A Novel EEG Feature Extraction Method Using Hjorth Parameter

Seung-Hyeon Oh, Yu-Ri Lee, and Hyoung-Nam Kim
Pusan National University/Department of Electrical & Computer Engineering, Busan, Republic of Korea
Email: hnkim@pusan.ac.kr

***Abstract*—When processing electroencephalography (EEG) signals in motor imagery case, it is essential to analyze them in both time and frequency domains. An EEG signal has a non-stationary property and its frequency feature also differs from individual to individual. Thus, we can infer that each subject has one's own dominant timing and frequency band for extracting distinguishable features. Based on this inference, after analyzing EEG signals with the Hjorth parameter, we select the principal frequency band and the timing using the Fisher ratio of the Hjorth parameter. By doing these, the performance of the feature extraction in EEG-based BCI systems was improved in terms of the classification accuracy by 4.4% on average.**

***Index Terms*—EEG, BCI, feature extraction, Hjorth parameter, motor imagery**

I. Introduction

Brain Computer Interface (BCI) is a system that directly controls or interacts with a computer through the brain activity. There are two methods to collect brain signals which are invasive and noninvasive methods. An invasive BCI method uses electrodes placed on the exposed surface of a brain to record electrical activity. It is required to surgical operation like an incision into the skull. It may involve big dangerousness to human. On the other hand, a noninvasive method does not need any surgical process although it suffers from low quality of measurement signals. Therefore, non-invasive BCI has been more preferable to invasive BCI. There are several non-invasive BCI methods, such as magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), EEG, and so on. Especially, EEG has some advantages compared to other noninvasive methods. It has better temporal resolution than fMRI or computed tomography (CT) [1]. It is also easy to use, and has low cost for set-up [2]. Therefore, EEG is the most generally used measurement method among non-invasive methods. BCI based on EEG uses an electrical neural signal appeared on the scalp.

EEG signals have specific patterns according to subject's states, such as hypnosis, arousal, exercise, concentration, and so on. Finding the relationship between a physical task and its corresponding EEG pattern has been an interesting research topic. The fact that EEG patterns are related to some physical tasks may be very applicable because it can be helpful for disabled people who can move a wheelchair or hit a key on a computer keyboard by controlling the BCI systems based on EEG signal. In addition, it can be also applied to ordinary human's life, including driving a car, controlling a cursor, playing a game, and so on. Regarding these applications, an imagination of moving own body is called motor imagery.

It is widely known that approximate frequency bands generally presenting a prominent feature are Mu band and Beta band in motor imagery EEG systems. However, the frequency band including the important feature slightly changes according to an individual. Further, EEG signals, especially about motor imagery, have an event-dependent property. Therefore, we need to analyze the changes of a signal feature with time. For these reasons, it is appropriate to analyze EEG signal both in time and frequency domains.

Considering these two problems, we have studied on time–frequency feature extraction methods. The short-time Fourier transform (STFT) has been popular for time-frequency analysis of non-stationary signals [3]. However, its high computational complexity and redundant frequency information remain still to be solved in real-time STFT applications. The Hjorth parameter proposed in [4] may be a good alternative for the STFT because it can extract useful information both in time and frequency domains through simple computation [5]. In this paper, we introduce the Hjorth parameter and compute its Fisher ratio to find the dominant frequency band and the timing in training EEG signals. Extracting a high-informative feature in test EEG signals is carried out by computing the Hjorth parameter of a test signal at the pre-determined frequency band and timing instant. Then, the feature is used for classification.

The remainder of the paper is organized as follows: In Section II, the STFT and the Hjorth parameter are introduced as conventional feature extraction methods. The proposed time–frequency feature extraction method is also described in Section II. Section III shows the performance improvement of the feature extraction method using the Hjorth parameter with selected

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frequency band and timing, comparing with the methods based on the STFT and the Hjorth parameter without any frequency band selection. Section IV presents the conclusion.

II. Feature Extraction in EEG Signals

There are several existing time-frequency feature extraction methods. Among them, the short-time Fourier transform (STFT) is one of the most conventional feature extraction methods. The Hjorth parameter can be also used as a good feature in real-time EEG applications. In this section, after introducing the STFT and the Hjorth parameter, our proposed method of extracting a high-informative feature will be presented in detail.

A. Short- Time Fourier Transform (STFT)

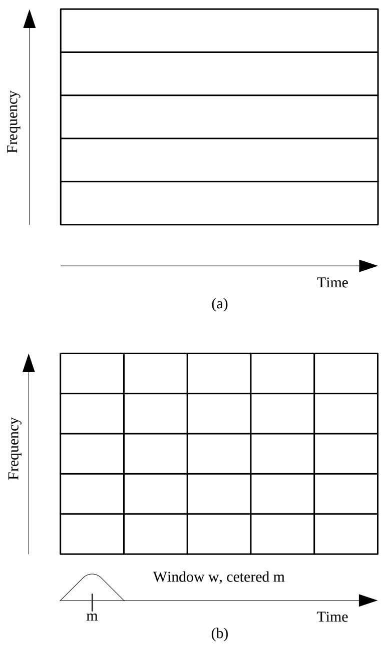

Figure 1. Comparison of the time-frequency plane (a) STFT and (b) Fourier transform.

Fourier transform is used for analyzing a signal in entire frequency domain and shows the relative power of each frequency. However, this method is not appropriate for analyzing non-stationary signals. As shown in Fig. 1, Fourier transform has no dependency on specific time because it calculates frequency response based on whole time, not local time. In this respect, the STFT method may become a good candidate for analyzing non-stationary signals [6]. It analyzes localized signal by windowing in frequency domain [3]. Letting $x[n]$ be a non-stationary signal, here EEG signal, the STFT can be applied to the EEG signal as follows:

$$X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n} \tag{1}$$

where $w[n]$ is a windowing function. As we can see in (1) and Fig. 1, the STFT represents the Fourier transform of the local windowed signal divided in time domain and shows the frequency response according to time variation. Thus, the STFT method can be used for extracting a feature of EEG signals.

B. Hjorth Parameter [4]

The Hjorth parameter is one of the ways of indicating statistical property of a signal in time domain and it has three kinds of parameters as in Table I: Activity, Mobility, and Complexity. Activity parameter, the variance of the time function, can indicate the surface of power spectrum in frequency domain. That is, the value of Activity returns a large/small value if the high frequency components of the signal exist many/few. Mobility parameter is defined as the square root of the ratio of the variance of the first derivative of the signal and that of the signal. This parameter has a proportion of standard deviation of power spectrum. Complexity parameter indicates how the shape of a signal is similar to a pure sine wave. The value of Complexity converges to 1 as the shape of signal gets more similar to a pure sine wave.

TABLE I. The Hjorth Parameter

Parameter	Notation
Activity	$\mathrm{var}(y(t))$
Mobility	$\sqrt{\dfrac{\mathrm{var}(y'(t))}{\mathrm{var}(y(t))}}$
Complexity	$\dfrac{\mathrm{mobility}(y'(t))}{\mathrm{mobility}(y(t))}$

While these three parameters contain information about frequency spectrum of a signal, they also help analyze signals in time domain. In addition, the lower computational complexity can be achieved with the use of them.

C. The Proposed Method

EEG signal generated by motor imagery has event-related desynchronization/synchronization (ERD/ERS) properties [7]. A decrease of power spectrum in Mu band (8-13Hz) is generally called ERD [8] and an increase of power spectrum in Beta band (13-30 Hz) is called ERS. As shown in Fig. 2, when a subject moves right hand, ERD is occurred at C4 electrode. The power spectrum of an EEG signal has a variety of shapes like ERD/ERS.

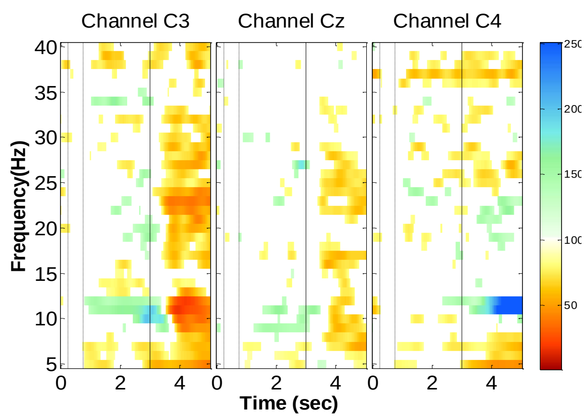

Figure 2. ERD/ERS property of motor imagery(right hand moving).

When a subject moves his arms or imagines that, the distribution of power spectrum is changed in Mu band and Beta band. The power in the Mu band decreases but that in the Beta band increases. On the other hand, the power spectrum is converged on Mu band when a subject is in the relaxed state. Because the Hjorth parameter can detect the difference of power spectrum, we can use it as a feature vector.

Considering that each subject has a slightly different timing and frequency band of ERD/ERS, we need to find the individual dominant band where ERD/ERS appears. To achieve this goal, we introduce the Hjorth parameter for analyzing EEG signals and then use a band-pass filter to get a significant frequency band by removing unnecessary bands where ERD/ERS does not occur.

It is important to select a significant feature in motor imagery for improving the performance of classification, because significant features can differ in every subjects. Therefore, we find the timing and the frequency band by using Fisher ratio as in the following :

After band-pass filtering in an initial frequency band, the filtered EEG signal is selected by windowing in time domain. The duration of a window is 1 sec and windows are overlapped each other for 0.5 sec. A feature is calculated by using the Hjorth parameter at each k th window. In this way, all features are obtained in all windowed durations of training EEG signals, and then the features of each class are ensemble-averaged. And this procedures are repeated, changing a frequency band to others. The frequency bands are selected as the following way. The n frequency points are defined within the frequency range of 5-30 Hz and a frequency band is composed of two points among n points. Then, the number of bands is the number of 2 combinations from frequency points, ${}_nC_2$.

In order to select the important timing and frequency band, the Fisher ratio $F(j,k,l)$, where j is the filter index ($j = 1, 2, \cdots, {}_nC_2$) , k is the window index, and l is the index of the Hjorth parameter (l=Activity, Mobility, Complexity), is calculated from the averaged features of two classes as

$$F(j,k,l) = \frac{|m_1(j,k,l) - m_2(j,k,l)|}{\sigma_1(j,k,l)^2 + \sigma_2(j,k,l)^2} \tag{2}$$

where $m_i(j,k,l)$ (i=1,2) denotes the average and $\sigma_i(j,k,l)^2$ stands for the variance of the Hjorth parameter l of each class i at k th window and j th filter. If the Fisher ratio of the extracted feature is high, two classes are distinguishable by the feature [10]. The prominent timing and frequency band are selected as

$$[\hat{j},\hat{k},\hat{l}] = \max_{j,k,l}(F(j,k,l)) \tag{3}$$

where $\hat{j}$ is the index of the prominent band, $\hat{k}$ is the index of the prominent timing, and $\hat{l}$ is the index of the chosen Hjorth parameter.

III. Experimental Results

A. Data Description

BCI Competition 2008(IV) Graz data set 2b was used for analysis [9]. This data set consists of EEG data from 9 subjects. The subjects were right-handed, had normal or corrected-to-normal vision and were paid for participating in the experiments. All participants were sitting in an armchair, watching a flat screen monitor placed approximately 1-meter away at eye level.

Three bipolar electrodes (C3, Cz, and C4), following the standard of ten/twenty electrode system, were recorded with a sampling frequency of 250 Hz. The Fz electrode was used as the EEG ground. The signals filtered between 0.5 and 50 Hz. The placement of three bipolar electrodes could be slightly different for each subject. Subjects conducted an experiment which was to imagine moving their own left or right hand in accordance with the timing schedule as given in Fig. 3.

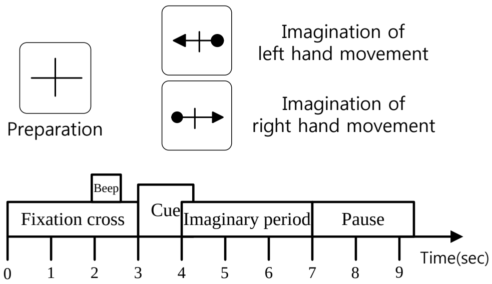

Figure 3. Timing schedule of one trial [9].

Experimental time per one trial was 8 secs long on average. Each trial started with the preparation phase for 3 secs and the short acoustic warning tone was sounded at 2 sec after the trial begins. At 1 sec after the warning tone, a visual cue was presented for 1.25 secs on the screen monitor. Each cue was a randomized arrow pointing left or right side. Next, the subjects imagined the corresponding hand movements according to the randomized cues. After imagining the task for 4 secs, a short break was followed up to 2.5 secs.

B. Feature Selection

We chose frequency points 5, 8, 13, 15, 20, 25, and 30 Hz to implement the proposed method. In this paper, the number of filters is 21. After filtering, the Hjorth parameter is calculated in each frequency band during 10 secs after the visual cue started. And then a band which has the highest Fisher ratio among the features is selected. Fig. 4 shows the Fisher ratio of each parameter at each time interval, as an example of subject 4. Comparing Fig. 4 (a) and (b) indicate the Fisher ratios of features extracted by the Hjorth parameter without and with filtering of subject 4, respectively. The Fisher ratio of features with band-pass filtering is higher than without the filtering. Fig. 4(b) shows that the largest Fisher ratio of Activity parameter in 8-20 Hz band and at 5.5 sec. Therefore, when a test process is performed for subject 4, the band-pass filtering with 8-20 Hz frequency band is applied and the timing of 5.5sec is extracted.

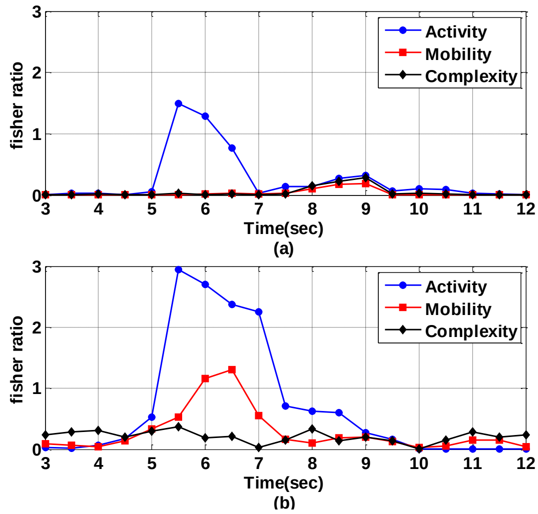

Figure 4. Fisher ratio of features extracted by Hjorth parameter of subject 4. (a) without band-pass filtering (b) with 8-20 Hz band-pass filtering.

In other subjects, the Fisher ratio of Mobility can be larger than that of Activity. However, the Complexity parameter is not selected as a feature because the Fisher ratio of that is very low in whole subjects. Consequently, Activity and Mobility parameter is proper feature vector except for Complexity.

C. Classification Result

Fig. 5 shows the classification result on the subject 4. The classification accuracy of the proposed method is higher than that of the method using the Hjorth parameter alone. Considering the occurrence of event in that time, the proposed method reflects the ERD/ERS property well. We can see that the proposed method outperforms the method without any filtering process in terms of classification accuracy.

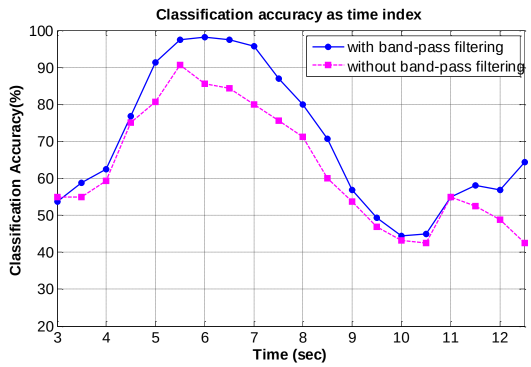

Figure 5. Comparison of classification accuracy between before/after band pass filtering (Subject 4)

Table II shows the classification accuracy obtained from 9 subjects when feature extraction methods are STFT, the Hjorth parameter, and the Hjorth parameter with selected band pass filtering respectively. Classification results with STFT is presented in paper [11]. Linear Discriminant Analysis(LDA) classifier [12] is used to classify for all the case. Because the dimension of feature space is one, It is simply classified with mean values of each class and variance. Comparing to classification accuracy between using STFT and the Hjorth parameter for extracting features, STFT has 3% higher classification accuracy in average. And the Hjorth parameter with band pass filtering is higher Classification Accuracy than general Hjorth parameter, even higher than STFT about 4.4% on average.

TABLE II. CLASSIFICATION ACCURACY

subject	STFT(%)	Hjorth parameter(%)	Proposed method (%)
S1	71.2	80.6	80.6
S2	55.7	53.1	61.6
S3	53.1	60.6	60.6
S4	93.8	86.8	98.1
S5	86.2	77.6	81.8
S6	83.8	61.2	84.3
S7	65.3	63.3	72.5
S8	83.8	86.2	86.2
S9	79.4	75	86
Average	74.7	71.6	79.1

TABLE III. SELECTED FEATURE INFORMATION FOR EACH SUBJECT

Subject	Parameter	Frequency band(Hz)	Time(sec)
S1	Activity	-	5.5~6.5
S2	Activity	5~15	5.5~6.5
S3	Mobility	-	4.5~5.5
S4	Activity	8~20	5~6
S5	Mobility	13~25	5.5~6.5
S6	Mobility	8~30	7.5~8.5
S7	Activity	5~15	5.5~6.5
S8	Activity	-	6~7
S9	Activity	8~20	5~6

Table III shows that each subject has their selected frequency band, time and parameter respectively. It underpins that each subject has specific time and band occurring ERD/ERS.

IV. CONCLUSION

In this paper, we employed the Hjorth parameter as a feature extraction method since it can efficiently represent ERD/ERS property of EEG signals in motor imagery. By band-pass filtering the significant band found using the Hjorth parameter and the Fisher ratio, it is confirmed that each case has own dominant frequency band and timing. The classification accuracy with the use of the proposed feature selection method is higher than that of the conventional feature extraction method, STFT. In further research, a study on automatic band selection methods would be needed.

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Seung-Hyeon Oh received the B.S. degrees in electronic and electrical engineering from Pusan National University (PNU), Busan, Korea, in 2013. He is currently working toward the M.S. degree at the Communications and Signal Processing Laboratory (CSPL), Department of Electronics Engineering at Pusan National University (PNU), Busan, Korea. His main research interests are in the area of digital signal processing, pattern recognition, bio signal processing.

Yu-Ri Lee received the B.S. and M.S. degree in electronic and electrical engineering from Pusan National University, Busan, Korea, in 2010 and 2012, respectively. She is currently working toward the Ph.D. degree at the Communications and Signal Processing Laboratory (CSPL), Department of Electrical & Computer Engineering at Pusan National University, Busan, Korea. Her main research interests are in the area of digital signal processing, bio signal processing, signal processing for digital broadcasting, and SCA.

Hyoung-Nam Kim (M'00) received the BS, MS, and PhD degrees in electronic and electrical engineering from Pohang University of Science and Technology (POSTECH), Pohang, Korea, in 1993, 1995, and 2000, respectively. From May 2000 to February 2003, he was with Electronics and Telecommunications Research Institute (ETRI), Daejeon, Korea, developing advanced transmission and reception technology for terrestrial digital television. In 2003, he joined the faculty of the Department of Electronics and Electrical Engineering at Pusan National University (PNU), Busan, Korea, where he is currently an associate professor. From February 2009 to February 2010, he was with the Department of Biomedical Engineering, Johns Hopkins University School of Medicine, as a Visiting Scholar. His research interests are in the area of digital signal processing, adaptive IIR filtering, bio signal processing, and RADAR/SONAR signal processing, in particular, signal processing for digital broadcasting, digital communications, and multimedia systems. Dr. Kim is a member of IEEE, IEICE, IEEK, and KICS.

