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AN EFFECTIVE LIFTING SCHEME METHOD FOR EEG DECOMPOSITION IN TARGETED FREQUENCY RANGE

Balbir Singh[1], Mayu Ichiki[1], Guangyi Ai[1] and Hiroaki Wagatsuma[1,2,3]

[1]Graduate School of Life Science and Systems Engineering
Kyushu Institute of Technology
2-4 Hibikino, Wakamatsu-Ku, Kitakyushu 808-0196, Japan
{ awana-balbir-singh; ichiki-mayu }@edu.brain.kyutech.ac.jp

[2]RIKEN Brain Science Institute
2-1 Hirosawa Wako City, Saitama 351-0198, Japan

[3]Artificial Intelligence Research Center, AIST
2-3-26 Aomi, Koto-Ku, Tokyo 135-0064, Japan
waga@brain.kyutech.ac.jp

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Abstract. *An advancement of brain-computer interface (BCI) has grown the demand for real-time EEG signal analysis. A lifting scheme method is used to reveal the electrical activity of the brain in terms of the frequency characteristics of high and low-frequency component changes from different recording regions and from different physiological and pathological brain states. We examined the set of intracranial EEG data with the eye open from epilepsy patient during the seizure in time series. It is possible to determine a nonlinear prediction of EEG signal in the spectral domain. We compared the frequency spectrum of the averaged raw EEG data, predicted and detailed EEG data. Results are distinguished between predicted and detailed EEG signal of the brain state using lifting scheme.*
Keywords: Brain computer interface (BCI), Wavelet decomposition, Lifting scheme, Electroencephalogram (EEG)

1. **Introduction.** The brain-computer interface (BCI) has been associated with the EEG signal features and system. The extraction of EEG features is necessary to provide valuable information to the automated and semi-automated systems, which helps in many applications on a real-time basis. It is also very popular for brain activities tool for clinical purpose and used for military medicine, advancements in biometric fields. The electrical brain activity can be inferred from different regions, different physiological and pathological brain states by placing electrodes on the surface of the scalp [1]. The potential measured from electrodes are used to classify the brain activity. They are represented by highly complex, non-stationary and nonlinear biological systems. The separation of a signal into their components is a great interest in these applications. The linear and nonlinear EEG signal processing methods would be used to distinguish or predict these brain activities. Therefore, time-frequency methods show the promising result [2]. The signal feature extraction methods use linear analysis in time-frequency domains such as fast Fourier transform (FFT), discrete wavelet transform (DWT), and eigenvectors [3]. The nonlinear methods such as principal component analysis (PCA), independent component analysis (ICA), and blind source separation (BSS) [4] have been studied to extract the target components from the raw EEG signals. Wavelets, PCA and ICA are still hot topics for the decomposition but still have limitations. PCA and ICA based methods are used to decompose the recorded data as off-line analysis. It also depended on the independence

of signals, while the sparsity is recently highlighted and this concepts effectively provide a representation in the linear analysis to be treated as mixed signals.

Wavelet based approaches have high expectations for online EEG signal decomposition with less computational costs and preserve time-frequency characteristics in the raw EEG signal to a maximum extent. The design of wavelet function has a set of restrictions to decomposition of raw EEG signal accurately [3, 5]. Shifts and dilation of a mother wavelet function has generated a series of orthogonal spaces. However, wavelets have been used to analyze the EEG signals both in frequency and time domain at a different level. The wavelets analysis has multi-resolution capability benefit over Fourier transform and cosine transform. The different families (Daubechies, Coiflets, and Symlets) in discrete variant have been used for classification of feature components [6, 7]. The wavelet function design has a complex issue, working with wavelet transform. The speed and accuracy of feature extractions from EEG signals are the critical issues in many applications and wavelet as temporal-spectral analysis of EEG method has been discussed as a solution for unstable signals if the mother wavelet has not introduced appropriately. The wavelet function does not categorize the EEG signal features accurately. Without accurate models, the nonlinear biological system applications of classical parametric and nonparametric signal processing methods based on stationary assumptions often fail to provide satisfactory results. The conventional convolution based implementation of the DWT has high computational complexity and memory requirements.

The fractal dimension of feature extraction on real-time bases in EEG signal such as detection of dementia, seizure onset detection in epilepsy and much more is today needs. The objective of this study is to analyze the specific characteristics of EEG signal taken from different physiological and pathological brain states in a time domain using lifting scheme. We used the lifting scheme to extract the features in a time domain. The lifting scheme offers the sufficient information to illustrate signal. The paper is organized as follows. The lifting scheme is explained in Section 2. Description of the EEG data and how the lifting scheme extracts features are presented in Section 3. Results are given in Section 4. The conclusions are presented in Section 5.

2. **Lifting Scheme.** The lifting scheme [8] was presented by Sweldens as a method for building second generation wavelets with some desired properties. It was originally developed to adjust wavelet transforms to complex geometries and irregular sampling leading. A lifting scheme is called a second generation method to build or realize as temporal-spatial domain, and offers a simple framework to design accurate model based on the requirement of the application [9, 10]. The lifting scheme relies on utilizing the spatial domain correlation to build second generation wavelets that do not shift and translate as in the first classical multiresolution-based wavelets. The local spatial interpretation is used to adapt the transform for the non-linear signal. Therefore, it is possible to construct and implement bi-orthogonal wavelets [11]. The feature extraction based on lifting scheme has been well established in image processing [12] and less work is done in EEG signal analysis. The lifting scheme has provided a wavelet-like decomposition of signals to extract the features. It requires less time and simplifies the computation mechanism and it is suitable for real-time applications. The lifting scheme is capable of handling data where Fourier analysis is not suitable or information is not available because it can be implemented in spatial or time domain. A lifting scheme is comprised of three steps and the basic steps are given below.

- Split: A signal is separated into its disjoint even and odd coefficients.
- Predict: In predict step, we predict the odd coefficients from the adjacent even coefficient. It can be considered as high frequency or detail coefficients of the signal.
- Update: The even coefficients as an approximation transform into low pass filter and smoother compared to the previous scale.

3. **EEG Data and Methodology.** The EEG data was obtained from the dataset mentioned in the paper of Andrzejak et al. [1] in 2001 and applied the lifting scheme for extraction of the EEG signal features effectively. These data were recorded from five healthy volunteers using a standardized electrodes placement arrangement. We consider one segment set, and this set belonged to volunteers when they were relaxed in an awake state with an eye open. The EEG data set comprised 100 single channel of 23.6 sec duration. These segments were selected and cut out from various multichannel EEG recording after visual inspection for artifacts, e.g., due to muscle activity or eye movements. EEG data were recorded with 128 channel amplifier system. Each trial having 4096 samples was chosen in such a way that the potential difference of first and last sample was within the range of potential difference of successive sample and the slope had the same phase. Therefore, these recorded data were analyzed to extract the distinctive features using the lifting scheme. Firstly, the EEG signal (S) has split into its even and odd index coefficients $s_e(n)$ and $s_o(n)$ respectively shown in Figure 1.

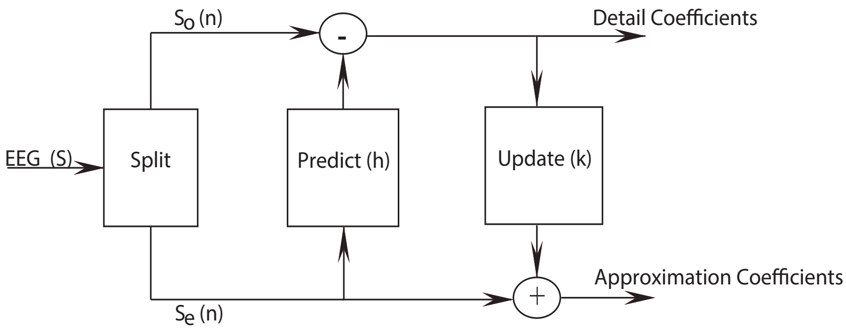

FIGURE 1. Lifting scheme block diagram consisting of three steps: 1) splits, 2) predict, 3) update

The even and odd coefficients are given by $s_e(n) = s(2n)$ and $s_o(n) = s(2n+1)$. By using lifting scheme, the odd coefficients s_o would be predicted from adjacent s_e. The predictor for odd coefficients s_o is the average of its two neighboring even coefficients s_{2n} and s_{2n+1}. Therefore, the even samples are used as predictor for the odd set. The predict step can be considered as high frequency or detail coefficients. It is given by Equation (1).

$$\beta_{j-1}(n) = s_o - h \times s_e \tag{1}$$

The wavelet coefficient β_n is the difference between the exact sample and its predicted value.

$$\beta = s_{2n+1} - \frac{s_{2n} + s_{2n+1}}{2} \tag{2}$$

where h is the predict operator. Here, we have considered wavelet filters such as the popular 'Cohen-Daubechies-Feauveau 9-7 (CDF9-7)' or 'cubic B-splines 5-3 (spl5-3)' [10, 13]. The filter coefficients given below are used for decomposition of EEG signal, in case nonlinear $h = 1.586134342, -0.05298011854, -0.8829110672, 0.4435068522, 1.149604398$; and linear $h = \frac{1}{2}, \frac{1}{4}$.

In the third step, the even coefficients have been considered as approximation coefficients of the raw EEG signal that become smoother signal and are used to recover the raw EEG signal. The even coefficients s_{2n} have been found as $s_{2n} = s_e$. After this, signal viewed as low pass filtering containing less high frequency components and the approximation coefficients was given by Equation (3)

$$\alpha_j(n) = s_e(n) + U \times \beta_{j-1}(n) \tag{3}$$

where U is the update operator. The even coefficients have been obtained by sub sampling; therefore, the aliasing effect has taken place. To reduce this U update operator is used to smooth the signal [14]. This process of computing a prediction and recording is called lifting steps. The EEG signal has been decomposed into number of 'j' level of interest that can be considered as power frequency band, which is given by $n = 2^j$, where n is the number of samples.

4. **Results.** The lifting scheme is used to decompose EEG signals. These EEG signals are taken when eye was open at awake state as discussed in Section 3. EEG signals are decomposed at 8 and 11 levels of interest that can be considered as power peaks appearing at a 10 and 50 Hz of frequency. Figure 2 shows the extracted approximation and detail coefficients of EEG signal at levels 8 and 11 by using linear 'spl5-3'.

Similarly, nonlinear 'CDF9-7' filter coefficients are used for decomposition as shown in Figure 3. We used the translation invariant; therefore, the samples size is the same as raw EEG signal. We considered all 100 single channels for analysis.

The extracted approximation and detail coefficients of EEG signals with nonlinear filter coefficients demonstrate the better results as compared to the linear filter coefficients. The redundancy (detail coefficients) of lifting method showed much more temporal-spatial information at each extracted level.

Figure 4 and Figure 5 demonstrated the power-frequency relation for the raw and (approximation coefficients, detail coefficients) EEG signals at different decomposition

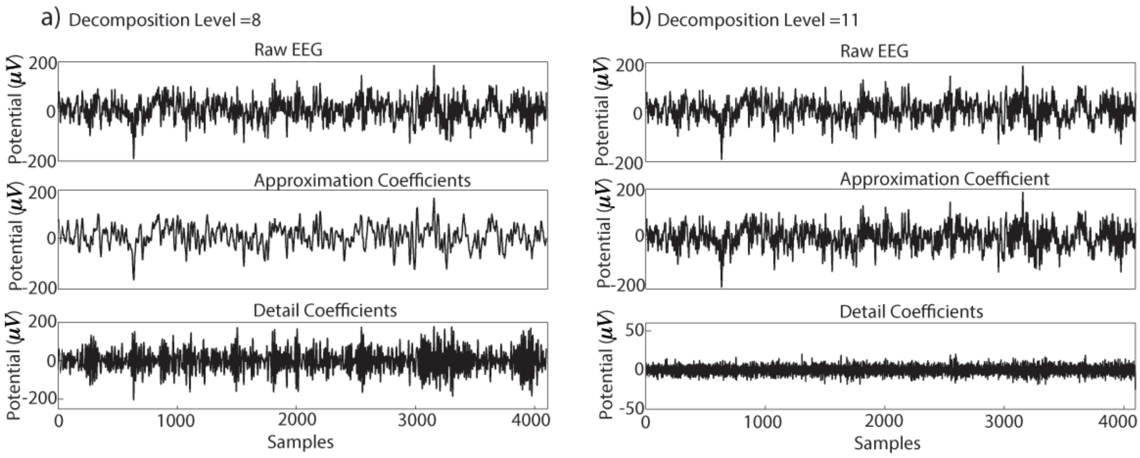

Figure 2. An example of an EEG signal decomposition by 'spl5-3' filter coefficients: a) decomposition level = 8, b) decomposition level = 11

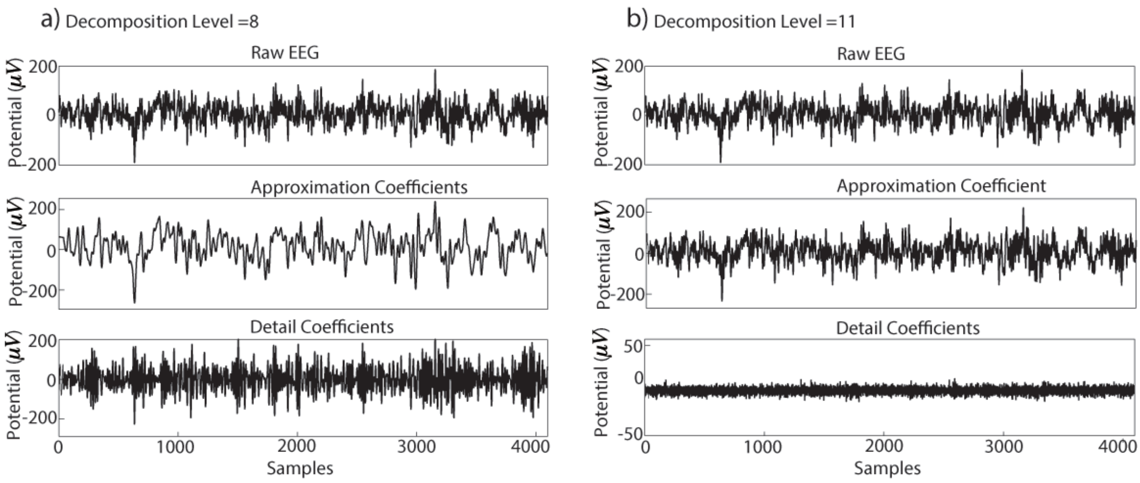

Figure 3. An example of an EEG signal decomposition by 'CDF9-7' filter coefficients: a) decomposition level = 8, b) decomposition level = 11

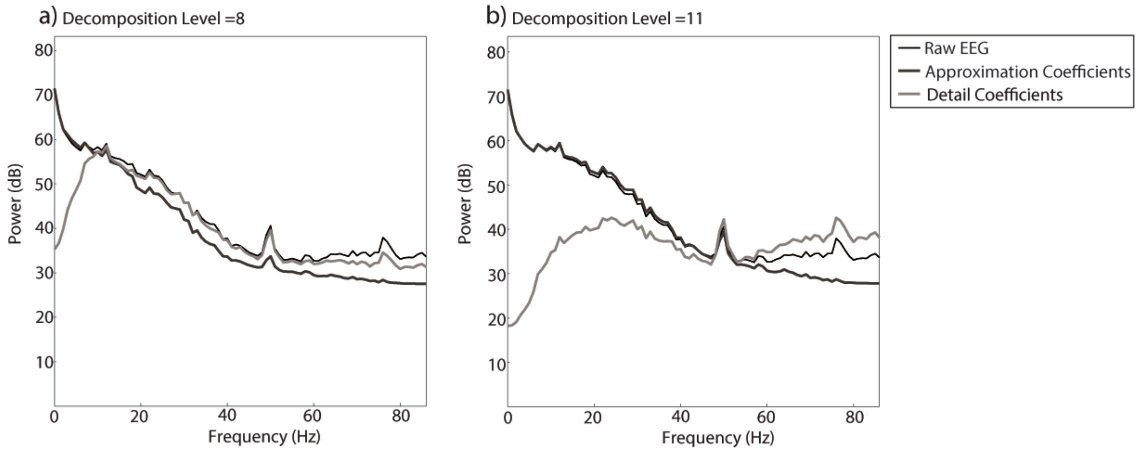

Figure 4. An averaged power spectrum of raw, approximation and detail coefficients from 100 EEG signals decomposed by linear 'spl5-3' filter coefficients at: a) decomposition level 8, b) decomposition level 11

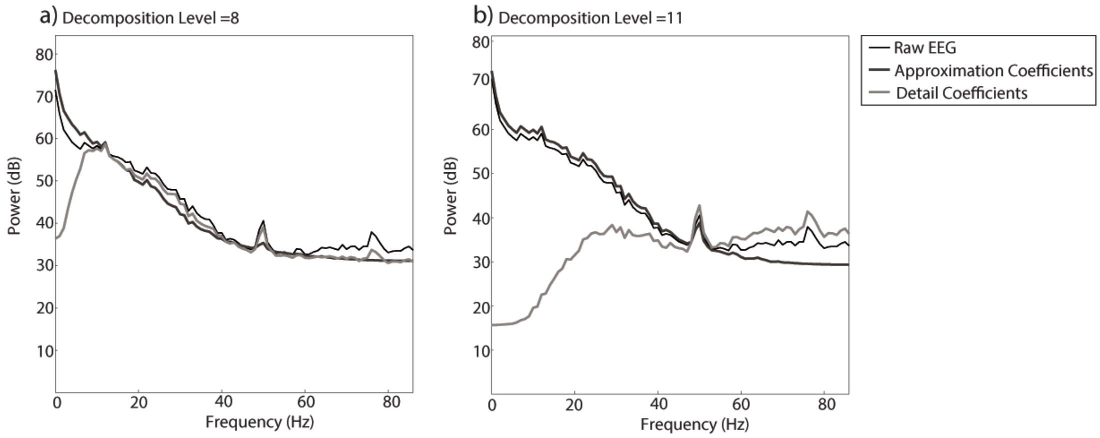

Figure 5. An averaged power spectrum of raw, approximation and detail coefficients from 100 EEG signals decomposed by nonlinear 'CDF9-7' filter coefficients at: a) decomposition level 8, b) decomposition level 11

levels. The tendency of the power spectrum (peak at particular frequency range) can be easily detected. This type of tendency is difficult to find with discrete wavelets. In a case of approximation coefficients of signal, the power spectrum peak disappears as we reduced the level of EEG signal decomposition.

Figure 6(a) showed the exact difference between averaged approximation coefficients of EEG signals. It is confirmed by averaged power spectrum shown in Figure 6(b).

5. **Conclusions.** This study demonstrated lifting scheme method is used to decompose the EEG signal with linear and nonlinear coefficients. The linear 'cubic B-splines 5-3' and non-linear 'Cohen-Daubechies-Feauveau 9-7' filter coefficients are used as lifting operator for decomposition of the EEG signals to get the targeted frequency range of EEG signals. The lifting scheme method may be used for removing the artifacts present in the EEG signal. The lifting operator inherits the property of (low and high) filtering that of initial filter possessed. The lifting scheme method provides more precise information in EEG analysis. This method further may be used for real-time EEG analysis by making hardware device. It does not use high computation memory; basically, it is worked on signal division approach. Therefore, lifting scheme method may apply for real-time EEG analysis.

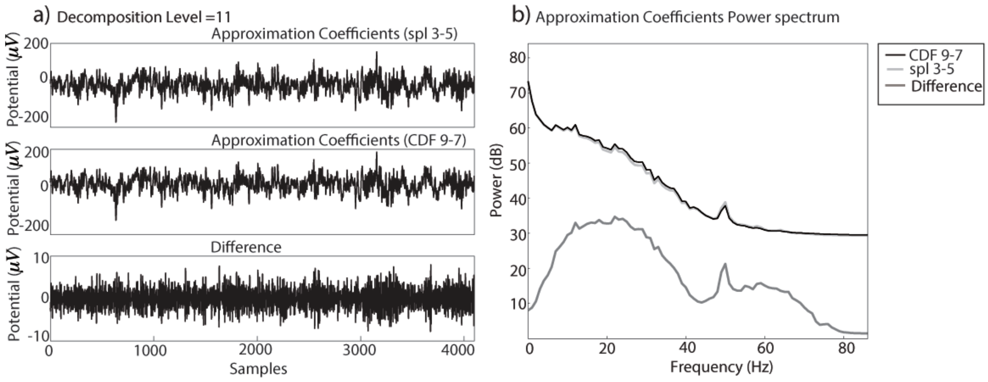

FIGURE 6. a) A comparison between an approximation coefficients of EEG signal decomposed at 11 level by linear and nonlinear filter coefficients respectively; b) power spectrum of approximated EEG signals decomposed by nonlinear 'CDF9-7', linear 'spl3-5' filter coefficients and difference between them

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