and the spectrum of most artifacts appear in frequency region (< 10 Hz). This means that having high frequency resolution in the lower frequency region is required. But, clearly due to uniform frequency resolution, STFT cannot satisfy such requirement. A nice solution of this issue is to use wavelet transform since it provides a decent time-frequency resolution for most biosignals.

Short-Time Fourier Transform

Short-Time Fourier transform (STFT) is one of the common time-frequency representation techniques which is obtained by segmenting the whole recording sequence

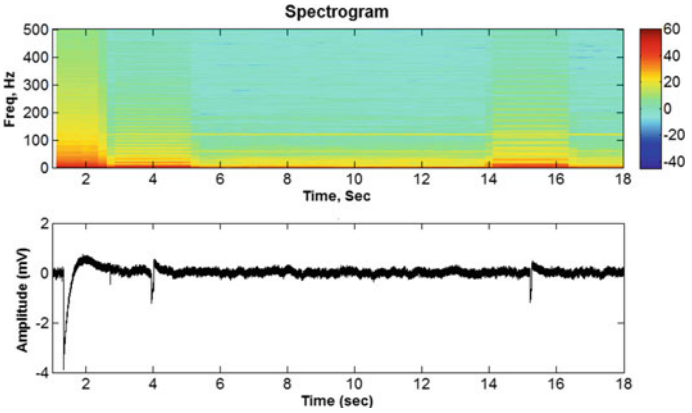

Fig. 2.16 Real neural signal contaminated with both type-1 and type-2 artifacts (bottom) and its Spectrogram (top) shows relatively high frequency components at the temporal locations of these artifacts

into many short-duration epochs by applying window function and then, its frequency representation is calculated by FFT for each of this epochs:

$$F_x(t, f; h) = \int_{-\infty}^{+\infty} x(u) * h(u-t)e^{-i2\pi uf}du \tag{2.9}$$

Here, $h(t)$ denotes the STFT sliding window. For a finite energy window it can be represented as:

$$x(t) = E_h \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} F_x(u, f; h)h(t-u)e^{i2\pi tf}dudf \tag{2.10}$$

where $E_h = \int_{-\infty}^{+\infty} |h(t)|^2 dt$. Consequently, STFT is used to determine the energy distribution of any time-series signal (e.g. biosignals) in simultaneous time-frequency domain. Figure 2.16 shows how STFT-based spectrogram can be useful in identifying artifacts by plotting the biosignal energy in both temporal and spectral domain simultaneously.

Wavelet Transform

Wavelets are localized in both temporal and spectral domains compared to the typical Fourier transform which is localized in only frequency. Although STFT offers time-frequency representation, but wavelets provide a better signal representation in terms of higher frequency resolution in lower frequency region and thus more suitable for

biosignal time series analysis as most biosignals have dominant frequency components in the low frequency region. The wavelet transform decomposes original signal f(t) into dilated and translated versions of a basis function ψ(t) known as mother wavelet [50]. Any Wavelet is generated from a mother wavelet via:

$$\psi_{j,k}(t) = 2^{j/2}\psi\left(2^{j/2}t - k\right) \tag{2.11}$$

where k is the translation in time with scaling factor of 2 and j indicates the resolution level. Wavelet decomposition follows linear expansion expressed as follows:

$$f(t) = \sum_{k=-\infty}^{+\infty} [c_k \varphi(t-k)] + \sum_{k=-\infty}^{+\infty} \sum_{j=0}^{\infty} d_{j,k}\psi\left(2^j t - k\right) \tag{2.12}$$

where $\varphi(t)$ is known as the scaling function or father wavelet and c_k and d_j, k are the coarse and detail level expansion coefficients, respectively. Theoretically, the expansion coefficients c_k and $d_{j,k}$ are calculated from the inner product of $f(t)$ with $\varphi(t)$ and $\psi(t)$, respectively. A function may serve as mother wavelet by satisfying the following condition:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{2.13}$$

There are various types of wavelet methods such as wavelet approximation and decomposition, wavelet packet decomposition (WPD), discrete and continuous wavelet transform (CWT), stationary wavelet transform (SWT), and so forth. Among them, Discrete Wavelet Transform (DWT) is the most commonly used technique. The relation between input and output of DWT can be expressed as:

$$x_{a,L}[n] = \sum_{k=1}^{N} x_{a-1,L}[2n-k]g[k] \tag{2.14}$$

$$x_{a,H}[n] = \sum_{k=1}^{N} x_{a-1,L}[2n-k]h[k] \tag{2.15}$$

where $g[n]$ is a low-pass filter mimicking scaling function and $h[n]$ is a high-pass filter similar to mother wavelet. Briefly, discrete wavelet transform decomposing a signal into its low frequency component and high frequency components through these two filters known as approximate and detailed coefficients. The wavelet filter decomposition structure is shown in Fig. 2.17.

Once the signal is decomposed, thresholding is applied to denoise the signal from artifacts. At that point the new sets of detailed and approximate coefficients are

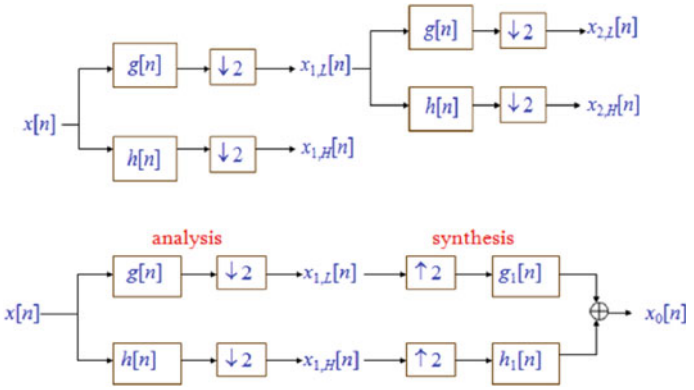

Fig. 2.17 The decomposition (analysis) and reconstruction (synthesis) structures of wavelet filters

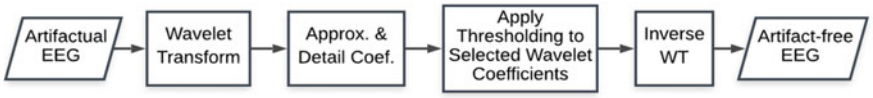

Fig. 2.18 Typical process flow of wavelet-based denoising technique

added up to reconstruct back the artifact-free signal. A typical wavelet denoising based artifact removal from EEG signal as an example is illustrated in Fig. 2.18.

In recent years, wavelet transform based denoising (e.g. DWT) have gained special attention in EEG signal processing due to their suitability in non-linear and non-stationary signal processing [51]. Wavelet transform can be used to separate the energy of the EEG recording into different frequency bands. When it is applied to artifactual EEG signal, it yields the wavelet coefficients representing correlation between the noisy EEG and the wavelet function. Based on the selection of mother wavelet, larger coefficients correspond to the artifactual segment, while smaller coefficients correspond to the actual EEG. It is important to note that suitable mother wavelet and thresholds are required to ensure the effective separation of the artifact coefficients and the EEG signal coefficients. The problem remains how to select the proper mother wavelet and how to choose the parameters for achieving best performance in an automatic fashion.

Empirical Mode Decomposition

Empirical mode decomposition (EMD) is an empirical and data-driven technique applicable for non-stationary, non-linear, stochastic processes, such as EEG signals. However, the computational burden of EMD is higher doubting its ability to perform in online applications. EMD algorithm decomposes the original signal, $s(n)$ into a sum of the band limited functions, $d_m(n)$ known as intrinsic mode functions (IMF)

with well-defined instantaneous frequencies [52–54]. An IMF should satisfy the following criteria: (i) at any point, the mean value of the two envelopes defined by local maxima and local minima is zero [54], (ii) the number of extrema has to be equal (or at the most differ by one) to that of the number of zero crossings. The flowchart of EMD algorithm to calculate IMF is shown in Fig. 2.19.

Enhanced Empirical Mode Decomposition (EEM is modified from EMD to make it robust to noise which will avoid the mode mixing complication arises in EMD. To achieve this EEMD uses mean value of the number of ensembles (IMFs) as optimal IMFs allowing it to offer a noise-assisted data analysis technique [42]. An example of simple EMD-based artifact removal process is shown in Fig. 2.20.

Wiener Filtering

Unlike adaptive filters, in Wiener filter a reference signal is not required. However, it assumes that both the signal and artifact are stationary linear random processes, where their spectral characteristics are known and also the signal and artifact are uncorrelated. But in reality, most of the biomedical signals exhibit non-stationary characteristics and are believed to be originated from a complicated non-linear stochastic process. Again, although the spectral characteristics of most biomedical signals are known, due to the uncertainty of different types of artifact sources, the spectral characteristics of artifacts cannot be determined accurately. In addition, the wiener filter is unable to be implemented in real-time, thus may not be suitable for applications where real-time processing is requires such as closed-loop Human-machine interfacing (HMI) through which external devices/machines (e.g. wheelchair, computer, prosthetic limbs) are controlled by biomedical signals (e.g. EEG, EMG, EOG, etc.).

Adaptive Filtering

Adaptive filters have been manifested to prove useful in great deal of biomedical applications. For example, most biosignals, such as ECG or EEG signal acquisition, the information-bearing signals may be contaminated by noise and disturbances caused by the 50/60 Hz power-line, high frequency interference and random body voltages. In such problems, both required signal and noise occur in an identical frequency band and so the noise cannot be discriminately filtered out by removing any specific frequency band. In such cases, filters that can adjust to the changing noise are required. Adaptive filters, systems with variable as an alternative to fixed filter coefficients, can overcome these difficulties. This is achieved by employing adaptive filters such as least-mean-square (LMS) algorithm, recursive-least-square (RLS) algorithm, and Kalman filter-type algorithms, as the analytical implementation of Bayesian filtering recursions for linear Normal state-space models. Adaptive filters are preferably designed as FIR filters, as shown in Fig. 2.21, known for their good stability properties and ease of implementation.

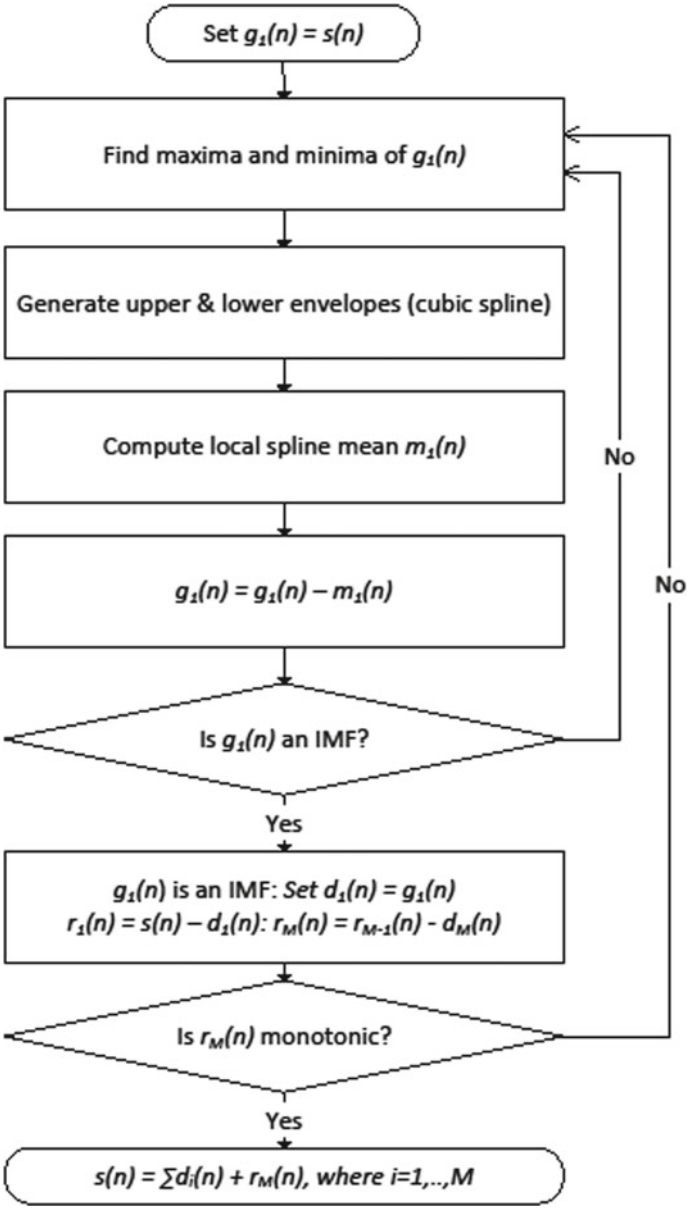

Fig. 2.19 The general process flow of EMD algorithm to generate IMFs

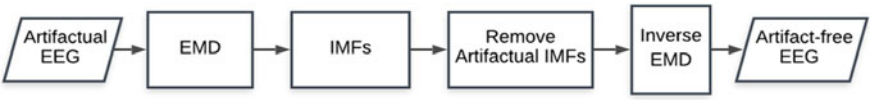

Fig. 2.20 Typical process flow of EMD-based denoising technique

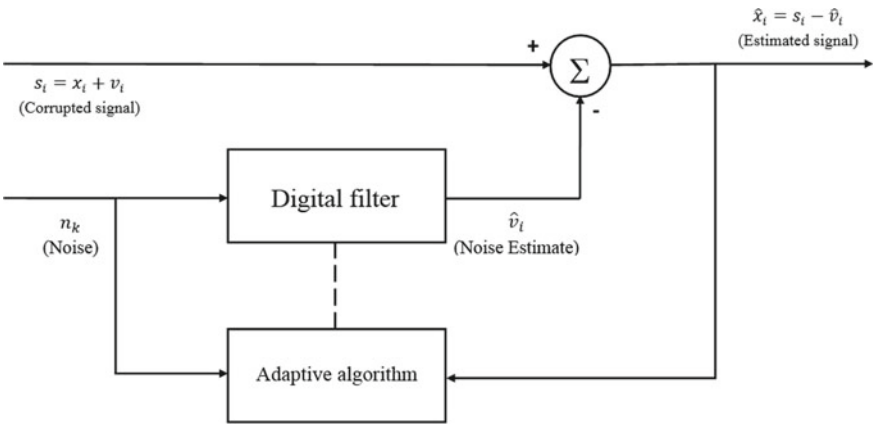

Fig. 2.21 General adaptive filter structure, with concept of interference cancellation

As mentioned earlier, adaptive filters have also been used for artifact removal from biosignals. In [55], a hybrid nonlinear adaptive filtering has been reported for removing motion artifacts from wearable photoplethysmography. In [56] an adaptive filtering algorithm has been developed for motion artifact removal from capacitive ECG signals. In this algorithm, the power-line interference (PLI) has been used to extract the required reference signal. Another adaptive filtering based algorithm for motion artifact removal from the ECG recordings has been reported in [57]. In this algorithm, the spectral energy variation during the input process of motion artifacts is used to develop a cosine transform LMS adaptive cancellation algorithm. In [58], a motion artifact removal algorithm has been proposed which uses a cascade of LMS adaptive filters, in conjunction with a reference noise estimation method. Kim et al. [59] developed a method using ICA and adaptive filtering for MI (motor imagery)-BCI applications. They showed that this method can remove Ocular Artifacts from the EEG signals without measuring Electrooculogram (EOG). In [60], a neural network-enhanced adaptive filtering algorithm has been reported for EEG artifact removal. In order to remove EOG artifacts from EEG recording, it is usually required to have multi-channel EEG recording or an additional EOG recording in real-time. In [61] a new method has been developed which uses a cascade of RLS adaptive filters and sparse autoencoder (SAE) to remove EOG artifacts from EEG recordings. A novel time-domain linear filtering algorithm to remove ocular artifacts from EEG signals has been introduced in [62], where the eye-blink signal is obtained by a small

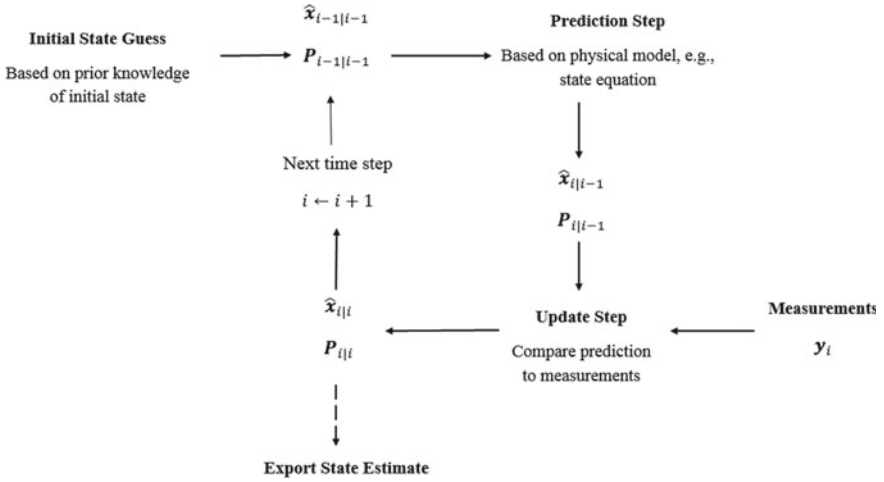

Fig. 2.22 A schematic of the Kalman filter structure

number of frontal electrodes (instead of directly estimating the artifact-free signal) and applying a multichannel Wiener filter (MWF).

Kalman Filtering

Kalman Filter is an estimator based on Minimum Mean Square Error (MMSE) which is often used to extract or smooth physiological signals. Moreover, Kalman filtering may be used to denoise, separate signals or fuse sensor data, all three in a single architecture. The main advantage of Kalman filter, compared to other filtering or signal separation techniques, is its lower systemic delays in real-time computations.

In order to apply the Kalman Filter, the observations should follow a state-space model. In this model an equation shows the evolution of the state model, and the other equation describes the relation of the parameters with the observations:

$$\boldsymbol{x}_i = \boldsymbol{A}\boldsymbol{x}_{i-1} + \boldsymbol{w}_i \tag{2.16}$$

$$\boldsymbol{y}_i = \boldsymbol{B}\boldsymbol{z}_i + \boldsymbol{v}_i \tag{2.17}$$

In the above model $\boldsymbol{x}_i$ are represents the state of model at time i, $\boldsymbol{y}_i$ are the noisy measurements (observations), $\boldsymbol{w}_i$ is the state noise, $\boldsymbol{v}_i$ is the observation, $\boldsymbol{B}$ is the observation matrix and $\boldsymbol{A}$ is the state transition matrix. A schematic diagram of the Kalman Filter is demonstrated in Fig. 2.22.

The Kalman filter consists of two prediction and update steps, which are sequentially executed through time. In the prediction step, the available the data up to time $i+1$ is used to estimate $\boldsymbol{x}_i$. The forecast is denoted as $\hat{\boldsymbol{x}}_{i|i-1}$ and subject to uncertainty

quantified by the prediction error covariance $\boldsymbol{P}_{i|i-1}$. When the new measurement $\boldsymbol{y}_i$ is available, the update step is performed. In this step, $\boldsymbol{y}_i$ is leveraged to correct $\hat{\boldsymbol{x}}_{i|i-1}$ and generate an updated estimate $\hat{\boldsymbol{x}}_{i|i}$. At this step $\boldsymbol{P}_{i|i-1}$ is also updated to obtain $\boldsymbol{P}_{i|i}$ to quantify the uncertainty imposed on $\hat{\boldsymbol{x}}_{i|i}$.

Particle Filtering

Particle filter is a kind of filter based on Bayesian approach which overcomes the limitation of Kalman filter as it does not require the data follow a linear model or the distribution to be unimodal. But it still needs a priori user input which may not be available always in EEG-based applications. And there is very little work has been done by far to use particle filter to remove artifacts in EEG signals. Hence it is not guaranteed to be a successful choice, but one can definitely try to observe the outcome of such filter implementation in removing artifacts.

Spatial Filtering

Principal Component Analysis (PCA) is one kind of spatial filtering that typically transforms the original dataset from temporal domain to a new domain by rotating the axes in an N-dimensional space (N is the no. recording channels) where each dimension in the resultant space having minimum variance as well as axes are being orthogonal to each other [63]. It reduces dimensionality of the dataset and highlights dominant features of data that are usually hard to detect in the original domain. In [64] a robust PCA is used after wavelet-based denoising is done as preprocessing while in [65], a comparison is made between PCA and ICA for artifact removal and it is found that ICA outperforms PCA. Since both these articles evaluated the performance qualitatively; therefore, it is difficult to assess the efficacy of the use of PCA in artifact removal. One significant drawback of PCA is that it cannot be used to identify artifacts when signal and artifact amplitudes are comparable to each other (e.g. ocular artifacts from EEG) as it relies on the higher order statistics of the data [36].

Hybrid Methods

In recent years, many works are reported that have utilized the advantages of different SPTs by combining two or more techniques in multiple stages into a single technique for detecting and removing artifacts from biosignals. Some of such hybrid methods are described as follows:

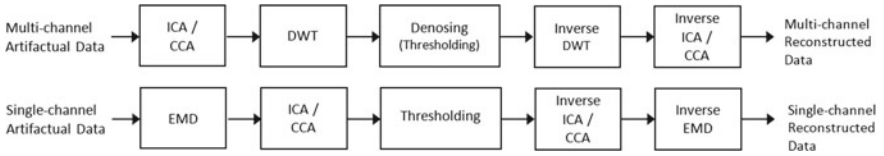

Fig. 2.23 General process flow of wavelet-BSS and EMD-BSS methods

Wavelet-BSS

Wavelet-BSS is formed by combining two commonly used methods: wavelet transform in the first stage followed by blind source separation in the later stage. It is mainly inspired since BSS based separation of artifactual independent components (i.e. ICs) is often flawed as the separated IC may also contain residual biosignals which eventually results in significant distortion in reconstructed signals. To overcome this issue, multi-channel biosignal recordings are converted to ICs or CCs by applying BSS and then potential artifactual component is further decomposed by wavelet decomposition into detail and approximate coefficients of different frequency bands. After that, wavelet denoising is applied which eventually preserves the residual bio signals of low amplitude after thresholding is used to remove the higher amplitude artifactual segments. The reference articles are [66–68] for wavelet-ICA, [69, 70] for wavelet-CCA. On the other hand, for single-channel recording, reversing the order of wavelet transform and BSS i.e. BSS-Wavelet may be used. E.g. [71, 72] reported artifact removal by first decomposing signal into wavelet coefficients; after that BSS is applied on the artifactual coefficients to separate artifacts from background neural/bio signal. However, the former method is more popular to the research community which is known as wavelet enhanced ICA (wICA) or wavelet enhanced CCA (wCCA).

EMD-BSS

It includes BSS with EMD technique. The initial stage of EMD-BSS is to decompose the signal into IMFs by applying EMD or EEMD and then BSS (either ICA or CCA) is applied on the IMFs to identify artifactual components and finally rejecting the artifactual ICs or CCs. (E)EMD-BSS are reported in [42, 73, 74]. Figure 2.23 illustrates typical steps involved in both wavelet-BSS and EMD-BSS based methods.

BSS-SVM

A hybrid BSS-SVM was reported in [20] for removing eye blink and ECG artifacts from EEG recordings where features extraction is performed from separated source components (after BSS is applied) to feed the SVM classifier to separate artifact components followed by removal of the artifact components. Finally in order to

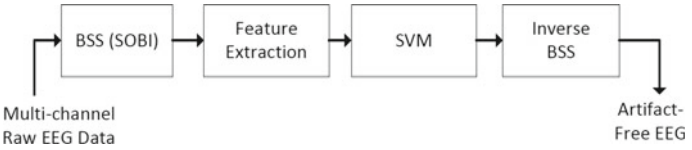

Fig. 2.24 Typical process flow of BSS-SVM method for artifact removal

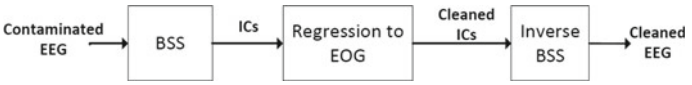

Fig. 2.25 Process flow of REG-BSS hybrid method for artifact removal

reconstruct artifact-free EEG, the remaining source components are re-projected. The whole process is illustrated in Fig. 2.24.

REG-BSS

In [31] a hybrid methodology was reported by combining BSS and regression for removal of ocular artifacts where both vertical EOG and horizontal EOG were used as reference channels as shown in Fig. 2.25. Similar approach has been proposed by Guerrero-Mosquera [26] to remove ocular artifacts by involving ICA and adaptive filtering. Another work [75] proposed to combine ICA and Auto-Regressive eXogenous (ARX) to implement a robust ocular artifact removal where ARX reduced the negative effect induced due to ICA.

Other Approaches

Nguyen et al. [76] reports removing EOG artifacts from EEG using the combination of Wavelet decomposition and Artificial Neural Network, i.e. WNN where EOG reference channel is only required during training of ANN classifier. Another work [77] proposed a hybrid method combining DWT and ANC (Adaptive noise canceller) to remove EOG artifacts (the reference signal is estimated from DWT coefficients required for the adaptive filter). On the other hand, [78] proposed the use of both EMD and adaptive filter (using RLS algorithm) to remove cardiac artifacts from EEG recordings. The authors in [16] reported a new hybrid method to remove EOG and EMG artifacts from EEG recordings by combining functional link neural network (FLNN) and adaptive neural fuzzy inference system (ANFIS).

2.3.5.3 Statistical Features

Statistical features are also used in machine learning in feature extraction stage or during calculation of threshold value used in different SPTs (wavelet, EMD, ICA, etc.) for identifying artifacts from biosignal of interest. Some of the commonly used features are discussed below:

Time Domain Features

Among time domain features, most commonly used features are: Entropy, Kurtosis, Line Length, NEO, Maximum, Minimum, Variance, Mean, etc. [51].

Frequency Domain Features

Among spectral domain features, most commonly used features are mean, maximum, minimum and variance of the absolute value of FFT or PSD. E.g. EEG rhythms are non-overlapping frequency bands and therefore, spectral features may be useful to separate artifacts from a targeted EEG rhythm in consideration for a specific application.

Spatial Features

Spatial distribution of the recordings can be known from spatial features which allows to identify the origin of brain signals as well as some artifact types (e.g. ocular artifacts are mostly found in frontal electrodes as closest to the origin of that artifact). In addition, global artifacts (e.g. eye blinks) can be differentiated from local artifacts based on spatial mapping. Therefore spatial features of data with both temporal and spectral contents can be useful to separate artifacts from EEG signals [14, 79].

Auto-Regressive Features

Refer to Sect. 3.5.1.1, the AR model parameters, α_i can be considered as features for classification.

2.3.6 Summary and Comparison Between SPTs

See Table 2.4.

Table 2.4 Comparison of different SPTs used in artifact removal from different biosignals

Main methods used	References	Type of bio signal	Type of artifacts/noise	Applications	Remarks
Adaptive filtering/ANC	[55–61]	PPG, ECG, EEG	Motion/Ocular/EMG + ECG + EOG/	Cardiac diagnosis	Extra channel (EOG, ECG, Accelerometer, Gyroscope, Eye tracker, motion captured camera, contact impedance measurement, etc. required to record reference signal
Kalman Filtering	[80–82]	ECG	Gaussian/Non-Gaussian/muscle artifact/PLI	Cardiac diagnosis	Automated and real-time processing, no a-priori info required, not suitable for non-linear and non-stationary process like EEG

(continued)

Table 2.4 (continued)

Main methods used	References	Type of bio signal	Type of artifacts/noise	Applications	Remarks
Wiener Filtering	[62]	EEG	Eye Blink	General	Proposed for multi-channel EEG recording. Also can work on single-channel data. A-priori user input required and cannot operate online in general
(c)ICA	[31–35, 37, 39, 83]	EEG	Mostly ocular, few motion and other Physiological artifacts	Epilepsy diagnosis, BCI, general purpose	Most of them are semi-automated, few require additional sensor(s) while
CCA	[84, 85]	EEG	Muscle/ocular	Ictal EEG source imaging, Epilepsy monitoring	Not online/real-time processing, requires multi-channel recordings
PCA	[35, 57, 64]	EEG	General	SSVEP for emotion detection	Robust PCA

(continued)

Table 2.4 (continued)

Main methods used	References	Type of bio signal	Type of artifacts/noise	Applications	Remarks
Wavelet transform	[51]	EEG	All types: ocular, muscle	Epileptic seizure detection	Can work for both single and multi-channel recordings, no extra reference channel required
Tensor decomposition	[46, 86]	EEG	Ocular	Epileptic Seizure detection and localization, diagnosis in Preterm babies and many other EEG related applications	Tensor decomposition may involve wavelet transform, ICA, etc.
(E)EMD	[42, 54]	EEG	EOG	General	Extra reference of Fractional Gaussian Noise required and can work for single channel recordings
Hybrid methods					

(continued)

Table 2.4 (continued)

Main methods used	References	Type of bio signal	Type of artifacts/noise	Applications	Remarks
Wavelet-BSS (W-ICA/W-CCA)	[66–69, 71]	EEG	Ocular + muscle + electrical shift	General	Mostly applicable for multi-channel recordings
(E)EMD-BSS (ICA/CCA)	[42, 73, 74]	EEG	Muscle, motion, EOG	Ambulatory single-channel applications, ictal EEG, diagnosis	Can work for single channel and mostly automated
BSS-SVM	[20]	EEG	Eye blink	General; e.g. ERP analysis	Applicable only for multi-channel recordings
REG-BSS	[31, 87, 88]	EEG	Ocular	General	vEOG and hEOG reference channel required
Others (WNN/DWT-ANC/EMD-ANC/ICA-ANC/FLNN-ANFIS)	[16, 76–78]	EEG	EOG, ECG, EMG	General, diagnosis, portable applications	Reference channels are required for ANC related methods

2.3.7 Currently Available Software Plug-Ins

Different biosignal processing and analysis toolboxes are listed in the following table where it is shown what are the SPTs used for these toolboxes along with type of biosignal and artifact types handled.

2.4 Discussion

2.4.1 Limitations and Suitability of the SPTs

2.4.1.1 Real-Time/Online Implementation

There are some applications that require real-time or online processing of biosignals such as HMI or real-time seizure detection (i.e. BCI, neural prosthetics, EOG-controlled wheelchair, etc.). Therefore, choice of artifact removal technique for such application would be such that it has the required low computational complexity to be compatible with real-time/online processing. In that case, trade-off between computational complexity and performance of the artifact removal algorithm is to be made. On the other hand, there are applications such as diagnosis of neurological disorders/diseases that may allow offline processing. In such case, one can only focus on achieving highest performance without much considering about computational time.

2.4.1.2 Single or Multi-channel

As seen from both Tables 2.4 and 2.5 that some SPTs are suitable for both single and multi-channel biosignal recordings while few of them (such as BSS based techniques) require multi-channel recordings to be applied. On the other hand, wavelet or EMD based techniques can be applied for a single-channel recording. So it is critical to select SPT for appropriate application considering the no. of channels in mind.

2.4.1.3 Reference Channel

Refer to Table 2.5, some of the available SPTs require an additional dedicated reference channel to record artifact source for functional. Example of such reference channels: EOG, ECG, Motion Sensors, and Contact Impedance Measurement channels to remove ocular artifact, cardiac/pulse artifact, motion artifacts, artifacts due to electrode popup or movement, respectively. However, having an extra reference channel is not always feasible in some applications such as portable and continuous monitoring if the reference sensor is not integrated with the original biosignal

Table 2.5 Existing software toolboxes for handling different types of artifacts from biosignals

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
EEGLAB	[10]	ICA, Time-frequency Analysis, standard averaging	EEG, MEG, ECoG	Almost all types of Artifacts except motion artifacts	Supports importing of multi-format database, high-density recordings scrolling, artifact removal (semi-automated), EVENT and channel location handling, forward and inverse head or source modeling, over 100 advanced plug-ins/extensions	MATLAB	Y
BCILAB	[89]	Similar to EEGLAB	EEG	Almost all types of artifacts except motion artifacts	BCI Applications and classification	EEGLAB/MATLAB	Y
Bio-SP	[90]	Signal-specific algorithms Mainly IIR digital filtering (Elliptic, Gaussian, or Butterworth)	Peripheral Physiological Signals (ECG, EDA, EMG, BP, or ICG)	General types of artifacts and noises including PLI	Feature extraction and critical events or parameters detection	MATLAB (Any version) Windows, macOS, Linux	Y

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
BioSig	[91]	Linear regression for EOG artifacts removal from EEG, and time/frequency domain features such as slope, amplitude or spectral edge frequency for EMG artifacts detection from EEG	EEG, ECoG, ECG, EOG, EMG, and Respiration signals	Removal EOG artifacts and only detection of EMG artifacts from EEG	Real-time BCI system implemented in MATLAB and Simulink	MATLAB or octave and python	Y
ANSLAB	[92]	Threshold-based, digital filtering	ECG, EDA, EMG, eye blinks, respiration signals	General types	Analysis of long-term recordings from ambulatory settings	MATLAB	Open ANSLAB—Y ANSLAB Professional—Partly
Clean rawdata	[93]	ASR and digital filtering	EEG	Low-frequency drifts, flat line, eye blinks, muscle activity, sensor motion	default EEGLAB method for removing artifacts from EEG	EEGLAB/MATLAB	Y
BioSigKit	[94]	RLS adaptive Filter, variable leaky ALE filter	ECG, EMG and EEG	Motion artifacts	Fetal-ECG extraction from both single and multi-channel maternal ECG	MATLAB	Y

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
biosppy	[95]	Digital filtering	BVP, ECG, EDA, EEG, EMG, Respiration	Out of band noise and DC offset	Support for various biosignal processing, detection of events and clustering	Python	Y
WFDB	[96]	Not found	ECG, EEG, EMG, fetal ECG, PLETH (PPG), ABP, respiration, etc.	Not mentioned	Allows reading, writing, and processing of physiological signals and time series signals from PhysioBank databases	MATLAB/Octave	Y
BSP	[97]	Non-linear filtering (Rank Filters, Median Filters)	ECG, ABP, ICP, and SpO2	Movement artifact and quantization noise	Nonlinear filtering, detection algorithms, spectral analysis, multi-signal analysis, non-stationary signal visualization.	MATLAB	Y
EMGLAB	[98]	Digital filtering	EMG	Low frequency artifacts, DC offset, out of band noises	Decomposing EMG into MUAP trains and averaging MUAP waveforms	MATLAB	Y

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
SASICA	[99]	Reject/select independent components based various features/properties	EEG	Muscle artifacts	Semi-automated guided selection of artifactual ICs	EEGLAB/MATLAB	Y
FASTER	[100]	ICA	EEG	EOG, EMG artifacts, linear trend and white noise	Fully automated and unsupervised; supports high-density EEG recordings	EEGLAB/MATLAB	Y
OSET	[101]	Semi BSS and digital filtering	Any Bioelectric signals	Cardiac and EOG artifacts	Biological signal generation, modeling, processing, and filtering	MATLAB and C ++	Y
AAR	[102]	Regression/adaptive algorithms (LMS, RLS), BSS and Spatial Filters + ICA	EEG	Ocular and muscular artifact	Automated algorithm (ICA-based)	EEGLAB/MATLAB	Y
ADJUST	[14]	ICA	EEG	Ocular (blinks, eye movements)	Automated; no MATLAB toolbox is needed to run	EEGLAB/MATLAB	Y
FOOBI	[103]	Underdetermined blind source separation	EEG	Ocular	Automated, no extra channel required	–	–

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
LAMIC	[104]	Temporal extension of ICA (TDSEP) followed by clustering based on AMI	EEG	Ocular, EMG and ECG	Automatic clustering algorithm	–	–
FORCe	[83]	Combination of WT, ICA and thresholding	EEG	Eye blink, EOG and EMG artifacts	Fully online and automated artifact Removal for BCI applications	MATLAB Wavelet Toolbox/EEGLAB	Y
PRANA	[105]	Digital filtering + BSS	EMG, ECG, EEG, EOG, EDA, pulse oxymetry, respiration, blood pressure, temperature, sound, light intensity activity, etc.	Not mentioned (mainly ocular artifacts)	GUI for different Biosignals processing and time series analysis	MATLAB	Y
PFEIFER	[106]	Digital filtering	ECG	Signal noise, drift, etc.	Computationally efficient GUI	MATLAB	Y

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
Brainstorm	[107]	Signal Space Projections, ICA, Digital filtering	MEG, EEG, fNIRS, ECoG, invasive neural recordings	Eye blinks, ECG	Supports wide verities of data file formats and brain recording modalities with automated detection of artifacts, 2D/3D visualization, time-series analysis, head and source modeling, functional connectivity, decoding and pattern analysis	MATLAB (executable, OS platform independent, doesn't require to own a License)	Y
FieldTrip	[49]	Digital filtering and ICA	MEG, EEG, iEEG and NIRS	EOG, ECG, EMG artifacts and line noise	Both manual and automatic artifact rejection. Allows time-frequency analysis, dipoles-based source reconstruction, and non-parametric statistical testing	MATLAB	Y

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
REST	[108]	Online RLS Whitening, Online ICA	EEG	General noise	Real-time source localization	MATLAB/EEGLAB	Y
BERGEN	[109]	Digital IIR filters (band-pass) and Moving average correction based on artifact templates	simultaneous EEG-fMRI	Gradient artifacts from fMRI	Head movements are taken into account for better removal of gradient artifacts	EEGLAB/MATLAB	Y
CIAC	[110]	ICA (semi-automated)	EEG	Electrical artifacts originating from cochlear implants	Allows to identify and cluster artifactual ICs across subjects	EEGLAB/MATLAB (Statistics toolbox)	Y
CORRMAP	[111]	Template based identification (Semi-automatic) and clustering of independent components	EEG	Ocular and heartbeat artifacts	Allows to identify and cluster artifactual ICs across subjects	EEGLAB/MATLAB (Statistics toolbox)	Y
FMRIB	[75]	FASTR: FMRI artifact slice template removal	EEG-fMRI	fMRI-environment artifacts: e.g. gradient artifacts, BCG artifacts and scanner-related artifacts from EEG	GUI software	EEGLAB/MATLAB	Y

(continued)

Table 2.5 (continued)

Name of toolbox	References	Main methods used	Type of bio-signal	Type of artifacts/noises	Extra features or specs	Platform/compatibility	Free/open source?
MARA	[112, 113]	Linear classifier to classify independent components as 'accept' or 'reject'	EEG	Ocular artifacts, muscular artifacts and loose electrodes	Not limited to a specific artifact type; uses supervised machine learning algorithm	EEGLAB/MATLAB (toolboxes required: Statistics, Optimization and Signal Processing)	Y
REGICA	[31]	Regression performed on ICA components	EEG	EOG artifacts	Semi-automated	EEGLAB/MATLAB	Y
CleanLine	[114]	ICA + Regression technique (frequency-domain)	EEG	50/60 Hz line noise + harmonics	Both manual and automatic artifact rejection, supports computationally efficient GUI	EEGLAB/MATLAB	Y

recorder. In addition, these reference channels must synchronize (e.g. in terms of sampling rate or dynamic range), with relevant biosignal recordings to be able to apply regression or adaptive filtering technique.

2.4.1.4 Robustness

Robustness is another important issue to decide on the selection of any artifact removal technique since diverse types of artifacts contaminate and/or affect different biosignals differently for different recording protocols and for different environments. In order to evaluate a particular SPT on its ability to detect and remove artifacts from a specific biosignal, it is very critical to prove its robustness under different experimental setups (or different applications or environments) and different set of subjects.

2.4.2 Future Challenges and Opportunities

With the advancement of technology (e.g. improved sensors, flexible and wearable electronics, analog front-ends, wireless data transfer, cloud computing, AI and machine learning), biomedical signals are going to be recorded and processed real-time in an ambulatory settings where the subjects can move freely and able to perform daily activities. The purpose of such continuous ambulatory recording is not only to monitor patient's condition or to diagnose diseases, but also to predict future health condition and utilize continuous biomedical signals for preventive healthcare. In addition to that, such recording will be used in the area of games and sports and evaluation of one's overall fitness. This potential future scope will come up with new challenges such as handling extreme motion artifacts due to subject's movements in daily activities. Another challenge will be the processing of huge amount of data samples for such continuous recording which will require advanced SPTs to be able to operate in real-time. In addition to that, transferring the samples wirelessly and eventually to store this big data for future reference is another potential challenge to address. In such case, before transferring the samples wirelessly, instead of transferring raw data, extracted and selected features along with compression may be important which again requires new improved SPTs to be proposed and tested.

2.4.3 Recommendations

2.4.3.1 Application Specific Models

The choice of SPT should be application specific. Often it is not required to remove each and every artifact type for a particular application, instead the preference should

be given only on those artifacts that affect the application most. For example, in Motor Imagery based BCI, the frequency bandwidth of EEG signal of interest is $8 - 32$ Hz (i.e. Alpha and Beta rhythms) which means artifacts present in that frequency range must be handled carefully and removed without distorting targeted signal of interest. Artifacts due to muscle activities (EMG) lie in that frequency range while EOG/ECG or motion artifacts belong to less than 8 Hz frequency bandwidth. This implies that one should not bother about removing EOG/ECG/motion artifacts that much for MI based BCI applications, rather concentrate on only removing EMG artifacts as it affect both the Alpha and Beta rhythms most. Therefore, to choose the right SPT for removing artifacts, one should consider the particular application and required specifications to be met given a certain computational resources and recording protocol available. Only those artifacts should be removed which affect the later stage decision making. If an extra reference channel is available to record artifact source (e.g. EOG, ECG, motion sensors, etc.), then SPTs such as regression or adaptive filtering technique may be applied. In case of ambulatory and continuous monitoring applications, no. of channels is lower and reference channel is not available, then it is recommended to use computationally efficient methods that are capable of functioning without reference channel and with single or few channels. Examples of such SPTs are wavelet based methods. In some applications, if prior knowledge about artifacts is available and some training samples are available, and finally if the it only requires to identify artifacts without removing them, at that time machine learning may be a realistic choice. If the biosignals have high-density channels, then PCA can be applied to reduce the dimensionality of the data before applying SPTs for artifact removal (e.g. BSS involved techniques). If the application does not require real-time computation (i.e. involves offline analysis), then computationally expensive techniques with high performance such as cICA or EEMD may be applicable. An example of different application-specific models is as follows:

- Biosignal Specific: EEG, iEEG/ECoG, ECG, EMG, etc.
- Diagnostic/Clinical Application Specific:
- Artifact Specific: Ocular, Muscle, or Motion artifacts.

2.4.3.2 Standard Performance Evaluation

Lack of standard performance evaluation metrics/criteria for the SPTs is a big concern. Most works proposing SPTs for artifact removal found in the literature mentioned some qualitative plots in either time or frequency domain to visually assess the performance (e.g. assessment by clinical experts). (K. T. Sweeney et al. [52] proposed a recording protocol for correct assessment and comparison between different SPTs for physiological signals which may be suitable for some applications that allow intervention to the recording protocol and an extra artifact reference channel is available. However, applications such as portable EEG recordings for ambulatory monitoring may not be compatible with this proposed method. Although it is highly encouraged to evaluate a particular SPT by the domain experts, however,

such qualitative assessment varies from one expert to another and therefore difficult to compare between SPTs for different recording protocols or different biosignals. Therefore, it is high time to develop few standard evaluation criteria for the SPTs which may consist of both qualitative and quantitative metrics to make it more realistic and have a fair comparison.

2.4.3.3 Ground Truth Data

The unavailability of ground truth data (i.e. clean reference biosignals) is another reason for not being able to evaluate performance of a SPT quantitatively. Thus it is also essential to develop a public database with clean biosignal of all types, especially EEG. This is because EEG is the most prone to noise and artifacts among all other non-invasive biosignal recordings and there is no ground truth data of EEG found to the best of our knowledge. So to record ground truth biosignals, recording protocols and experiment should be designed carefully. In addition to that an acceptable mathematical model to generate/simulate basic biosignals may also be developed for quantitative evaluation of any existing or future SPTs. Finally, more research is required to identify and characterize artifacts as many as possible. Therefore, it will be feasible to label both ground truth biosignals as well as artifact templates.

2.5 Conclusions

The chapter summarizes different sources of artifacts and their characteristics found in different biomedical signals and discusses the advances in signal processing techniques and their suitability for handling these artifacts from different perspectives in a variety of biosignal based applications starting from patient monitoring to disease diagnosis, basic physiology/neuroscience research to brain-machine interfacing, evaluating therapeutic intervention to preventive healthcare, etc. The motivation of deciding to use a particular SPT to remove artifacts must be followed by enhancing the overall detection or classification performance, e.g. it in terms of reduction of false alarms for epileptic seizure detection or increasing accuracy for BCI studies. If it does not add any significant value to the later-stage performance, then it is better not to use that SPT for removing artifacts or noises since only improving SNR will not make any sense then. Finally, this chapter discusses the current limitation of the available SPTs, possible future challenges, and potential recommendations to overcome those challenges. More research will be required in developing new SPTs such that they can handle extreme motion artifacts during ambulatory recordings, enabling online/real-time processing, allowing on-chip implementation (if applicable), being compatible with cloud-computing, storing and utilizing the recorded Big data for appropriate decision making and more importantly customizable for different applications and/or different biosignal types.

Appendix

Abbreviation	Definition	Abbreviation	Definition
AAR	Automatic Artifact Removal	LAMIC	Lagged Auto-Mutual Information Clustering
ABP	Arterial Blood Pressure	LFP	Local Field Potential
ADJUST	Automatic EEG artifact detector based on the joint use of spatial and temporal features	LMS	Least Mean Square
ALE	Adaptve Line Enhancer	LTI	Linear Time Invariant
ANC	Adaptive Noise Canceller	MARA	Multiple artifact rejection algorithm
ANFIS	Adaptive Neural Fuzzy Inference System	MCA	Morphological Component Analysis
ANN	Artificial Neural Network	MCMC	Markov Chain Monte Carlo
ARX	Auto-Regressive Exogenous	MEG	Magnetoencephalography
ASR	Artifact Subspace Reconstruction	MI	Motor Imagery
AWGN	Additive White Gaussian Noise	MMSE	Minimum Mean Square Error
BCG	Ballistocardiography	MUAP	Muscle Unit Action Potential
BCI	Brain-Computer-Interface	MWF	multichannel Wiener filter
BioSigKit	BioSignal Analysis Kit	NB	Naïve Bayes
Bio-SP	Biosignal-Specific Processing (A toolbox)	NEO	Non-linear Energy Operator
Biosppy	Biosignal Processing in Python (toolbox)	OSET	Open-source electrophysiological toolbox
BSP	biomedical signal processing toolbox	PCA	Principal Component Analysis
BSS	Blind Source Separation	PCG	Phonocardiogram
CCA	Canonical Correlation Analysis	PFEIFER	Preprocessing Framework of Electrograms Intermittently Fiducialized from Experimental Recordings
CWT	Continuous Wavelet Transform	PLI	Power Line Interference
DWT	Discrete Wavelet Transform	PPG	Photoplethysmogram
EAP	Extracellular Action Potential	PRANA	Polygraphic Recording Analyzer
ECG/EKG	Electrocardiography	PSD	Power Spectral Density
ecg-kit	A Matlab toolbox for cardiovascular (ECG, EKG, ABP, PPG) signal processing	REM	Rapid Eye Movement
ECoG	Electrocorticography	RLS	Recursive Least Square

(continued)

(continued)

Abbreviation	Definition	Abbreviation	Definition
ECoG	Electrocorticography	RMS	Root Mean Squares
EEG	Electroencephalography	SAE	Sparse Autoencoders
EEMD	Ensemble Empirical Mode Decomposition	SCG	Seismocardiography
EMD	Empirical Mode Decomposition	SNR	Signal to Noise Ratio
EMG	Electromyography	SOS	Second-Order Statistics
EOG	Electrooculography	SPT	Signal Processing Techniques
ERP	Event Related Potential	SSS	Subspace Signal Separation
FASTER	Fully Automated Statistical Thresholding for EEG Artifact Rejection	SSVEP	Steady State Visual Evoked Potential
FFT	Fast Fourier Transform	STFT	Short Time Fourier Transform
FIR	Finite Impulse Response	SVD	Singular Value Decomposition
FLNN	Functional Link Neural Network	SVM	Support Vector Machine
FOOBI	Fourth-order Tensor method	SWT	Stationary Wavelet Transform
FORCe	Fully online and automated artifact removal for BCI	TDSEP	Temporal De-correlation source SEParation
HCI	Human-Computer Interfacing	VBA	Variational Bayes Approximation
HMI	Human-Machine Interfacing	W-CCA	Wavelet Enhanced CCA
IAP	Intracellular Action Potential	WFDB	WaveForm DataBase
ICA	Independent Component Analysis	W-ICA	Wavelet Enhanced ICA
iEEG	intracranial electroencephalography	WNN	Wavelet Neural Network
IIR	Infinite Impulse Response	WPD	Wavelet Packet Decomposition
k-NN	K- Nearest Neighbor	WT	Wavelet Transform

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