Artifact suppression and analysis of brain activities with electroencephalography signals

Md. Rashed-Al-Mahfuz¹, Md. Rabiul Islam¹, Keikichi Hirose², Md. Khademul Islam Molla²,³

Abstract
Brain-computer interface is a communication system that connects the brain with computer (or other devices) but is not dependent on the normal output of the brain (i.e., peripheral nerve and muscle). Electro-oculogram is a dominant artifact which has a significant negative influence on further analysis of real electroencephalography data. This paper presented a data adaptive technique for artifact suppression and brain wave extraction from electroencephalography signals to detect regional brain activities. Empirical mode decomposition based adaptive thresholding approach was employed here to suppress the electro-oculogram artifact. Fractional Gaussian noise was used to determine the threshold level derived from the analysis data without any training. The purified electroencephalography signal was composed of the brain waves also called rhythmic components which represent the brain activities. The rhythmic components were extracted from each electroencephalography channel using adaptive wiener filter with the original scale. The regional brain activities were mapped on the basis of the spatial distribution of rhythmic components, and the results showed that different regions of the brain are activated in response to different stimuli. This research analyzed the activities of a single rhythmic component, alpha with respect to different motor imaginations. The experimental results showed that the proposed method is very efficient in artifact suppression and identifying individual motor imagery based on the activities of alpha component.

Key Words
neural regeneration; brain activity; brain waves; data adaptive filtering; electroencephalography; electro-oculogram artifact; topographic mapping; Wiener filtering; neuroregeneration

Research Highlights
(1) Electroencephalography is a convenient tool used to monitor brain activities and for psychophysiological research. Electro-oculogram is a dominant artifact which has a significant negative influence on further analysis of real electroencephalography data. The perfect separation of electro-oculogram artifact from the raw electroencephalography data is a crucial step for the application of brain-computer interface.
(2) A novel data adaptive filtering technique is introduced to suppress the electro-oculogram artifact without any loss of original electroencephalography data. Different frequency filtering-based approaches are already proposed to remove the artifacts. Such types of filtering destroy electroencephalography information and hence decrease the performance in brain computer interface applications. The proposed energy based adaptive thresholding method performs electro-oculogram removal without any training phase.
(3) A Wiener filter based approach is developed to separate the alpha rhythm which potentially represents brain activity. Thus the Wiener filter based adaptive filtering enhances the detection rate of brain activity.
The electroencephalography signals recorded from the scalp surface are usually contaminated by the external interferences such as electric power or other electromagnetic radiation sources. It is easy to split such types of interfering signals from electroencephalography signals depending on their electrical characteristics. The human body contains multiple electrophysiological signal sources which produce non-linear and non-stationary signals and such signals are treated as artifacts with respect to the targeted electroencephalography. The mixing process of the artifacts is also considered non-linear. Electro-oculogram has the largest potential to contaminate the recorded electroencephalography signal. It is a serious obstacle to many neuroscience experiments including the application for brain-computer/machine interface [17-23]. In topological mapping, the true energy of the electroencephalography signal is very important. The artifacts produced by non-neural sources distort the electroencephalography signals and hence the actual topological mapping of the brain is not possible unless we suppress the artifacts [24].

A number of scholars have turned to independent component analysis to project the recorded electroencephalography data into statistically independent components using higher order statistics [25-29]. It is not always guaranteed that the extracted components will accurately correspond to the artifacts and purify the electroencephalography signals. Another problem of using independent component analysis is that the extracted components do not confirm the original scale and sequences. The adaptive filtering is another powerful method to suppress the artifacts from the electroencephalography signals [30], whereas, it introduces some spectral distortion of the expected electroencephalography signal which is harmful for further applications. Recently, empirical mode decomposition and bivariate empirical mode decomposition are employed as data adaptive filtering to separate the electro-oculogram artifacts [31-32]. The bivariate empirical mode decomposition requires higher computational cost. Empirical mode decomposition instead of bivariate empirical mode decomposition is employed in this paper to suppress the electro-oculogram artifacts from recorded electroencephalography signals. The electro-oculogram signals are considered as low frequency and high energy trend in the recorded electroencephalography signals. A

**INTRODUCTION**

Electroencephalography is a test to measure the electrical activity of the brain generated by scalp surface after being picked up by metal electrodes and conductive media. Proper classification of electroencephalography data is the main task in electroencephalography based brain computer interface. Such interface transforms neural activities into signals to establish a new mode of communication which can be used by subjects with severe motor disabilities [1-6].

Electrical brain activity can be mapped like an image on the surface of human scalp. The mapping of the human brain activity over the scalp corresponds to the spatial activities of different brain waves represented by the spectrogram. The electroencephalography signals of the imaginary left and right hand movements are used here. For better discrimination of electroencephalography signals during the imaginary left and right hand movements, optimal electrode position and frequency components are necessary [7-8].

Functional MRI is a technique for measuring brain activity by detecting the changes in blood oxygenation and blood flow that occur in response to neural response. It can be used to produce activation maps showing which parts of the brain are involved in a particular mental process. Although functional MRI has good spatial resolution it suffers from low temporal resolution as well as some biological disadvantages due to a powerful magnetic field [10-13]. While the strong static magnetic field has no known long-term harmful effect on biological tissue, it can cause damage by pulling in nearby heavy metal objects converting them to projectiles. On the other hand, it is easy to capture neural activities through electroencephalography. It has very good temporal resolution, whereas, the spatial resolution is limited by the number and placement of electrodes on the scalp. The combined investigation of electroencephalography and functional MRI makes use of the advantages of these two methods, high spatial (functional MRI) and time (electroencephalography) resolution to advance the investigation of brain function [14-16]. The electroencephalography signal obtained simultaneously with functional MRI is highly distorted by technical and biological artifacts.

(4) The topographic brain map is derived to monitor the spatial activities of the alpha wave yielding the classification of different motor imaginations.
The second part of this paper is the topographic analysis of the regional brain activities on the basis of the brain waves (rhythmic components) extracted from the purified electroencephalography signals. In applied clinical neurophysiology, the topographic mapping of electrical brain activity has been popular over the last two decades\[33-35\]. Neural activity in the brain measured by frequency analysis and topographical mapping of the electroencephalography signals is useful when CT scan or other brain imaging methods are not able to detect the defects\[34\]. The perfect extraction of the rhythmic components is the key issue for proper topographic analysis\[36-39\]. Different techniques of rhythmic component extraction are employed based on the classification algorithms used in topographic studies\[33-36\]. We chose the data adaptive Weiner filter to extract the rhythmic components from the electroencephalography signals. Only the alpha rhythm (brain wave) is taken into consideration for topographical mapping of regional brain activities.

MULTIBAND REPRESENTATION OF ELECTROENCEPHALOGRAPHY WITH EMPIRICAL MODE DECOMPOSITION

The principle of the empirical mode decomposition technique is to decompose a signal $s(t)$ into a set of band-limited functions $C_m(t)$ called intrinsic mode functions. Each intrinsic mode function is considered as a AM-FM oscillatory component satisfying two basic conditions: (i) in the whole data set, the number of extrema and the number of zero crossings must be the same or differ at most by one, (ii) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The first condition is similar to the narrow-band requirement for a stationary Gaussian process and the second condition is a local requirement induced from the global one, and is necessary to ensure that the instantaneous frequency will not have redundant fluctuations as induced by asymmetric waveforms. However, a special “sifting” process is employed to extract all of the intrinsic mode functions and this sifting process is described as follows. Firstly, the upper and lower envelopes of the signals $s(t)$, as well as their mean value $\mu(t)$, are calculated respectively. The first step of the sifting process is to calculate the difference $h_1(t) = s(t) - \mu_1(t)$. However, $h_1(t)$ rarely satisfies the two intrinsic mode function properties and is not taken as the first intrinsic mode function of the signals straightway. Therefore, the sifting usually has to be implemented for more times, where the “difference” obtained in the previous sifting is taken as “signals” in present sifting. If after $(d+1)$ sifting, corresponding difference, $h_d(t) = h_{d-1}(t) - \mu_d(t)$, satisfies the intrinsic mode function properties, then it can be taken as the first intrinsic mode function component, denoted by $C_1(t)$, that is, $C_1(t) = h_d(t)$. In practice, to determine whether or not $h_d(t)$ well satisfies the intrinsic mode function properties, we usually use so-called standard deviation ($\delta$) criterion, i.e., to check if the following inequality holds\[40\].

$$\delta_s = \frac{\sum_{i=1}^{T} |h_{d-1}(t) - h_d(t)|^2}{\sum_{i=1}^{T} |h_{d-1}(t)|^2} \leq \eta, \quad (1)$$

where $T$ is the frame length and $0.2 \leq \eta \leq 0.3$. Next, taking residual data $r_1(t) = s(t) - C_1(t)$ as “new” signals and implementing the sifting process on it, we can obtain the second intrinsic mode function $C_2(t)$. This procedure should be repeatedly used for $M$ (total number of intrinsic mode function components) times until the last residue $r_M(t)$ becomes a monotonic function. At the end of the decomposition, the signal $s(t)$ is represented as

$$s(t) = \sum_{m=1}^{M} C_m(t) + r_M(t) \quad (2)$$

where $C_1(t), C_2(t), \ldots, C_M(t)$ are all of the intrinsic mode functions included in the signals and $r_M(t)$ is a negligible residue.

Another method used to explain how empirical mode decomposition works is that it first extracts out the highest frequency oscillation that remains in the signal. Thus locally, any intrinsic mode function contains a lower frequency component than the order immediately lower than it. Being data adaptive, the basis usually offers a physically meaningful representation of the underlying processes. There is no need to consider the signal as a stack of harmonics and, therefore, empirical mode decomposition is ideal for analyzing non-stationary and nonlinear data.

Each intrinsic mode function is considered as a mono-component contribution such that the derivation of instantaneous amplitude and frequency provides a physical significance. The advantage of this time-space filtering is that the resulting band passed signals preserve the full non-stationary property in physical
space. This filtering method is intuitive and direct, its basis is a posteriori and data adaptive. The completeness of the decomposition is given by the equation (2). The empirical mode decomposition of a fractional Gaussian noise and recorded electroencephalography data is shown in Figure 1.

\[
\zeta(t) = \sum_{k=1}^{K} c_k(t) \quad (3)
\]

where \( K \) is the largest intrinsic mode function index prior the remaining intrinsic mode functions representing signal trend contamination. The intrinsic mode functions \( c_k(t); k = 1, 2, ..., K \), represent relatively higher frequency oscillations \( i.e. s(t) = h(t) \). The optimized \( k = K \) is chosen when the energy at index \( k \) departs significantly from the energy of the reference signals\([40]\). The ending index of the intrinsic mode function to separate the high frequency components of the electroencephalography signal (representing purified electroencephalography) is determined by comparing the intrinsic mode function energy with that of the reference signal. The fractional Gaussian noise is used here as the reference signal. The energies of the intrinsic mode functions of fractional Gaussian noise are computed and then its upper and lower limits of 95% confidence interval are derived. There exists an intrinsic mode function of electroencephalography signal say, \( n^{th} \) one which exceeds that upper confidence limit. Then the \((n-1)^{th}\) intrinsic mode function is selected as the upper bound of the high frequency oscillatory components. All the lower order intrinsic mode functions (of recorded electroencephalography signal) up to \((n-1)^{th}\) are summed up to construct the high frequency \( h(t) \) representing the purified electroencephalography signal. Then low frequency (and high energy) trend \( y(t) \) representing electro-oculogram artifact is obtained as:

\[
y(t) = s(t) - h(t) \]

**SUPPRESSION OF ELECTRO-OCULOGRAM ARTIFACTS**

As a preprocessing stage, the low frequency and high energy signal components representing electro-oculogram are suppressed from the recorded electroencephalography. The analyzing electroencephalography signal \( s(t) \) consists of a slowly varying trend (electro-oculogram) superimposed to a high frequency fluctuating process \( h(t) \), and the trend is expected to be captured by intrinsic mode functions of large indices (plus the final residue)\([40]\). A process of detrending \( s(t) \), which corresponds to estimating \( h(t) \) relates to the computation of the partial, fine-to-coarse, reconstruction.

**Empirical mode decomposition based electro-oculogram suppression algorithm**

The algorithm for separating electro-oculogram artifacts using empirical mode decomposition based data adaptive threshold technique is given below:

1. Apply empirical mode decomposition on the fractional Gaussian noise and then compute \( \log_2 \) (energy) of individual intrinsic mode function and its upper and lower bound of 95% confidence interval.
2. Apply empirical mode decomposition on the recorded electroencephalography.
3. Compute the \( \log_2 \) energies of its intrinsic mode functions.
4. Find the intrinsic mode function (obtained from electroencephalography) with energy exceeding the upper limit of 95% confidence interval derived in step 1 say it is the \( n^{th} \) intrinsic mode function. The selected nth (in Figure 2, \( n = 7 \)) intrinsic mode function is the starting index to reconstruct electro-oculogram signal.
5. The electro-oculogram artifact is separated by
summing up the intrinsic mode functions starting from nth up to the residue of electroencephalography signals.

It is observed in Figure 3 that the 7th intrinsic mode function is the first intrinsic mode function that exceeds the upper limit of confidence interval and the total number of intrinsic mode function is 12. The 7th intrinsic mode function is the starting point of lower frequency components. The electro-oculogram is separated by summing the intrinsic mode functions 7 to 12 as well as the residue. By subtracting electro-oculogram from raw electroencephalography, we get the purified electroencephalography that reflects the actual neural activities. The electro-oculogram suppression results for a single channel of recorded electroencephalography are illustrated in Figure 2 in which the separated electro-oculogram and purified electroencephalography signals are shown in the second and third rows respectively.

RHYTHMIC COMPONENTS EXTRACTION

The rhythmic components are extracted from the purified electroencephalography signal by using Wiener filter. It has already provided acceptable solution in a wide range of application on biomedical signal analysis. In the minimum mean square error sense, Wiener filter provides optimal filtering with the knowledge of the statistical properties of the signal and noise. The signal and noise are assumed uncorrelated with each other. The coefficients of a Wiener filter are calculated to minimize the average distance between the filter output and a desired signal.

The sequential steps of calculating the coefficient vector $\mathbf{b}$ are illustrated by equation (4) to equation (12). The filter is taken as the input signal $h(t)$, and produces an output signal $\beta(t)$, where $\beta(t)$ is the minimum mean square error estimate of the rhythmic component say $x(t)$. The filter input-output relation is given by

$$\beta(t) = \sum_{i=0}^{T-1} b(i) h(t - i) \quad (4)$$

And the mean square error of estimation is given by

$$E[e^2(t)] = E[x(t) - \beta(t)]^2 \quad (5)$$

It will be minimum with respect to $b(0), b(1), \ldots, b(T-1)$. The expanded form of equation (5) is expressed as

$$E[e^2(t)] = E\left[ x(t) - \sum_{i=0}^{T-1} b(i) h(t - i) \right]^2 \quad (6)$$

To get the optimal estimation corresponding minimization is given by

$$\frac{\partial E[e^2(t)]}{\partial b(j)} = 0 \quad j=0, 1, \ldots, T-1 \quad (7)$$

It can be written as

$$E\left[ x(t) - \sum_{i=0}^{T-1} b(i) h(t - i) \right] h(t - j) = 0 \quad (8)$$
where,  \( j = 0, 1, 2, \ldots, T-1 \). From equation (8) we get,
\[
\sum_{i=0}^{T-1} b(i) R_{x_j}(j-i) = R_{x_j}(j) \quad j=0, 1, \ldots, T-1
\]  (9)

The minimum mean square error Wiener filter is obtained from equation (9) and in matrix form it is given by
\[
R_{HH} b = r_{XH}
\]  (10)

or, equivalently,
\[
b = R_{HH}^{-1} r_{XH}
\]  (11)

In an expanded form, the Wiener filter solution equation (11) can be written as
\[
\begin{pmatrix}
b_0 \\
b_1 \\
b_2 \\
\vdots \\
b_{T-1}
\end{pmatrix} =
\begin{pmatrix}
r_{xx}(0) & r_{xx}(0) & r_{xx}(2) & \cdots & r_{xx}(T-1) \\
r_{xx}(1) & r_{xx}(0) & r_{xx}(2) & \cdots & r_{xx}(T-2) \\
r_{xx}(2) & r_{xx}(0) & r_{xx}(2) & \cdots & r_{xx}(T-3) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
r_{xx}(T-1) & r_{xx}(T-2) & r_{xx}(T-3) & \cdots & r_{xx}(0)
\end{pmatrix}
\begin{pmatrix}
r_{uu}(0) \\
r_{uu}(T-1)
\end{pmatrix}
\]  (12)

The coefficient vector \( b \) obtained from equation (12) is used to filter the desired frequency components.

Before going to extract rhythmic components from real electroencephalography signal using Wiener filter, it is better to test its efficiency with synthetic signals. To evaluate the performance, we have considered two synthetic signals-sine wave and fractional Gaussian noise and its mixture as shown in Figure 4. Then the separation result of the target sine eave from mixture is shown in Figure 5.

The synthetic fractional Gaussian noise (fGn) of 1 second length is generated to extract the rhythmic components-delta, theta, alpha, beta and gamma using fast Fourier transform based bandpass filter. In Wiener filtering, the reference signal is required to extract the target signal from the mixture. The fractional Gaussian noise is a generalization of white noise without any dominant frequency band. The extracted components will be used as the reference signals to separate the target components from purified electroencephalography. The top panel shows the synthetic fractional Gaussian noise of 1 second length and the other panels illustrate the rhythmic components. sec: Second.
Thus generated rhythmic components are used as the reference signals for the extraction of brain waves from real electroencephalography signals using Wiener filter to investigate regional brain activities.

**EXPERIMENTAL RESULTS**

Electroencephalography signals are recorded (in Advanced Brain Signal Processing Laboratory, Riken, Japan) from head scalp and electrodes were connected to the head channels C1, C2, C3, C4, C5, C6, T7, T8, CP1, CP2, CP3, CP4, CP5 and CP6 as in extended 10/20 electroencephalography recording systems with sampling rate at 0.5 kHz. The spatial distribution of the electrodes on the scalp in 10/20 electroencephalography system is illustrated in Figure 7.

Four healthy male subjects participated in the recording of such brain responses and fourteen electrodes were used to record the electroencephalography signal. These subjects were graduate students of around 25 years old, working in the field of computational neuroscience. In the experiments, the subjects were asked to perform three events – relaxing session, imagination of left and right hand movements to take place. A preliminary training was provided to the subjects to perform such an imagination. The suitable visual stimuli were used to instruct the subjects to perform those movement imaginations during the experiment. Between left and right hand movement imagination, the subject was also instructed to relax for certain time. For a single trial, the total length of the epoch was 82 seconds. The first 10 seconds was allotted for relaxing session. The imaginary hand movement stimulus was started at 10 seconds and finished at 14 seconds. At 3 minutes after relaxing session, the subject was instructed by visual stimuli to imagine right hand movement for four seconds. There were total five imaginary left hand movements and five imaginary right hand movements. The recorded electroencephalography signals were preprocessed to suppress the electro-oculogram artifacts and then the rhythmic components (brain waves) were extracted for topographic mapping of regional brain activities.

**Electro-oculogram suppression**

The electro-oculogram artifact was a potential obstacle in further processing of the electroencephalography signals. It was manifested as high energy trend in the recorded electroencephalography data. Efficient suppression of this artifact was achieved by applying the proposed data adaptive algorithm described in section "empirical mode decomposition based electro-oculogram suppression algorithm". The recorded raw electroencephalography, separated electro-oculogram and the corresponding purified electroencephalography signals are shown Figure 8. Although 14 channels were used in electroencephalography recording, only the first seven channels (C1, C2, C3, C4, C5, C6, T7) were illustrated here for better visualization. It is noticed that the electro-oculogram artifacts as well as the electroencephalography were properly separated from the recorded raw electroencephalography.
Extraction of rhythmic components

The analysis of the Wiener filter using the synthetic signals confirms that its performance was satisfactory enough when a priori information of the desired signal was available. The rhythmic components (brain waves) extracted from purified electroencephalography signals were performed using data adaptive Wiener filter.

The extracted (from electroencephalography) brain waves and their Fourier spectra are illustrated in Figure 9 and Figure 10 respectively. It is observed from the spectral representation that the energy of extracted individual rhythmic component was occupied only within the specified frequency ranges. It confirms the perfect extraction of the brain waves.

The best known and most extensively studied rhythm of the human brain is the alpha (8–12 Hz). It is well known that alpha can be usually observed better in the posterior and occipital regions of the head on both sides in comparison to other regions and it emerges with closing of the eyes and with relaxation, and attenuates with eye opening or mental exertion. The alpha rhythm has been classified into at least three groups: occipital alpha rhythm, Rolandic µ rhythm[41], and so-called third rhythm[42]. Because of different locations of these alpha rhythm generators, the spatial distribution of alpha source would provide information about the state of the subject. The alpha brain wave was associated with a completely relaxed body and mind. This rhythm was generally related with above average levels of creativity.

Moreover, it mostly improves one’s natural ability to passively absorb large amount of information. Due to such distinguished characteristics of alpha wave, we analyzed the activity map of alpha rhythm by which the electrodes were activated even in relaxed mood. The extracted alpha components from the 14-purified electroencephalography channels are illustrated in Figure 11. The data 2 seconds in length are illustrated here for better visualization. Thus extracted alpha rhythm was used to represent the regional brain activities with topographic mapping.

Topographical mapping of brain activity

The scalp topography map was used to characterize electrical brain activity quantitatively in terms of neural response strength, and scalp location. For a two-dimensional display, the signals of alpha rhythmic components (extracted from purified electroencephalography signals) are transformed to images of the electrical landscape of brain activity for given frequencies. In a similar way, the results of frequency analysis of the extracted rhythmic component
can be displayed. In the results of topographical transformations, the scalp distribution of brain activity is shown in the relaxing session, imaginary right hand and left hand movements for given frequencies. Such functional imaging is very susceptible to state changes, processing demands of the organism and sequences of neuronal activation patterns can be characterized non-ambiguously. Figure 12 shows the topographical brain map for the alpha band during relaxing session. The 10/20 electroencephalography electrode map (shown in Figure 7) was used here to illustrate the topographic mapping.

The comparison of scalp distribution fields of power at a given frequency is employed to test which electrodes are more activated during relax, left-hand and right-hand movement.

In Figures 12–14, each color trace represents the spectrum of the activity of alpha rhythmic component in one data channel. The leftmost scalp map in Figure12 shows the scalp distribution of power at 8.8 Hz, in which alpha band is concentrated on electrode C1, C3, C5, and T7. The other scalp maps (Figure 12) indicate the distribution of power at 9.8 Hz, 11.2, 12.2 and 13.2 Hz. At the frequency range 8–11 Hz, the alpha wave is more active in central region of left hemisphere (C1, C3, C5 and T7). In the higher frequency range 11–13 Hz, the alpha energy is concentrated in central-parietal region of right hemisphere (CP2, CP4 and CP6).

In the overall observation of the scalp maps, the electrodes CP2, CP4, CP6 in the right hemisphere are the channels at which the powers of alpha rhythmic components are maximal prominent during relaxing session at a frequency of 11–13 Hz. Similar experiments are shown in Figures 13 and 14 for left hand and right hand movements respectively. We observed that the brain region of electrode positions C1, C3, C5, CP1 and CP3 in the left hemisphere was more activated for alpha band of imaginary left hand movement at a lower frequency 8–10 Hz. The electrodes C2, C4, CP2 and CP4 in the right hemisphere are more activated during right hand movement at high frequency alpha (11–13 Hz).

Topographical brain maps for alpha band during relax mode, imaginary left-hand and right-hand movement for four subjects are shown in Figure 15. We observed from the left trace (Figure 15) where electrodes of the posterior head surface are more activated until 10 seconds can predict the relax-mode. After 10 seconds the subject was instructed to imagine left hand movement where electrodes of left-hemisphere of the head scalp are more activated (middle trace in Figure 15) that can guess imaginary left hand movement of the subjects. After 10 seconds of imaginary left hand movement, the subjects were instructed to imagine right hand movement for 6 seconds where the electrodes of right hemisphere of the head scalp are more activated (right trace in Figure 15). In the relaxed mode, the alpha wave was more active in back region, whereas, the mu rhythm was active in the central area of the head. It is noted that a prominent mu wave was realized with the motor activity related to visualization.
**Figure 12** Topographical map of brain for alpha rhythm for relax event. The individual color line indicates the energy contributed by alpha wave to each electrode. The color bar represents the power intensity to illustrate the topological brain map in which red and blue represent highest and lowest power respectively considering the scale of red > yellow > green > blue. ‘L’ and ‘R’ indicate left and right hemispheres respectively; ‘*’: multiplication.

**Figure 13** Topographical map of brain for alpha rhythm during imaginary left hand movement. The alpha rhythm is active only at lower frequency 8–10 Hz in central region which includes the electrodes C1, C3, C5, CP1 and CP3. Noticeable energy is not found at the higher frequencies (10–12 Hz) of the alpha band. In some epochs there exists alpha rhythm around a single frequency only. The color bar represents the power intensity to illustrate the topological brain map in which red and blue represent highest and lowest power respectively considering the scale of red > yellow > green > blue. ‘L’ and ‘R’ indicate left and right hemispheres respectively; ‘*’: multiplication.
Figure 14  Topographical map of brain for alpha rhythm during imaginary right-hand movement.
At the lower frequency range 8–11 Hz the alpha wave is active with more energy than relax mode in central region of left hemisphere (C1, C3 and C5). In the higher frequency range 11–13 Hz, the alpha energy is mostly concentrated in central-parietal region of right hemisphere (C2, C4, CP2 and CP4). The color bar represents the power intensity to illustrate the topological brain map in which red and blue represent highest and lowest power respectively considering the scale of red > yellow > green > blue. ‘L’ and ‘R’ indicate left and right hemispheres respectively; ‘*’: multiplication.

Figure 15  Topographical map of brain for alpha band during relaxing session (left trace), imaginary left hand (middle trace) and right hand (right trace) movements for four subjects (A–D).
All subjects are male graduate students of age around 25 years and selected from a group working in computational neuroscience. The scale of the color map is red > yellow > green > blue; ‘L’ and ‘R’ indicates left and right hemispheres respectively.
The experiment to capture electroencephalography for imagery left and right hand movements is conducted with closed eyes of the subjects. Hence, there is a little change in getting an active mu wave. The alpha (8–12 Hz) and mu (8–13 Hz) contain overlapped frequency band and it is difficult to differentiate in engineering viewpoint.

This paper has confined to analyze the activity of alpha rhythm with respect to three motor imagery conditions of different subjects. In the future, the study will be extended to bridge the gap between engineering analysis and neurophysiological justification.

DISCUSSION

A data adaptive method is proposed to separate successfully electro-oculogram interference from multiple channels of raw electroencephalography recordings. The first stage of this paper focuses on removal of eye movement related artifacts which carry significant power in the form of electro-oculogram. It is difficult to remove such artifacts using independent component analysis or bandpass filtering. To tackle these problems, the current study used empirical mode decomposition, a technique to decompose pairs of signals for which one is introduced as a reference. It is a data adaptive detrending approach to separate the electro-oculogram effects from the recorded raw electroencephalography signals. The fractional Gaussian noise was used here as the reference signal. We use fractional Gaussian noise in a different way to fix the energy reference to extract the trend. The key benefit of using empirical mode decomposition is that it is an automatic decomposition and fully data adaptive. In this paper, we have successfully implemented the scheme of electro-oculogram suppression from raw electroencephalography signals using UEMD. The electro-oculogram signal is considered as the trend of the recorded electroencephalography signals. The trend is detected by comparing the energy of individual intrinsic mode function with that of the reference signals i.e. fractional Gaussian noise. The electro-oculogram artifact is separated from recorded electroencephalography in a data adaptive way without any training. The proposed method filtered out only the low frequency interference without disturbing the original electroencephalography whereas the traditional bandpass filtering method would cut off some information.

The purified electroencephalography signal is used to separate different brain waves (rhythmic components) by applying adaptive Wiener filter. Only the alpha component is employed to identify different event conducted in this experiment. The best-known and most extensively studied rhythm of the human brain is the normal alpha rhythm. Alpha activity is induced by closing the eyes and by relaxation, and abolished by eye opening or alerting by any mechanism (thinking, calculating). Alpha waves unlock imagination, bringing creative inspiration from deep within the currents of your own mind. In comparison, a child will have significantly greater amounts of alpha brain wave activities than an adult. Alpha brain waves have long been considered to be regarded as the healthiest brain wave range, but also the "safest" brain wave range to entrain – especially at 10 Hz. When we get continuously an alpha wave in our brain wave we decided that, all activities in our body are normal. The topological mapping of the alpha wave activities based on the placement of electroencephalography sensors for different imagination events (relaxing session, left and right hand movement imaginations). Individual subject has different types of spatial activities of alpha wave even for same imagination event.

CONCLUSION

A novel data adaptive thresholding approach was implemented to separate the electro-oculogram artifacts from the recorded electroencephalography signals. The pure electroencephalography signals are recently used in brain computer interface, whereas, the contaminated electro-oculogram signals is a potential obstacle in such applications. The proposed method separates electro-oculogram while keeping the scale of electroencephalography amplitude undistorted. The purified electroencephalography signals are used to extract the rhythmic components (brain waves) by employing Wiener filtering. The performance of the rhythmic component extraction method is tested with synthetic and real signals. Only the alpha rhythm is considered and extracted to analyze the regional brain activities. The activities are illustrated through topographic mapping for the events of relaxation, imaginary left and right hand movements. The analysis of regional brain activities with other rhythmic components in single and combined is under consideration as a future extension of this work.

Acknowledgments: We would like to thank Dr. Tomasz M. Rutkowski, University of Tsukuba, Ibaraki, Japan and Dr.
Toshihisa Tanaka, Tokyo University of Agriculture and Technology, Tokyo, Japan for providing the data used in this study.

**Funding:** This work is partially supported by a grant from the National Institute of Information and Communications Technology (NICT), Japan.

**Author contributions:** Md. Khademul Islam Molla designed this study, guided the whole study and wrote the manuscript. Md. Rashed-Al-Mahfuz performed the research and analyzed the data. Md. Rabuil Islam assisted in data analysis and manuscript writing. Keikichi Hirose revised the manuscript. All authors approved the final version of the paper.

**Conflicts of interest:** None declared.

**Ethical approval:** This study was approved by the Ethics Committee of University of Tsukuba, Japan.

**Author statements:** The manuscript is original, has not been submitted to or is not under consideration by another publication, has not been previously published in any language or any form, including electronic, and contains no disclosure of confidential information or authorship/patent application/funding source disputations.

**REFERENCES**

1. Pfurtscheller G, Flotzinger D, Kalcher J. Brain-computer interface—a new communication device for handicapped persons. J Microcomp Appl. 1993;16:193-299.

2. Pfurtscheller G, Kalcher J, Neuper C, et al. Online EEG classification during externally-paced hand movements using a neural network-based classifier. Electroenceph Clin Neurophysiol. 1994;99:416-425.

3. Wolpaw JR, McFarland DJ, Neat GW, et al. EEG-based brain-computer interface for cursor control. Electroenceph Clin Neurophysiol. 1991;78:252-259.

4. Wolpaw JR, McFarland DJ. Multichannel EEG-based brain-computer communication. Electroenceph Clin Neurophysiol. 1994;90:444-449.

5. Flotzinger D, Pfurtscheller G, Neuper C, et al. Classification of Nonaveraged EEG data by learning vector quantization and the influence of signal preprocessing. Med Biol Eng Comput. 1994;32:571-576.

6. Kalcher J, Flotzinger D, Neuper C, et al. Graz Brain-computer interface II—Toward communication between man and computer based on on-line classification of three different EEG patterns. Med Biol Eng Comput. 1996;34:382-388.

7. Pfurtscheller G, Flotzinger D, Pregenzer M, et al. EEG-based brain computer interface (BCI) Search for optimal electrode positions and frequency components. Med Prog Technol. 1996;21:111-121.

8. Pregenzer M, Pfurtscheller G, Flotzinger D. Selection of electrode position for an EEG-based Brain Computer Interface (BCI). Biomed Tech (Berl). 1994;39:264-269.

9. Wang Y, Hong B, Gao X, et al. Design of electrode layout for motor imagery based brain-computer interface. Electron Lett. 2007;43:557-558.

10. Kim SG, Richter W, Ugorbil K. Limitations of temporal resolution in functional MRI. Magn Reson Med. 1997;37:631-636.

11. Menon RS, Kim SG. Spatial and temporal limits in cognitive neuroimaging with fMRI. Trends Cogn Sci. 1999;3:207-216.

12. Hernandez L, Badre D, Noll D, et al. Temporal sensitivity of event-related fMRI. Neuroimage. 2002;17:1018-1026.

13. Bandettini PA. Functional MRI limitations and aspirations. Neural Correlates of Thinking. 2009;1:15-38.

14. Pooryaghooti MH, Golzan SM, Hakimpour F, et al. Combining EEG signals and fMRI images for brain mapping using interpolation techniques; a comparative study. 4th Europ Conf of the Intern Fede for Med and Biolog Eng. IFMBE Proc. 2009;22:414-420.

15. Sadaghiani S, Scheeringa R, et al. Alpha-band phase synchrony is related to activity in the fronto-parietal adaptive control network. J Neurosci. 2012;32:14305-14310.

16. Ostwald D, Porcaro C, Mayhew SD, et al. EEG-fMRI based information theoretic characterization of the human perceptual decision system. PLoS One. 2012;7:e33896.

17. Johyce CA, Gorodntitsky IF, Kutas M. Automatic removal of eye movement and blink artifacts from EEG data using blind component separation. Psychophysiology. 2004;41:313-325.

18. Looney D, Li L, Ruthowskim T, et al. Ocular artifacts removal from EEG using EMD. Advances in Cogn Neurodynam ICCN 2007. Netherlands: Springer. 2008.

19. Ruthowski TM, Cichocki A, Tanaka T, et al. Multichannel spectral pattern separation—an EEG processing application. IEEE ICASSP. 2009.

20. Senthil Kumar P, Arumughanathan R, Sivakumar K, et al. Removal of artifacts from EEG signals using adaptive filter through wavelet transform. IEEE Conference on Signal Processing. ICSP. 2008.

21. Li MA, Yang LB, Yang JF, et al. Separation of EOG artifacts from EEG signals using Hilbert-Huang transform. IEEE International Conference on Electric Information and Control Engineering (ICEICE). 2011.

22. Ghandeharion H, Erfanian A. A fully automatic ocular artifact suppression from EEG data using higher order statistics: Improved performance by wavelet analysis. Medical Engineering and Physics. 2010;32:720-729.

23. Kierkels JJ, van Boxtel GJ, Vogten LL. A model-based objective evaluation of eye movement correction in EEG recordings. IEEE Trans Biomed Eng. 2006;53:246-253.

24. Fisch BJ. EEG Primer. 2nd ed. The Netherlands: Elsevier Amsterdam. 1991.

25. Vigario RN. Extraction of ocular artifacts from electroencephalography using independent component analysis. Electroenceph Clin Neurophysiol. 1997;103:395-404.
[26] Jung TP, Makeig S, Humphries C, et al. Removing EEG artifacts by blind source separation. Psychophysiology. 2000;37:163-178.

[27] Delorme A, Makeig S, Sejnowski TJ. Automatic artifact rejection from EEG data using higher-order statistics and independent component analysis. Paper presented at: International workshop on ICA; San Deigo, CA. 2001.

[28] Ghandeharion H, Ahmadi-Noubari H. Detection and removal of ocular artifacts using Independent Component Analysis and wavelets. IEEE/EMBS 4th International Conference on Neural Engineering. 2009.

[29] Tran Y, Craig A, Boord P, et al. Using independent component analysis to remove artifact from electroencephalographic measured during stuttered speech. Med Biol Eng Comput. 2004;42:627-633.

[30] Correa AG, Laciar E, Patirio HD, et al. Artifact removal from EEG signals using adaptive filters in cascade. J Phys: Conf Ser. 2007;90:1-11.

[31] Molla MK, Islam MR, Tanaka T, et al. Artifact suppression from EEG signals using data adaptive time domain filtering. Neurocomputing. 2012;97:297-308.

[32] Molla MK, Tanaka T, Rutkowski TM, et al. Separation of EOG artifacts from EEG signals using bivariate EMD. IEEE ICASSP. 2010.

[33] Garber HJ, Weilburg JB, Duffy FH, et al. Clinical use of topographic brain electrical activity mapping in psychiatry. J Clin Psychiatry. 1989;50:205-211.

[34] Nuwer MR. Frequency analysis and topographic mapping of EEG and evoked potentials in epilepsy. Electroenceph Clin Neurophysiol. 1988;69:118-126.

[35] Itil TM, Itil KZ. Quantitative EEG brain mapping in psychotropic drug development, drug treatment selection, and monitoring. Am J Ther. 1995;2:359-367.

[36] Nuwer MR. On the controversies about clinical use of EEG brain mapping. Brain Topogr. 1990;3:103-111.

[37] Satherley BL, Jones RD, Bones PJ. EEG spectral topography in neurology: I. A review of techniques. Australas Phys Eng Sci Med. 1996;19:172-182.

[38] Gurkan G, Uslu A, Cebeci B, et al. Topographic and temporal spectral analysis of EEG signals during anaesthesia. IEEE Conference on Biomedical Engineering Meeting (BIYOMUT). 2010.

[39] Lin YD, Chong FC, Sung SM, et al. The topographic mapping of EEG using the first positive Lyapunov exponent. IEEE Conference on Engineering in Medicine and Biology Society. 1995;2:859-860.

[40] Flandrin P, Rilling G, Goncalves P. Empirical mode decomposition as a filter bank. IEEE Signal Process Lett. 2004;11:112-114.

[41] Jasper H, Andrews H. Normal differentiation of occipital and precentral regions in man. Arch Neurol Psychiatry. 1938;39:96-115.

[42] Niedermeyer E. Alpha-like rhythmic activity of the temporal lobe. Clin Electroencephalogr. 1990;21:210-224.

(Reviewed by Tsytarev V, Elkholy S)
(Edited by Li CH, Song LP)