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Data Adaptive Filtering Approach to Rhythmic Component Extraction from EEG Signal

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Abstract:

Electroencephalography (EEG) signal collected from scalp surface is a non-invasive approach to study human brain activities. The rhythmic components of EEG signal illustrate the neural activities and effective to implement brain computer interface (BCI). This research presents an effective method of rhythmic component extraction (RCE) from multi-channel EEG. The proposed approach is based on multivariate empirical mode decomposition (MEMD). It decomposes multichannel EEG signal into a finite set of subband signals termed as intrinsic mode functions (IMFs). Such decomposition is fully data adaptive and effective for non-stationary signal. Each IMF is a time varying band limited signal. It is filtered using a Fourier Transform based zero phase bandpass filter for a specific rhythmic component. The rhythmic component obtained from all the IMFs of the EEG channel are summed up yielding the channel's rhythmic component. Therefore, majority of the desired components of individual channels are extracted using the same method. The energies of different extracted rhythmic components are compared as a function of channels. To further improve the proposed method, the inter-channel correlation is taken into consideration during decomposition with MEMD hence it is very much effective for RCE from multichannel EEG signal.

Keywords — **Bandpass filtering, electroencephalography (EEG), multivariate empirical mode decomposition (MEMD), rhythmic component.**

I. INTRODUCTION

The design of brain computer interface (BCI) applications with electroencephalography (EEG) is one of the most challenging task, which translates the mental imagination of movement to commands without any muscle movement or activities of any peripheral nervous system [1, 2, 3]. There are a number of BCI applications including the field of brain science, neural engineering, and rehabilitation. They make use of prosthetics, robots, and other devices which are fully controllable by mental intentions [1], [4, 5, 6]. There exist some various EEG signal properties for BCI that distinguished brain task. The EEG signal is a collection of some rhythmic components also called brain waves. There are five major rhythmic components distinguished with their own frequency limits [7]. The EEG is the electrical activity of the brain's neurons recorded at the scalp surface [8]. They consist of several rhythm bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (>30 Hz). Because the rhythms reflect different physiological and pathological information, EEG rhythms extraction has been widely applied in many areas. Examples include portable and wearable EEG devices, mental fatigue assessment, disease diagnosis, and brain computer interface systems [9].

Individual rhythmic carries important information of the overall EEG signal which represents the brain activities. The extraction of each component implies to filter out a specific range oscillating frequencies from the multichannel signals collected from the EEG sensors. The extraction method is efficiently used to detect brain rhythm which is the cause of specific activity. Thus extracted brain waves i.e. rhythmic components are used to implement brain computer interface (BCI) [10]. During the recording of EEG, physiological noises are inherently added with the pure brain activity signals. The rhythmic component extraction (RCE) from the noisy EEG is very much challenging, whereas, the effective extraction of the brain waves is a crucial stage to apply the EEG in clinical diagnosis and/or so-called BCI implementation. The traditional signal processing methods such as linear filtering or the Fourier transform are not effective to detect the rhythmic signal especially if the noise power so higher than a level [5].

The EEG signal is mostly multichannel and hence the RCE is developed to extract a rhythmic oscillatory components or brain waves with multivariate signal processing approach [11]. Traditionally, the desired rhythmic components are extracted by applying linear combination of the multichannel recorded signal signals and the respective coefficients. The method only uses the physically underlying frequency information. It effectively separates the signal representing desired rhythmic components having the energy mostly in the frequency of the component. Additionally, the rhythmic component is independent of subjects and method of learning of the extraction system. The band-pass filtering through frequency analysis is a well-established method to work with a single channel signal. The time-invariant band-limited filtering by applying Fourier transform is as effective way to the desired frequency component [12]. It is noted that the Fourier transform based filtering is not suitable for non-stationary signal like EEG. To handle such signal, the classical time-frequency analyzers like short-time Fourier transform (STFT) and wavelet transforms (WT) [10] is more suitable. The Fourier based approach directly makes use of priori basis function. Although WT is considered as data adaptive method it also employs basis wavelet function. Hence the both methods are very much model dependent rather than data.

In this paper, a data driven subband filtering is implemented to extract the rhythmic components from multichannel EEG signals. The traditional model-based filtering approach is not adequate for effective filtering of rhythmic components. Hence, data adaptive empirical mode decomposition (EMD) [13, 14] based approach is used for RCE. The EEG signal is naturally non-stationary and nonlinear and EMD is very much effective for its decomposition. It decomposes the signal into a finite number of subbands for a single channel signal. EEG is being multichannel the traditional EMD is not effective. The multivariate EMD (MEMD) [15, 16] is employed here to decompose multichannel EEG at a time producing the subband signals. Then band pass filtering s applied to obtain the intended rhythmic components.

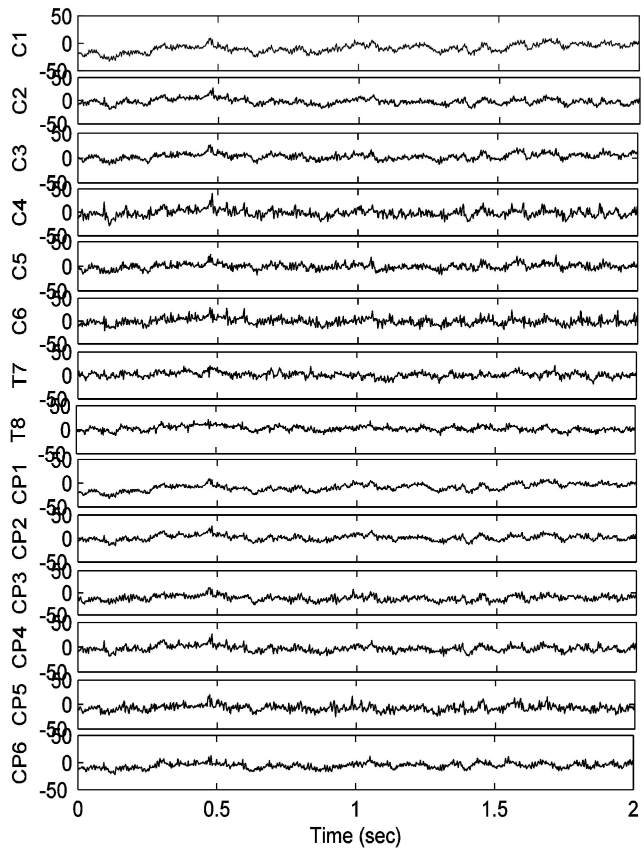

Fig. 1 A sample line graph using colors which contrast well both on screen and on a black-and-white hardcopy

II. Data Description

The data used in this study is obtained from the experiment conducted in Advanced Brain Signal

Processing Laboratory of RIKEN Brain Science Institute, Japan. The experiment is on the execution of motor imagery task for left hand and right hand movements. Each of movement imagery tasks is for four seconds. The EEG channels (electrodes) used in the experiment are $C1$, $C2$, $C3$, $C4$, $C5$, $C6$, $T7$, $T8$, $CP1$, $CP2$, $CP3$, $CP4$, $CP5$, and $CP6$ and a10-20 EEG system. The signals are recorded 512Hz sampling frequency using the g.USBamp bio-signal amplifier. The recorded signals are artifact free i.e. no physiological noise is included. The issue is confirmed by visual inspection. The EEG for single trial with 14 channels is illustrated in Fig. 1.

III. METHODOLOGY

All Rhythms extraction from electroencephalography (EEG) signals can be used to monitor the physiological and pathological states of the brain and has attracted much attention in recent studies. A flexible and accurate method for EEG rhythms extraction is demanding in BCI research. The accuracy of EEG rhythms extraction determines the physiological and pathological information it provides. Various methods have been proposed to extract the desired EEG rhythms. Filtering components have the ability to restrict a signal to a specific frequency band, and such bandpass filters were first used to extract EEG rhythms [17]. This method performed well in EEGs of high signal-to-noise ratio (SNR). Then, the wavelet transform (WT) method was used for EEG rhythms extraction [8]. By estimating the rhythms with a customized wavelet, the WT method can extract time-varying EEG rhythms with changes in brain state. To facilitate the EEG rhythms extraction, the independent component analysis (ICA) method was implemented previously. By incorporating priori information about the desired rhythms as reference signals, the ICA method can extract EEG rhythms automatically. However, the extracted rhythms using the bandpass filter, WT, and ICA methods were contaminated by noise and artifacts overlapping in time–frequency space [9].

The block diagram of the proposed method for rhythmic component extraction is illustrated in Fig. 2. The recorded EEG is usually contaminated by different physiological noises. The multichannel EEG signal is decomposed into a finite set of band limited signals using multivariate empirical mode decomposition (MEMD). The MEMD method is a multivariate extension of EMD. Standard EMD decomposes a signal into a finite set of oscillatory components called IMFs which represent the underlying temporal scales within the input data, by means of an iterative process called sifting algorithm. However, EMD considers only one-dimensional signals, and is prone to mode-mixing because of the overlapping of IMF spectra. For multivariate signals, e.g., EEG data collected from multiple channels, MEMD is explored by generating multi-dimensional envelopes, then taking signal projections along different directions, and finally averaging these projects to obtain the local mean [18].

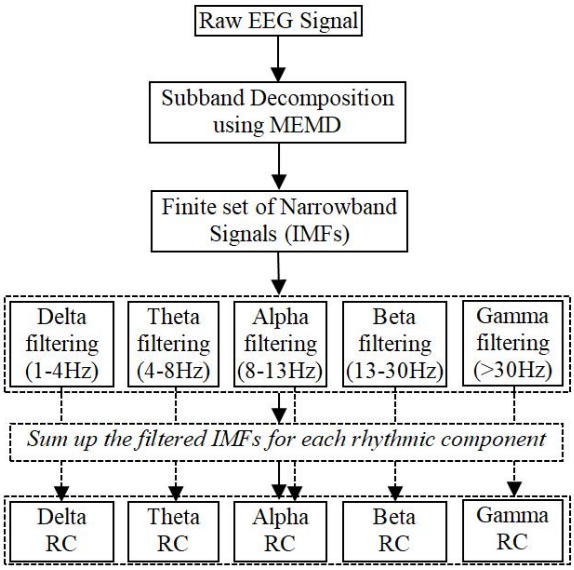

Fig. 2 Block diagram of the proposed method for rhythmic component extraction

Each of the IMFs is filtered using bandpass filter to extract one of the rhythmic components among delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (>30 Hz). For instance, all the IMFs obtained from any channel are bandpass filtered of frequency range 4 – 8 Hz. Thus, obtained components are summed up to reconstruct theta rhythmic component. Other rhythmic components are constructed in the similar way.

A. Subband Decomposition

The band-pass filtering is essential to separate the rhythmic components from EEG. The well-known

Fourier based signal analysis method is based on the assumption of linearity and stationarity of the analyzing signal. [13]. Even the WT and STFT are used by considering the signal as non-stationary but linear. Also there exist some methods to assume the data as non-linear but stationary [13]. It is currently demanding to have a method which is able to analyze the non-linear and non-stationary signal. A recently developed subband decomposition method is EMD that provides a fully data-dependent decomposition of non-stationary and non-linear signals [14]. It produces a set of linearly independent functions in which instantaneous frequency can be well-defined.

The multivariate EMD (MEMD) is implementation of univariate EMD to decompose multivariate signal [15]. It extracts all possible IMFs from individual channel of multivariate data like EEG signal. It is noted that same number of IMFs are extracted from each of the channels. The decomposition of multichannel EEG also preserves the covariation of the channels over time. The MEMD exposes the multivariate filter-bank structure with dyadic property [15]. The algorithm introduced in [14] is employed here to decompose the multichannel EEG signal $X(t)$ into a set of IMF components.

1. Produce the points based on the Hammersley sequence for sampling on (N-1)-sphere;
2. Compute the projection, represented by $p^{\theta_k}(t)\}_{t=1}^{T}$,of input signal $\{X(t)\}_{t=1}^{T}$ along the direction vector S^{θ_k} , for all k, with $p^{\theta_k}(t)\}_{k=1}^{K}$ as the set of projections;
3. Determine the time instants $t_i^{\theta_k}\}_{k=1}^{K}$ representing the maxima of the set of projected signals $p^{\theta_k}(t)\}_{k=1}^{K}$;
4. Make interpolation $[t_i^{\theta_k}, x(t_i^{\theta_k})]$, for all values of k, to find multivariate envelope $e^{\theta_k}(t)\}_{k=1}^{K}$;
5. For the set of K direction vectors, compute the mean $\mu(t)$ of the envelope as:

$$\mu(t) = \frac{1}{k}\sum_{k=1}^{K} e^{\theta_k}(t) \qquad (1)$$

6. Separate the "detail" $d(t)$ using $d(t) = X(t) - \mu(t)$. If $d(t)$ fulfills the stopping criterion for the multivariate IMF, $d(t)$ is obtained as the IMF. Apply the above procedure to $X(t)$-$d(t)$, otherwise apply it to $d(t)$.

When EEG signal of N channels is decomposed using MEMD, the n^{th} channel is represented as:

$$x_n(t) = \sum_{m=1}^{M} g_m^{(n)}(t) + r_M^{(n)}(t) \qquad (2)$$

where g_m is mth IMF, r_M is the final residue and M is the total number of IMFs extracted from each channel.

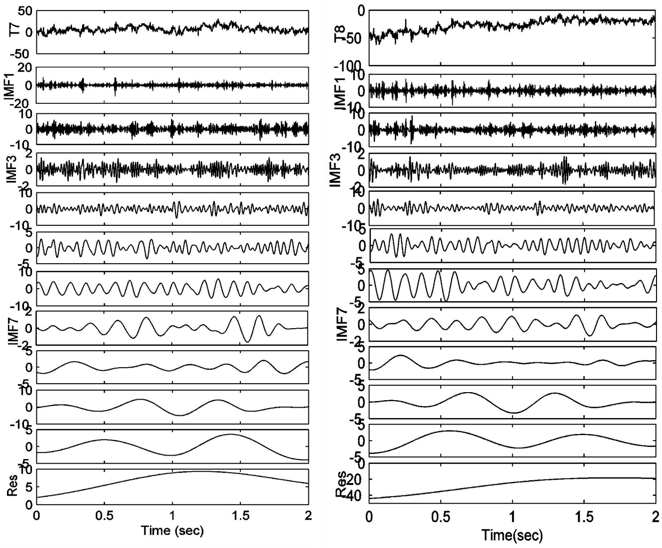

Fig. 3 The IMFs of channel $T7$ (left) and $T8$ (right) obtained by MEMD. The lower order IMFs represent the higher frequency components.

The multiband representation of individual EEG channel can be expressed in the similar way as in Eq. (4). It is noted that the same number of IMFs are generated by decomposing the both signals together. The MEMD method is fully data adaptive and the number of IMF depends of the nature of data. The IMFs obtained by decomposing channel $T7$ and $T8$ simultaneously are illustrated in Fig. 3.

B. Rhythmic Component Extraction

The rhythmic components in non-invasive EEG have numerous applications in BCI implementation [19]. In terms of neural activities, it is considered that the recorded EEG signal is composed of the predefined rhythmic components. Each of the components is responsible for some specific activities and sometimes a group of components plays role to execute the intended motor task. Hence the rhythmic components are the meaningful sources of neurophysiological task represented by underlying multichannel EEG recording. The brain state of the individual may make certain frequencies more dominant. We introduce a method to successively filter the desired brain wave (rhythmic component) from a series of subband signals obtained by applying a fully data-adaptive MEMD technique [14]. The method relies on a combination of subband decomposition and Fourier transformation (FT) based bandpass filtering. It is well known that FT is only suitable for stationary signals, whereas, the EEG signal is always non-stationary. MEMD is used to decompose EEG into time varying subband signals (IMFs) which are individually more stationary than EEG in full bandwidth. Hence, FT based filtering becomes more suitable for bandpass filtering applying to the IMFs. For the nth EEG channels, the individual IMF is filtered using bandpass filtering with specific bandwidth corresponding to desired rhythmic component. The filtered *m*th IMF of *n*th channel is defined as:

$$\hat{g}_m^{(n)}(t) = \hbar_l^h\left(g_m^{(n)}(t)\right) \tag{3}$$

where, $\hbar_l^h(.)$ is the bandpass filter function with lower and upper cutoff frequencies l and h respectively. Then the rhythmic component for the frequency range $l - h$ extracted from *n*th channel is represented as:

$$\rho_{l-h}^{(n)}(t) = \sum_{m=1}^{M} \hat{g}_m^{(n)}(t) \tag{4}$$

Each of the rhythmic components for individual channel is extracted by the same procedure.

C. Proposed Algorithm

Although the EMD acts as data adaptive multiband decomposition method it decomposes only one channel at a time into a finite number of subband signals called IMFs. On the other hand, MEMD decomposes each channel of multichannel data simultaneously and hence MEMD is employed here for rhythmic component extraction by following the steps mentioned bellow:

i. The multichannel EEG signal is decomposed using MEMD into a finite number of IMFs. Same number of IMFs is generated for individual channel of EEG. Even higher number of IMFs is generated than that of using univariate EMD. Hence, it confirms the better frequency disjoint in IMF domain.
ii. Each of the IMFs of a specific channel is filtered by using zero phase band pass filter for intended rhythmic component. The filtered IMFs contain only the energy of the specific component.
iii. The filtered IMFs of a channel are summed up to extract the component for which the band pass filter is applied.
iv. The steps b and c are repeated in sequence for each of the intended rhythmic components.

The above steps (ii) to (iv) are repeated to extract the intended components from all the channels used in EEG recording.

IV. Experimental Results

The proposed rhythmic components (brain waves) extraction method is evaluated using real EEG signals as described in Section II(A). MEMD is applied to decompose any trial of multichannel EEG. The obtained IMFs of channel are illustrated in Fig. 4. All the channels of the trial is decomposed simultaneously. It is noted that the same number of IMFs are generated for each of the channels.

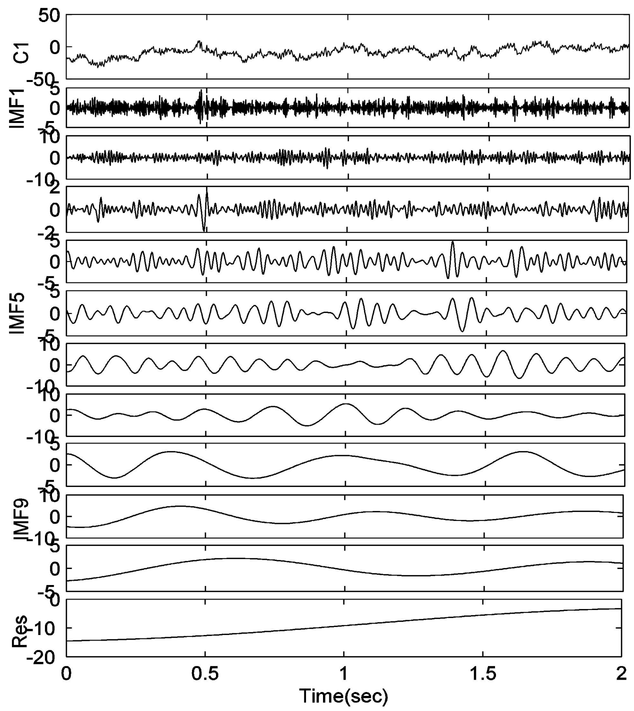

Fig. 4 The eleven IMFs obtained by applying MEMD on the first channel $C1$ of EEG signal.

The correlation and interrelation between the channels are considered during decomposition using MEMD. To extract the rhythmic components of EEG signals, the decomposition with MEMD is followed by band pass filtering. The band pass filtering is implemented with Butterworth zero phase filter such that it does not make any effect to the phase of the signal. The band pass filtering is applied to individual IMF for specific rhythmic component among delta (0.5-4Hz), theta (4-8Hz), alpha (8-16Hz) and beta (16-30Hz) as indicated in Eq (3). The delta components corresponding to each of the IMFs of channel $C1$ are illustrated in Fig. 5. It is observed that the energy of delta component is higher for lower frequency IMFs.

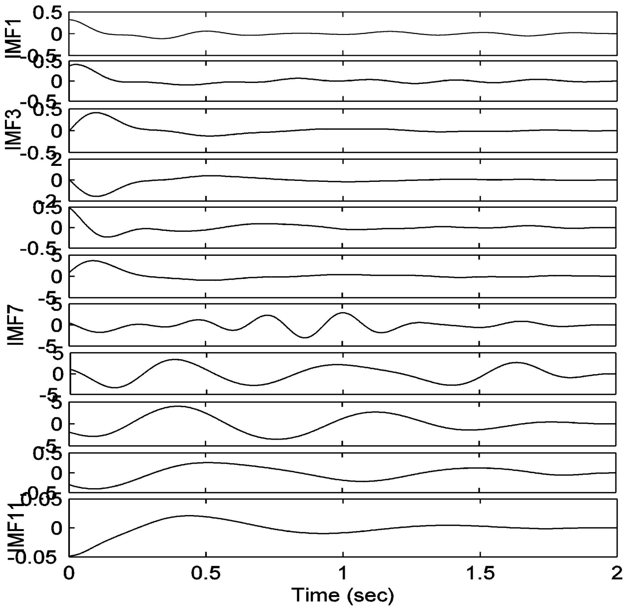

Fig. 5 The extracted delta component obtained by bandpass filtering of 11 IMFs of channel $C1$.

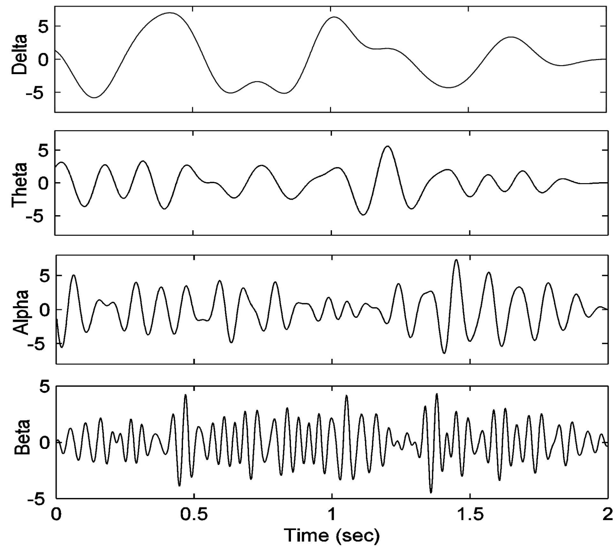

Fig. 6 The four rhythmic components obtained from channel $C1$ using MEMD followed by applying zero phase band pass filtering.

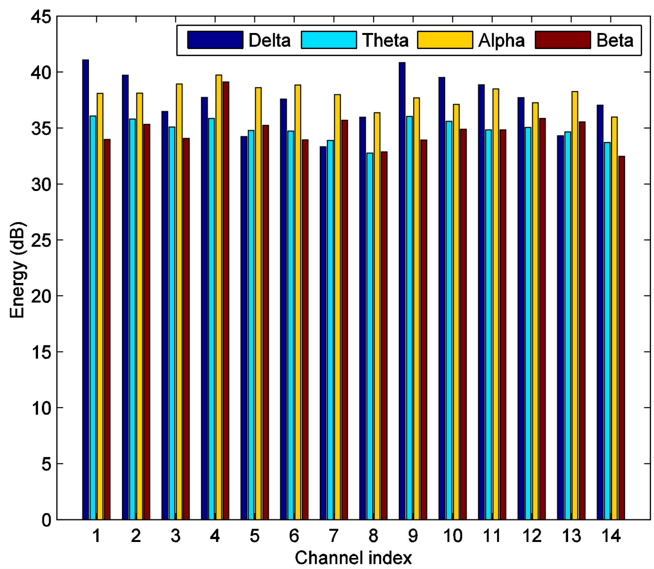

Fig. 7 The energy variation of different rhythmic components as a function of channel.

Any rhythmic component of a specific channel is recontructed by summing up the IMFs after filtering for corresponding component as defined by Eq. (4). For instance, the delta rhythm of C_1 channel can be extracted by summing up the filtered IMFs of Fig. 4. The extracted four rhythmic components from channel $C1$ are presented in Fig. 6. The components of other 13 channels can be extracted in the similar process.

There exists the variation of energies contributed by different rhythmic components in different channels. The amount of information contained by individual component is varied over the channels. It is very much justified in respect to the mechanism of neural activities. A specific region of human brain can produce neural response for specific task, whereas, the other regions are busy with other task. As a result, the variations of the energy of rhythmic components are distributed over the spatial domain. As a proof of the findings, the energies of different rhythmic components as a function of channel index are illustrated in Fig. 7. It is observed that the energy variation of different components is varied over the channels. Hence the proposed method is very much effective and efficient in extraction of rhythmic components from the multichannel EEG signal. It is well established that the Fourier transform based filtering is only effective for non-stationary signal. The MEMD produces IMFs which are band limited and more stationary than the original EEG signal. Hence the use of bandpass filter on IMF rather than directly on EEG is more effective and justified to extract the rhythmic components.

V. CONCLUSIONS

An effective and data adaptive method is implemented to extract rhythmic components from multichannel EEG signal. MEMD is employed here to decompose the multichannel EEG signal simultaneously into a finite number of subbands called IMFs. It considers the inter-channel dependency of different channels during the decomposition. It produces higher number of IMFs than univariate EMD and hence confirms better frequency disjoint in IMF domain. The IMFs of any channel are filtered using band pass filter for specific rhythmic components. Finally the filtered IMFs are summed up to reconstruct the intended rhythmic component. The same process is repeated for individual channel. The proposed approach is more noise robust and not affected by the physiological artifacts which are usually introduced in EEG. Thus extracted rhythmic components are useful in classification of neural activities leading to BCI implementation. The implementation of machine learning for EEG classification with extracted rhythmic components for BCI application is left for future work.

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