Chapter

Effective EEG Artifact Removal from EEG Signal

Vandana Roy

Abstract

An EEG (electroencephalography) provides insight into the status of the brain's electrical activity. EEG is based on the electrical activity measured in voltage at various sites in the brain. Generally speaking, these signals are non-stationery and time-varying. Various signal processing techniques can be used to examine these signals. Several statistical approaches to EEG data analysis are discussed in this chapter. In this Chapter, Electroencephalograph Signals and their generation process have been discussed; the EEG signal has been compared with fMRI and PET signals. The classification of the EEG signals on the amplitude, frequency, and shape have been elaborated in wave analysis of EEG, and applications of these components are presented. The artifacts of EEG have been explained in detail.

Keywords: EEG, artifacts, wavelet transform, BSS, EEMD

1. Introduction

One of the most complex structures on this earth is the human brain with an estimated approximately weight of 3lbs. The human brain is so much sophisticated that it has given so many brilliant research works which seem superficial at first look likewise ultra-modern supercomputer, aircraft and one of the missile technologies LGM-30G Minuteman-III, etc. [1]. It controls one's whole human body and consists of approximately 100 billion cells, known as a neuron, a part of the human nervous system. These neurons communicate with each other by sending an electrical potential (charge) down the axon and across the synapse to the very next neuron. Since neurons are not connected physically, it uses a chemical messenger entitled neurotransmitters, which crosses the synaptic gap to carry-forward messages to the next neuron [2]. This chemical messenger (neurotransmitters) then activates receptors corresponding to it in the postsynaptic neuron, this action generates postsynaptic currents this process keeps going on for the next synapse. As this communication passes current (electrical potential) using neurotransmitter, a chemical messenger, it can be considered as communication is a process that is electrical and chemical both.

As shown in **Figure 1**, the neurons are activated using an electrochemical concentration gradient, local current flows are produced.

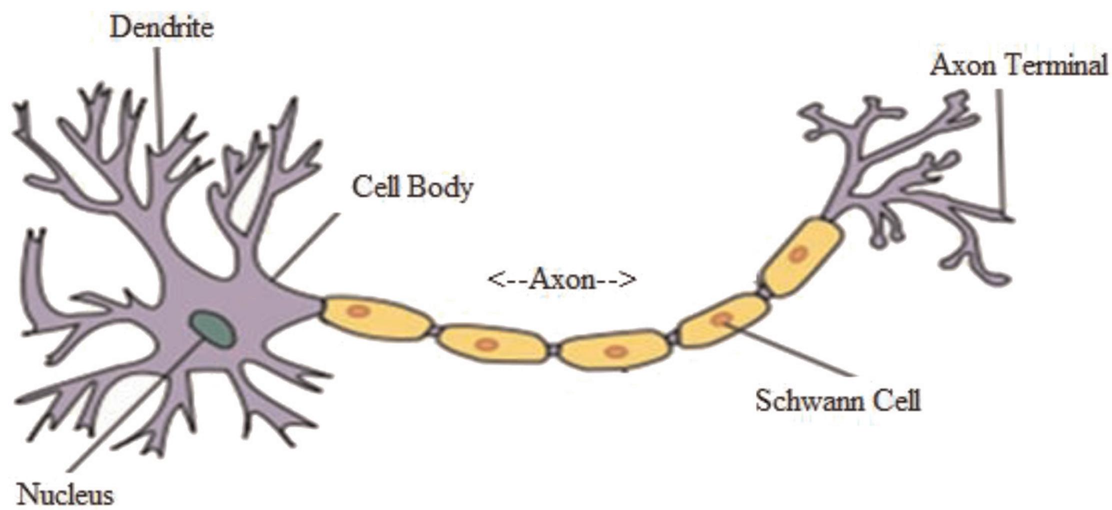

Figure 1.
Typical neurons structure.

1.1 Importance of EEG over fMRI and PET

EEG works as a good tool to explore brain activity and can detect changes within milliseconds. Depending upon the type of neuron, an action potential takes 0.5–130 milliseconds approximately to propagate across a single neuron. Whereas, other methods likewise fMRI and PET has time resolution in terms of seconds and minutes and makes these methods less efficient.

Moreover, EEG directly measures the brain's electrical activity, whilst other methods such as SPECT, fMRI record changes in blood flow, or PET record changes in metabolic activity, which are indirect markers of electrical activity belonging to the brain. The electrical activity is a superposition of the huge number of electrical charges arising from multiple sources likewise brain cells i.e. neurons and artifacts. It is possible to place electrodes inside the human head via surgery for direct measurement from different centers in the human brain, but this is a painful and risky procedure for the subject [3, 4]. However, the desirable technique is to calculate electrical signals of interest invaded on the scalp as shown in the following **Figure 2**.

Signals obtained by an above-maintained process are weighted sums of neuron activity, whose weights depend on the signal path from a specific brain cell to the connected electrodes. Since the same electrical potential is being recorded from more than one electrode, signals being occurred from those electrodes are supposed to be highly correlated [4]. Henceforth, Scientists and Researchers collect these recordings by attachment of tens or hundreds of electrodes, which are positioned in pairs, at various locations on the surface of the subject's head. These electrical potentials (Charges) are tested simultaneously via individuals' channels or amplifiers. Recording for each channel represents the difference in electrical potential between two areas under each electrode's pair [5] as represented in **Figure 3**. In **Figure 3**, the differences between the two electrodes are measured through an operational amplifier for generating EEG signal recording. A machine that is used for this purpose is known as an electroencephalograph, and recordings collected through these amplifiers are known as electroencephalogram (EEG) signals.

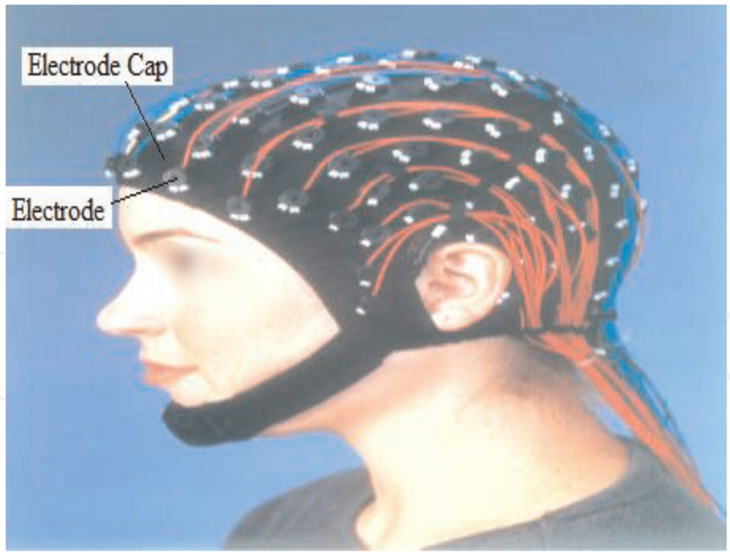

Figure 2.
EEG electrodes placement on a subject, monitoring various sectors of the brain for activities.

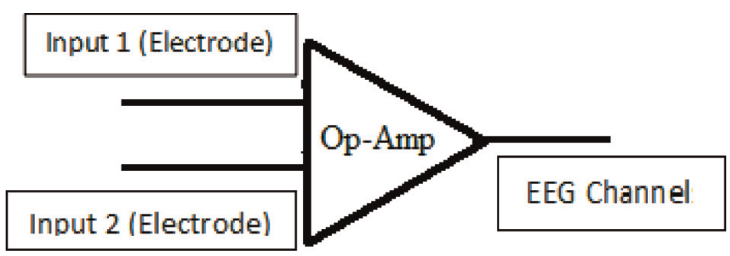

Figure 3.
Differential amplifier for EEG recording/signal.

1.2 Electroencephalograph measuring system

Currently, so many different types of electroencephalographs are available; over which 10–20 system is the internationally standardized method for describing the location of scalp electrodes and is based upon the relationship between an electrode's location and cerebral cortex underlying area and usually employs 21 electrodes. Its positions are determined by dividing the skull into the perimeters by connection of a few reference points lying on the human head.

In this, every perimeter has a letter, that helps in the identification of the lobe, and either a number or another letter for identification of the hemisphere location. Letters that are used are as follows:

1. "F"-Frontal lobe

2. "T"-Temporal lobe

3. "C"-Central lobe

4. "P"-Parietal lobe

5. "O"-Occipital lobe.

Furthermore, numbers (2, 4, 6, 8) refer to the right hemisphere, whereas odd numbers (1, 3, 5, 7) refer to the left hemisphere.

In the below-shown **Figure 4**, the "Z" refers to an electrode placed on the midline; the position of the electrode can be determined by the magnitude of the number, the smaller magnitude represents that electrode is much closer to the midline. The figure given below presents the actual electrode placement on the head and from these points, skull perimeters are measured in the transverse and the median planes [4].

Figure 3.4 presents the system "10" and "20" shows the fact that the actual distances between two adjacent electrodes are in percentage of either 10% or 20% of the three main measurements:

1. nasion, is the delve at the upper portion of the nose, and in level with the eyes.

2. inion, is the bony lump at the base of the skull on the midline of the back of the head.

3. pre-auricular points and circumference of the head.

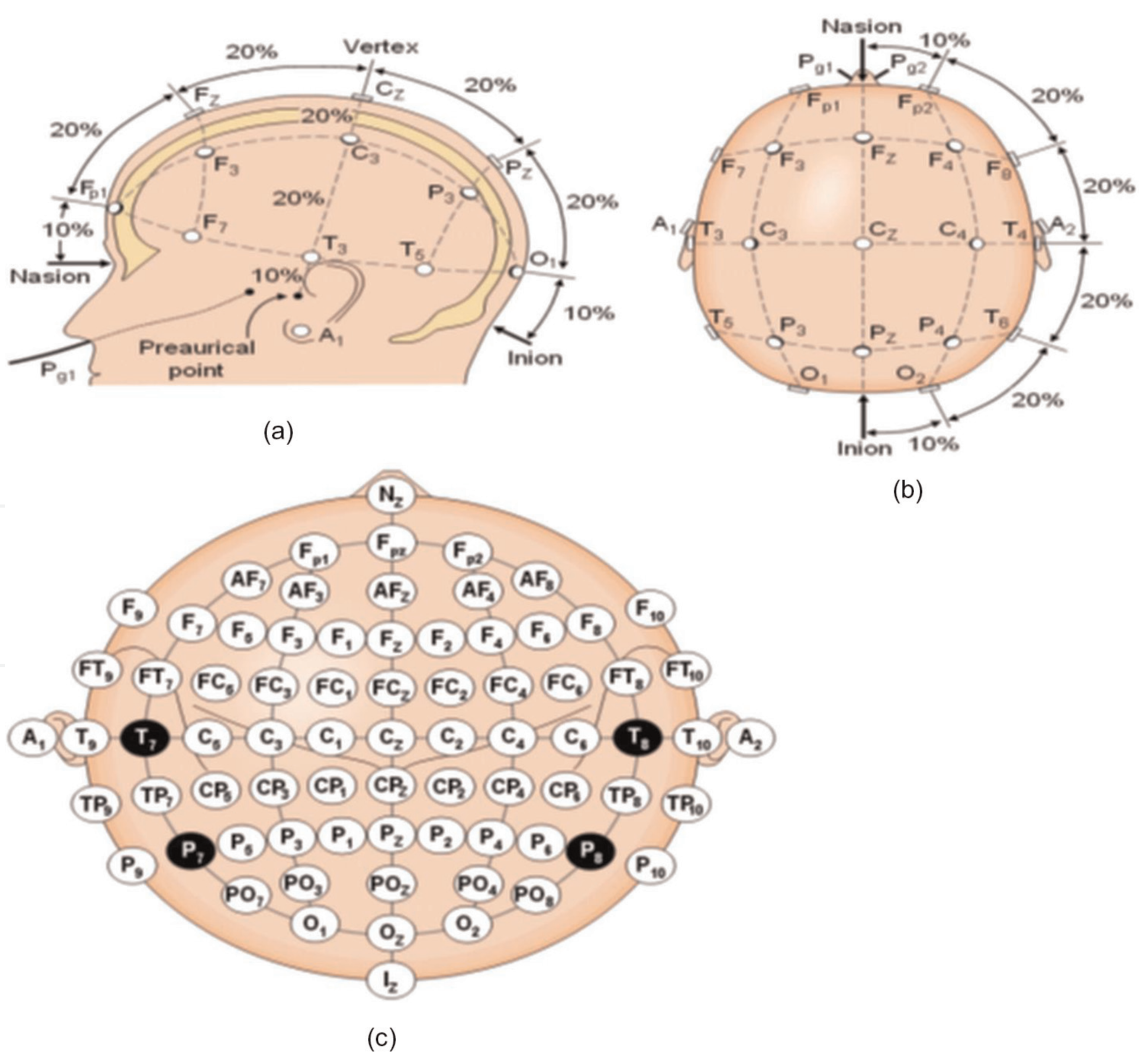

Figure 4.
The international 10–20 system seen from (a) left and (b) top (c) standard location and nomenclature of the intermediate 10% electrodes.

1.3 Wave analysis of the EEG

In the human brain, most of the neurons, which work in synchrony, possess common characteristics, that as much larger the amplitude (potential) of the electrical oscillations in microvolt (mV), will have much faster the neurons work together, and also much higher the frequency of the oscillations in Hertz (Hz). Hence, amplitude and frequency, and shape are important primary characteristics of human brain waves. EEGs are the recordings of these tiny electrical charges (potentials or waves) that are generally less than 300 μV [6]. EEG frequency bands or the brain rhythms arranged according to increased frequencies are shown in **Figure 5**.

The most common classification is based on the frequency of EEG signals (i.e. alpha, beta, theta, and delta). The brain waves with their frequency band and the corresponding brain activities are revealed in **Table 1**.

The EEG signals have been broadly categorized into six classical categories as shown in **Figure 5**. They cause a high level of difficulty to interpret the huge amount of data/information being received from one single EEG recordings. Subsequently, it is highly required to understand every aspect of these categories, which have been explained below in brief:

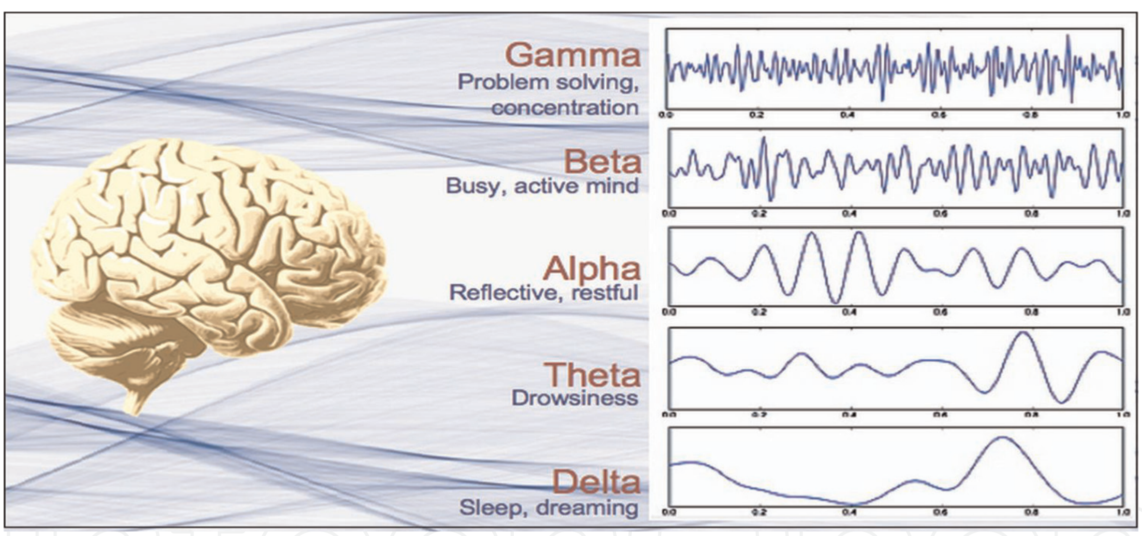

Figure 5.
Fundamental EEG bands classification.

Name	Frequency band (Hz)	Predominantly brain activity
Delta	0.5–4	Sleeping
Theta	4–8	Dreaming, Meditation
Alpha	8–13	Relaxation
Beta	13–36	Alert/Working Problem Solving
Gamma	36–100	Multisensory semantic matching Perceptual function

Table 1.
Electroencephalography (EEG) signal frequency bands.

1.3.1 Alpha (α) waves

The Alpha waves have been discovered around 1908 by Hans Berger. Its frequency ranges from 8 to 13 Hz and is usually seen in the posterior regions of the head on each side of an adult when the patient is relaxing [7]. It appears when closing the eyes and relaxing, and tends to attenuate with open eyes or alerting by any mental exertion.

1.3.2 Beta (β) waves

Its frequency ranges from 14 Hz to about 30 Hz. Beta activity is a “fast” activity and is also called normal rhythm activity. It is usually seen on both sides of the hemisphere in symmetrical distribution and is most evident in the frontal areas. Sedative-hypnotic drugs affect this activity [7]. It may be missing or reduced in regions of cortical damage. It is accentuated in patients who are very anxious or have their eyes open.

1.3.3 Theta (θ) waves

It has a frequency range from 4 to 7 Hz and is classified as “slow” activity. It is found in every person during sleep and in meditation. It can be seen in the state of arousal for adults [7]. Excess theta in adults represents abnormal activity.

1.3.4 Delta (δ) waves

The Delta Waves have a frequency range of up to 4 Hz or below. It is likely to have a higher amplitude but has a low frequency. It is normal as the dominant rhythm in infants of up to one year and stages 3 and 4 of sleep. It is usually more prominent in the frontal part in adults and the posterior part in children [7].

Theta and delta waves are known collectively as slow waves.

1.3.5 Gamma (γ) waves

Its frequency ranges from 30 to 100 Hz. Gamma rhythms represent the binding of an enormous collection of neurons assimilated for carrying out a certain cognitive or motor function [8].

1.3.6 The flow of EEG Waves

The amplitude of EEG signals is very closely related to the level of consciousness of a person [9]. An example of these waves is shown below in **Figure 6**.

From **Figure 6**, the conclusion is drawn that the slow waves Theta and Delta occur in the third and fourth stages of human sleep. The awake condition presents a high level of consciousness with Beta waves. This 90 minutes of the cycle is repeated the whole night with repeated EEG wave activity.

1.4 Artifacts in EEG

The EEG signal is one of those signals which are most widely used for studying brain functions and for the diagnosis of neurological disorders by physicians, researchers, and scientists. A single misinterpretation can become a cause of

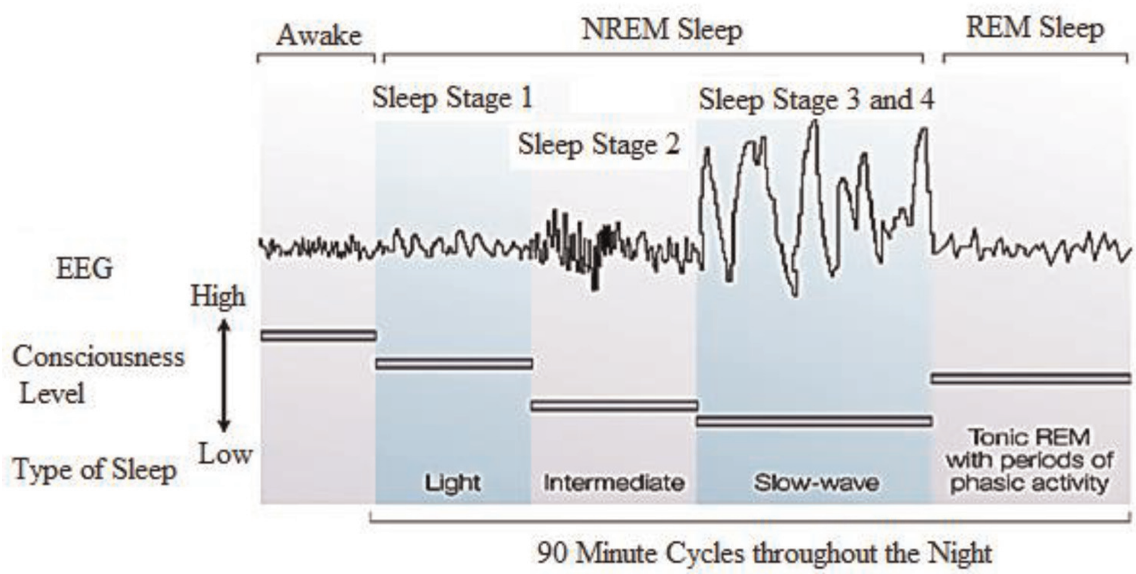

Figure 6.
EEG activity is solely dependent on the level of the subject's consciousness.

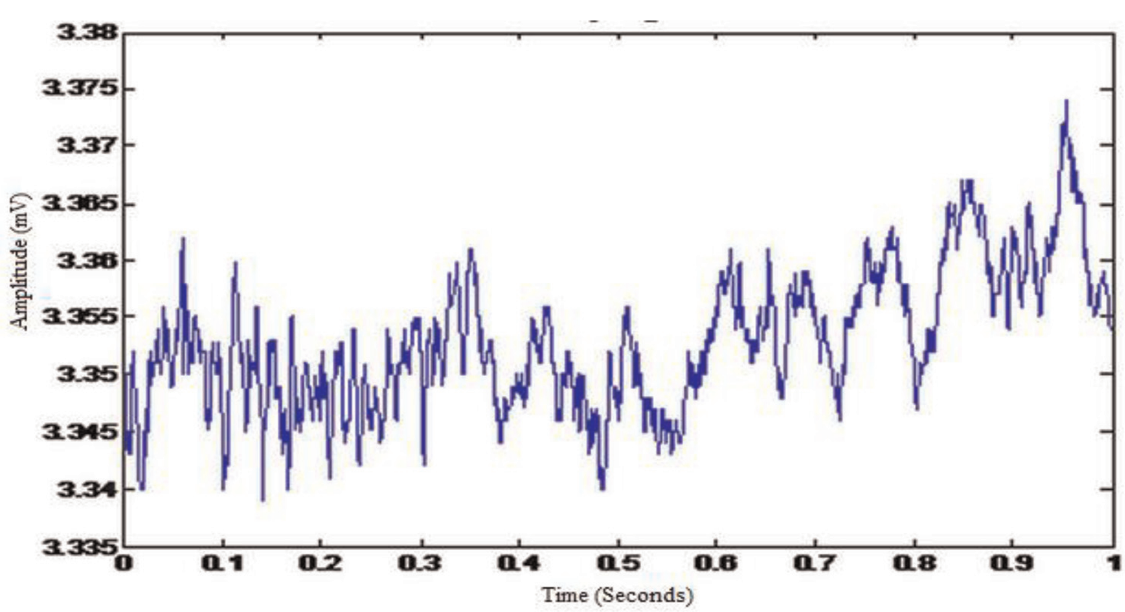

Figure 7.
One second recording of clean pure EEG signal.

misdiagnosis. Henceforth, it is imperative to have a very right and clear image about brain activities being represented by EEG signals shown in **Figure 7**. Skull's low conductivity is the main reason for the poor spatial resolution of scalp EEG.

Furthermore, scalp EEG signals are highly sensitive to the movement of the subject and noises being introduced due to externally likewise human head activation, eye movements, musculature, nearby electrical device interference and because of one's movement conductivity in the electrodes get varies or physicochemical reactions occurred at the electrode sites [6]. Some of the EEG artifacts distributions are displayed in **Figure 8**. All these additional activities are indirectly associated with the subject's current cerebral process and are collectively referred to as background activities. Henceforth, EEG signals are highly enervated and mixed with these non-cerebral

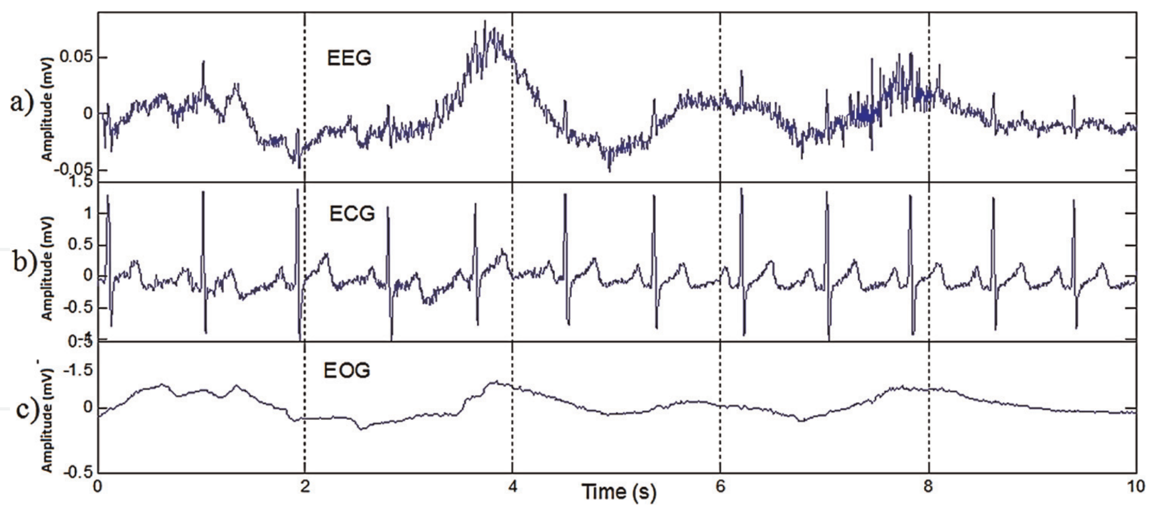

Figure 8.
ECG and EOG artifacts.

impulses known as artifacts or noise. These artifacts or noise fall into two major categories being considered as physiologic and extra-physiologic [5]. Only after removing these artifacts, a true diagnosis can be achieved. Physiologic Artifacts can be produced by any of any sources present in the human body that has an electric dipole or which can generate an electrical or magnetic field that can become a cause of physiologic artifacts.

The following are the types of physiologic artifacts:

- Muscle artifacts
- Glossokinetic artifacts
- Eye blink artifacts
- Eye movement artifacts
- ECG artifacts
- Pulse artifacts
- Respiration artifacts
- Skin artifacts

The following are the types of extra-physiologic artifacts:

- Electrode popping artifacts
- Alternating current artifacts
- Artifacts due to movements in the environment

Some of the most EEG corrupting artifacts are discussed as follows:

1.4.1 Electrooculogram (EOG)

This is mainly used to measure the eye artifacts. Since these measurements are contaminants of EEG signal and so it is not possible to remove this kind of artifacts from the subtraction process only when the exact model of EOG diffusion across the scalp is available [2]. These artifacts are of two types:

I. Eye Blinking.

It is an artifact that is very common in EEG data. This artifact possesses a very high amplitude signal sometimes much greater than the EEG signals of interest. Further, it can corrupt data availed on all electrodes, even those signals too, that are at the back of the head [2].

II. Eye Movement.

It is occurring because of the reorientation of the retained corneal dipole [4]. Eye movement's diffusion across the scalp is greater than that being produced by the eye blink artifact.

EOG artifact can be given in the following form:

$$\beta = \frac{\sum (X_i - \widehat{X}_i)(Y_i - \widehat{Y}_i)}{\sum (X_i - \widehat{X}_i)\text{^}2} \tag{1}$$

where,
β = Estimated EOG present in EEG analysis; X = EOG signal; Y = EEG signal; n = Number of iterations.

1.4.2 Cardiograph (ECG/EKG)

Cardiograph is generally used to measure pulse or heartbeat, which occurs by an electrode on or near a blood vessel as shown in **Figure 8**. The voltage recording changes due to the expansion and contraction of the vessel [2]. The artifact signal generally has frequency proximity to 1.2 Hz and appears as a sharp spike or smooth wave but it can have a variation that solely depends on the state of the patient. An example has been illustrated below where an EEG signal mixed with ECG/EKG signal and got corrupted due to line interference.

Electrocardiogram signal artifacts can represent by using the following equation:

$$\mathrm{ECG}(t) = R \cdot s_m(t) + R \cdot s_f(t) + N(t) \tag{2}$$

Where R is a random unit vector, $s_m(t)$ and $s_f(t)$ are the three components of the dipole model for the maternal and fetal cardiac vectors, respectively and $N(t)$ is the noise in each ECG channel at time t.

1.4.3 Electromyogram (EMG)

Electromyogram (EMG) artifacts could be produced because of some movement disorders. Essential tremor and Parkinson's disease could also be responsible for rhythmic 4–6 Hz sinusoidal artifacts which may be mimicked cerebral activity [2].

Following equation shows the EMG signal:

$$x(n) = \sum_{r=0}^{N-1} h(r)e(n-r) + w(n) \tag{3}$$

Where.

$x(n)$ represents EMG signal;

$e(n)$ point processed, that represent the firing impulse;

$h(r)$ represents the MUAP (Motor Unit Action Potential);

$w(n)$ represents zero-mean additive white Gaussian noise;

and N represents the number of motor unit firings.

Extra-physiologic Artifacts

These include interference due to electrical equipment, kinesiology artifacts because of the human body or movements of electrodes, and mechanical artifact because of human body movement.

1.4.4 Motion artifact

The movement of the patient or even disturbance just during the electrodes settling could become the cause of electrode pops variations of the conduction between electrodes and the skin. Linguistically these signals appear either in the form of single or multiple sharp waveforms due to abrupt variations in the impedance. It can be easily identified by its characteristic appearance and its usual distribution, which is restricted to a single electrode [4]. In usual manners, sharp transients which occur at a single electrode should be considered artifacts, until it has not been proven. **Figure 9a** and **Figure 9b** present the pure EEG signal and motion artifact contaminated EEG signal. **Figure 9b** shows the high amplitude broad spectrum distribution because of motion artifact in the EEG signal.

Figure 9a shows the original EGG signal and (b) represents the motion artifact contaminated EEG signal. **Figure 9b** presented the motion artifacts contamination on the EEG signal.

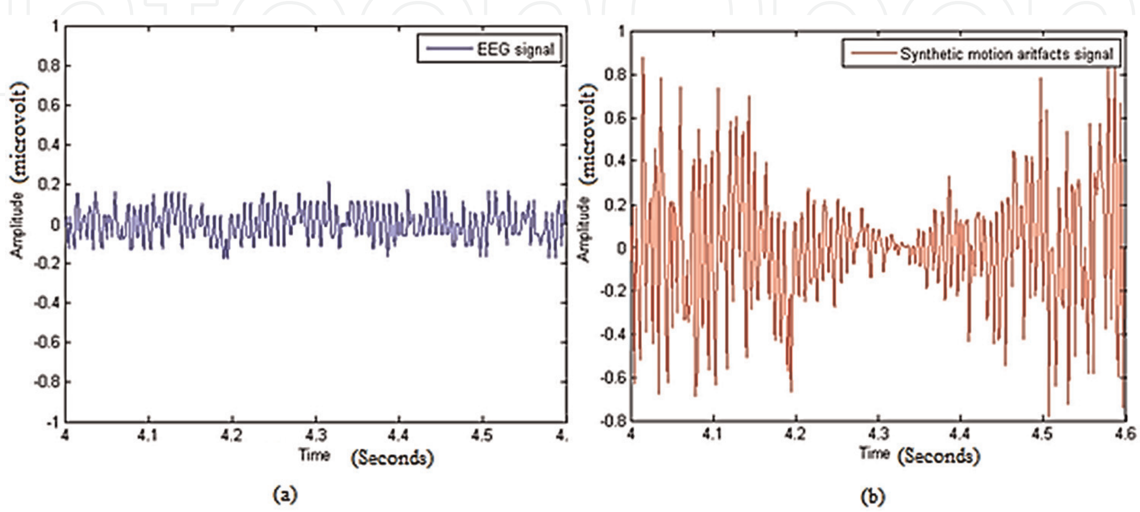

Figure 9.
(a) Original EEG signal (b) EEG signal contaminated with motion artifact.

1.4.5 Power lines

Alternating Currents, ranging from 50 to 60 Hz, that is strong signals from Alternating Current (A/C) power supplies could also corrupt EEG data since it gets transferred to a recording device from the scalp electrodes. Issues co-related to power lines-based artifacts come into the picture when an active electrode has a higher impedance than impedance between the electrodes and the amplifier's ground. In such kinds of scenarios, the amplifier's ground starts to work as an active electrode which solely depends upon its location and implements/generates 50–60-Hz artifact. Usually for removal of these artifact notch filters are used, but still, it could produce a problem of useful information removal, furthermore lower frequency line noise and harmonics are undesirable [10]. If the line noise or harmonics produce in frequency bands of interest it interferes with EEG signals which occur in the same frequency band [9].

Power line noise as shown in **Figure 10** can be presented mathematically as:

$$P(t) = \beta_0 \sin(2\pi * 60 * t) \tag{4}$$

In the above equation β_0 represents power line noise weight.

1.5 De-noising EEG signals

During the recording process, there is always a possibility of occurrence of contamination in EEG data at multiple points. Over which most of the artifacts that occurred here belong biologically generated by sources and are external to the brain. By significant improvement in existing technology, these externally generated artifacts could be removed, thus it is important to study efficient de-noising (a process for noise removal) procedures that would be able to remove these biological overlays from EEG signals. Actual EEG recordings are the summation of artifacts with the pure EEG signal, and can be defined mathematically:

$$E(t) = S(t) + N(t) \tag{5}$$

Where:-.
$S(t)$ is a pure EEG signal,
$N(t)$ is the artifact,
$E(t)$ represents the recorded signal and t is the time when recording has been taken.

The presence of these artifacts introduces spikes that can create issues while reading neurological rhythms. So many methods have been proposed and presented by scientists and researchers to perform the artifacts removal process in EEG.

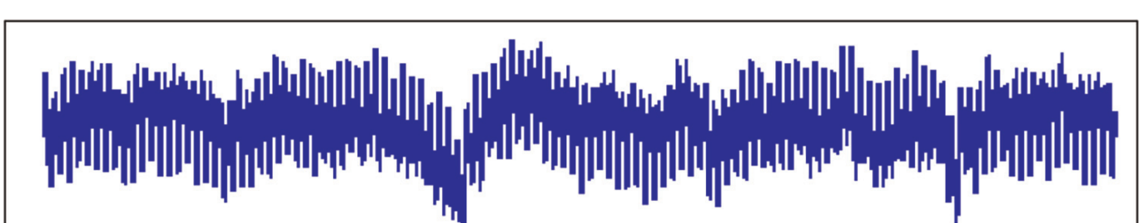

Figure 10.
Line interference of 50 Hz.

1.6 Methods for artifacts removal

To remove artifacts from an EEG recording can be classified into two groups, which are following:

i. Artifact rejection—This method is used for removal of EEG signal that comprises the artifact and

ii. Artifact correction—This method is used for the removal of artifacts from EEG signals while keeping and maintaining the pure EEG signal.

1.6.1 Artifact rejection

1. Basic Artifact Rejection.

The most commonly used de-noising techniques for eliminating all EEG epochs which comprise artifacts larger than some pre-defined threshold EEG voltage level, known as artifact rejection. This method is most commonly and widely used when a limited amount of data or artifacts such as EOG is available. These artifacts occur too frequently in nature that raises elimination of those epochs which are contaminated with the artifacts, which becomes the cause of considerable loss of information and which makes this process impractical for being used in clinical data. As EEG and some artifacts occupy the same frequency band, this method is not that effective [7].

2. Regression Method.

Conventionally artifacts correction processes used a regression-based approach which is based on either time domain or frequency domain [3]. In this method, after a clear measure of artifact signals, it is subtracted from EEG signals and has been recorded. The major issue that comes into existence is bi-directional contamination. As if artifacts potentials are capable of contaminating EEG recordings, then the electrical activity of the brain is also capable of contaminating the artifacts recordings. Henceforth, diminishing a linear combination of the recorded artifacts from the EEG recordings may not only abolish artifacts but also the cerebral activity of interest. Review work for these techniques is discussed in [4, 8].

3. Filtering Method

Low-pass filtering of the artifacts eliminates all high-frequency activity from EOG signal, from both cerebral and ocular origins [7]. Adaptive filtering usage before applying regression correction can substantially reduce issues produced due to bidirectional contamination [3]. However, it is imperative to use adaptive digital filters for artifact removal, which necessitates a suitable reference model for training the filter.

1.6.2 Artifact correction

1. Principal Component Analysis (PCA).

These methods are based on EEG and artifacts decomposition into spatial components, which is inclusive of recognizing artifactual components and reassembling the EEG without those artifactual components that have been recognized, but it is problematic in the case of PCA. The PCA algorithm first decomposes the EEG signals into uncorrelated, but it is not required that these must be independent of each other which are spatially orthogonal and that's why it cannot deal with higher-order statistical dependencies. Furthermore, it is not practically possible to completely separate artifacts from interested brain signals specifically when both of these signals have comparable amplitudes.

The following expression describes principal component decomposition:

$$\beta_1 = \phi_1 X'_0 \tag{6}$$

where,

β_1 is set of first principal component scores whose mean equals to zero;

ϕ_1 represents the first principal component;

$\phi_1 X'_0$ could be considered as a vector or matrix transposition.

By maximizing the variance of$\phi_1 X'_0$, $\phi_1$can be simply calculated as:

$$\phi_1 = \arg\max \mathrm{Var}\left(\phi_1 X'_0\right); \text{where } ||\phi_1|| = 1 \tag{7}$$

$$\phi_1 = \arg\max \phi_1 X'_0 X_1 \phi'_1; \text{where } ||\phi_1|| = 1 \tag{8}$$

Successive principal components can easily be obtained iteratively by demising the first k principal components from X_0, presented as below:

$$X_k = X_{k-1} - X_{k-1}\phi'_k \phi_k \tag{9}$$

Now to find ϕ_{k+1}, X_k has been treated as a data matrix that can be done by maximizing the variance of $\phi_{k+1} X'_k$ using following equation:

$$\phi_{k+1} = \arg\max \mathrm{Var}\left(\phi_{k+1} X'_k\right) \tag{10}$$

Subject to $||\phi_{k+1}|| = \mathrm{sqrt}\left(\sum_{j=1}^{p} \phi_{k+1\,j}^2\right) = 1$ and $\phi_{k+1} \perp \phi_k$for j = 1, 2 ... k.

Alternatively, Singular Value Decomposition (SVD) is the simplest and efficient way that can be applied to find a centered data-matrix X_0, that can be expressed as:

$$X_0 = \mathrm{UDV}' \tag{11}$$

Where $K \leq \min(n, p)$; $U'U = V'V = I_k$;

D is a diagonal matrix with $d_1 > \ldots d_2 > d_k$ on the diagonal.

UD matrix constitutes principal component scores, which are variable coordinates in the case of principal components [3].

2. Independent component analysis (ICA)

This method was developed to handle issues that occurred due to Blind Source Separation, abbreviated as BSS to form the components which must be as independent as possible [8] and can be represented mathematically:

$$X = A\,s + n \tag{12}$$

Where X is the observed signal, n is the noise, A is the mixing matrix, and s is the independent components (ICs) or sources. To find linear transformation W of X, for determining the independent outputs as:

$$u = W\,X = W\,As \tag{13}$$

Where u is the estimated ICs and it is highly required that components must be statistically independent instead of a mixture.

After a thorough investigation and deep analysis and research work conclusion has been drawn that ICA provides much better results for de-noising [6]. A whole chapter has been devoted to describing ICA, which belongs to existing work in Single-Stage Artifact Removal Algorithm.

3. Canonical correlation analysis (CCA)

This algorithm has been developed by H. Hotelling and is considered as a way to measure the linear relationship between two multidimensional variables. It detects two bases with the correlation matrix between the variables of interest that are in diagonal form and the correlations on the diagonal get maximized, in such a way that the dimensionality of these new bases is either less than or equal to the smallest dimension of the two variables [5].

Canonical correlation analysis (CCA) is first proposed by Hotelling. CCA is an algorithm for the determination of the linear association between two set variables. This is done with the help of the variance and covariance matrix of the data [6].

A set of linear combinations named A and B are considered as:

$$A_P = [a_{11}, a_{12}, \ldots ..a_{1m}]^T \tag{14}$$

$$B_Q = [b_{11}, b_{12}, \ldots ..b_{1n}]^T \tag{15}$$

Let C_{pp} and C_{qq} be the variance of the A_p and B_Q respectively and C_{pq} is the covariance between A_P and B_Q. Then the above equation can be rewritten as:

$$P^* = \frac{A_p^T C_{pp} B_Q}{\sqrt{A_p^T C_{pp} A_p}\sqrt{B_q^T C_{qq} B_q}} \tag{16}$$

This P^* should be maximum to achieve the best self-correlation. Therefore, this optimization can be solved by

$$C_{pp}^{-1} C_{pq} C_{qq}^{-1} C_{qp} A_P = \rho A_P \tag{17}$$

$$C_{qq}^{-1} C_{qp} C_{pp}^{-1} C_{pq} B_Q = \rho B_Q \tag{18}$$

This ρrepresents the Eigenvalue which is equal to the square of P^*.

$$\rho = \sqrt{P^*} \tag{19}$$

This canonical pair will be calculated and separated by calculating self-correlation and a mutual decorrelation between input sources.

4. Wavelet transform

Wavelet Transform (WT) has good localization properties in the time and frequency domain [6], and so it is a widely accepted and successful method being used for de-noising [11]. Currently, so many approaches are available at the algorithmic level to de-noise using Wavelet Transform, which is mainly based on shrinkage, where the EEG signals get decomposed in the form of wavelets and then noise removal is performed using shrinkage and thresholding. The quality of Wavelet Transform in transforming a time-domain signal into time and frequency localization assists in comprehending the signal's behavior in a much better way.

The Wavelet Transform could be defined as the following equation, which is the inner product or cross-correlation of $\{x_n[m]\}$ signal with scaled and time-shifted wavelet $\Psi a,b[m]$, that is:

$$WT_{x_n}[a,b] = \left(x_n, \psi_{a,b}\right) \tag{20}$$

where,

$$\psi_{a,b}[m] = |a|^{-\frac{1}{2}}\psi^{\frac{m-b}{a}}$$

a—Scale parameters.
b—Translation parameters.
$\psi_{a,b}[m]$ - Appropriate wavelet function.

5. Empirical mode decomposition

Empirical mode decomposition is a non-linear method to represent a non-stationary signal into the sum of zero-mean sub-components. This method decomposes a signal into several intrinsic mode functions through an iterative method known as sifting. At the first level, the Intrinsic Mode function (IMF1) is the mean of the upper and lower envelop of the original EEG signal x(t). Then the residual signal is obtained by subtracting IMF1 from x(t). This process is iterated till the stopping criterion is fulfilled (Residual signal energy content is close to zero). The remaining residual signal is

$$P_n(t) = P_{n-1}(t) - IMF_n(t) \tag{21}$$

where, $P_n(t) = x(t)$.
Finally, the signal is reconstructed by adding all IMFs and residual signals as

$$x(t) = P_n(t) + \sum_{i=1}^{N} \mathrm{IMF}_i(t) \tag{22}$$

The method of detecting IMFs is sensitive to the amalgam of undesired signal components present in surroundings. These noises affect the EMD process. Thus, mode mixing is used to overcome the disparate scale oscillations with amplitude in the near range of the IMFs peaks which can be available randomly in the whole dataset. Consequently, a more powerful and noise-assisted version of the EMD algorithm was presented termed as Ensemble Empirical Mode Decomposition (EEMD), which solves this mode mixing quandary and employs the average value of EMD ensembles that filters out the IMFs for the given signal. Moreover, this method also depends on the added noise amplitude to the input signal and the number of trials [6, 9].

6. Conclusion

In this Chapter, Electroencephalograph Signals and their generation process have been discussed; the EEG signal has been compared with fMRI and PET signals. The classification of the EEG signals on the amplitude, frequency, and shape have been elaborated in wave analysis of EEG, and applications of these components are presented.

The artifacts of EEG have been explained in detail. There are two main types of artifacts to be considered; namely, physiological and non-physiological artifacts. Non-physiological contain artifacts such as movement artifacts, electrode pop artifacts, sweat artifacts, and 50/60 Hz noise. Typically, these artifacts are not explicitly monitored, and as such, they need to be filtered out by their characteristics alone. For example, sweat artifacts tend to be of really low frequency, 50/60 Hz noise is contained within a narrow frequency band, and electrode pop artifacts are not necessarily time-aligned in two corresponding electrodes on the two sides of the scalp. Physiological artifacts take the form of ocular artifacts, cardiac artifacts, muscle artifacts, glossokinetic artifacts, and respiratory artifacts. Most of these artifacts can be monitored with another channel, which in turn can be used during the EEG artifact removal.

Subsequently, artifact removal methods have been classified in the form of artifact correction and artifact rejection. The artifact rejection comprises Regression and filtering as the main method. Whereas, artifact correction method comprises Principal Component Analysis (PCA), Independent Component Analysis (ICA), Canonical Correlation Analysis (CCA), Wavelet Transform (WT), and Empirical Mode Analysis (EMD). These all single-stage artifact removal methods and their implementation with results are discussed in the subsequent chapter.

Conflict of interest

The authors declare no conflict of interest.

Author details

Vandana Roy
DoEC, GGITS, Jabalpur, India

*Address all correspondence to: Vandana.roy20@gmail.com

References

[1] McMenamin BW, Shackman AJ, Greischar LL, Davidson RJ. Electromyogenic artifacts and electroencephalographic inferences revisited. Neuroimage. 1 Jan 2011;**54**(1): 4-9. DOI: 10.1016/j.neuroimage.2010.07.057. Epub 2010 Aug 2. PMID: 20981275; PMCID: PMC2962711

[2] Sweeney KT, McLoone SF, Ward TE. The use of ensemble empirical mode decomposition with canonical correlation analysis as a novel artifact removal technique. IEEE Transactions Biomedical Engineering. 2013;**60**(1):97-105. DOI: 10.1109/TBME.2012.2225427. Epub 2012 Oct 18. PMID: 23086501

[3] Zeng H, Song A, Yan R, Quin H. EOG artifact correction from EEG recording using stationary subspace analysis and empirical mode decomposition. Sensors. 2013;**13**:14839-14859

[4] Soomro MH, Badruddin N, Yusoff MZ. Comparison of blind source separation methods for removal of eye blink artifacts from EEG. 2014 5th International Conference on Intelligent and Advanced Systems (ICIAS). 2014; **2014**:1-6. DOI: 10.1109/ICIAS.2014.6869470

[5] Liu Q, Liu A, Zhang X, Chen X, Qian R & Chen X. Removal of EMG artifacts from multichannel EEG signals using combined singular spectrum analysis and canonical correlation analysis. Journal of Healthcare Engineering. 2019: 4159676. DOI: 10.1155/2019/4159676

[6] Anastasiadou M, Hadjipapas A, Christodoulakis M, Papathanasiou ES, Papacostas SS, Mitsis GD, Detection and removal of muscle artifacts from scalp EEG recordings in patients with epilepsy, In: IEEE (14th) international conference on bioinformatics and bioengineering (BIBE). US: Boca Raton; 2014. pp. 291–296

[7] Sweeney KT, McLoone SF, Ward TE. The use of ensemble empirical mode decomposition with canonical correlation analysis as a novel artifact removal technique. IEEE Transactions Biomedical Engineering. 2013;**60**:97-105. DOI: 10.1109/TBME.2012.2225427. Epub 2012 Oct 18. PMID: 23086501

[8] Soomro MH, Badruddin N, Yusoff MZ, Jatoi MA, Automatic eye-blink artifact removal method based on EMD-CCA, In: International Conference on Complex Medical Engineering (ICME). 2013. pp. 186–190. DOI: 10.1109/ICCME.2013.6548236

[9] Roy V, Shukla S. Designing efficient blind source separation methods for EEG motion artifact removal based on statistical evaluation. Wireless Personal Communication. 2019;**108**:1311–1327. DOI: 10.1007/s11277-019-06470-3

[10] Xun C, Chen H, Hu P. Removal of muscle artifacts from single-channel EEG based on ensemble empirical mode decomposition and multiset canonical correlation analysis. Journal of Applied Mathematics. 2014;**2014**:10. Article ID: 261347. DOI: 10.1155/2014/261347

[11] Roy V, Shukla S. A methodical health-care model to eliminate motion artifacts from big EEG data. Journal of Organizational and End User Computing. 2017;**29**(4):84-102. DOI: 10.4018/JOEUC.2017100105