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On-line Independent Component Analysis of EEG signals for Brain-Computer Interfacing

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뇌-컴퓨터 접속을 위한 뇌전위 신호의 온라인 독립 성분 분석

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Abstract: Independent component analysis (ICA) has been successfully applied for processing of EEG signals with interesting and promising results due to its remarkable ability to separate each independent brain source from various environmental artifacts. These separated signals need to be properly classified as brain sources or artifacts for further development of practical EEG applications. This paper demonstrates a brain-computer interfacing (BCI) system that is trained by the learning vector quantization (LVQ) neural network with features extracted from ICA separated sources. Quantitative analysis is performed on the separated sources to establish two meaningful features, event-related desynchronization (ERD) and fractal dimension (FD). The experimental results show that the proposed BCI system can effectively discriminate the left and right cases of EEG signals accompanied by both actual and imagery hand movements.

Key words: Brain-Computer Interfacing, Independent Component Analysis, EEG, Neural Networks

요 약: 독립 성분 분석법(ICA)은 다양한 주변 장애신호로부터 독립 뇌 신호원을 분리해내는 뛰어난 성능 때문에 흥미롭고 유망한 결과를 도출하며 뇌전위신호(EEG)의 처리에 성공적으로 응용되어 왔다. 이렇게 분리된 신호들은 이후에 실용적인 EEG 응용제품의 개발을 위해서 뇌신호원과 장애신호로 적절히 구분되어야 한다. 본 논문에서는 ICA로 분리된 신호원으로부터 추출된 특징을 사용하여 LVQ신경회로망에 의해 학습되는 BCI 시스템을 선보인다. 이벤트 관련 비동기화(ERD)와 프랙탈 차원(FD)이라는 두 개의 의미없는 특징이 분리된 신호원으로부터 만들어지고 정량적인 분석이 수행된다. 실험결과는 제안한 BCI 시스템이 실제의 손동작과 손동작의 상상에 따라 수반되는 EEG 신호로부터 왼쪽과 오른쪽의 경우를 효과적으로 판별함을 보인다.

주요어: BCI, 독립 성분 분석, 뇌전위, 신경회로망

Introduction

Development of a computer system that is able to consistently infer the volition of human by analyzing on-line EEG signal will establish a new direct channel between the human brain and the computer. Such a system is referred to as brain-computer interfacing (BCI). Most desirable aspect of the system comes from the fact that no actual muscle activity, including speech, is required in communicating with the computer[1]. Hence, it is promisingly regarded as intelligent rehabilitation equipment for patients who suffer from severe motor impairments.

In developing the BCI system, two major difficulties

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are of concern. First, considerably large amount of data need to be acquired and analyzed in real-time and second, when we inspect the acquired data, it is found that EEG signals of micro-volt range are intermingled with various artifacts, up to milli-volt range, such as eye blinking, muscle activity and power-line noise. Thanks to enhanced computing powers, the first issue seems to be no longer a serious problem. In case of artifacts, however, the problem is more complex and challenging.

If there is only one artifact such as eye blinking, autoregressive modeling[2] might be a good solution. Unfortunately, there are various artifacts, which are sometimes unable to be modeled, that no single mathematical operation can successfully separate EEG signals from diverse artifacts.

From the first practical realization by Bell and Sejnowski[3], independent component analysis(ICA) has gained attentions on these blind source separation problems. In a viewpoint that a BCI system needs to separate unknown brain sources from also unknown artifacts, applying the ICA technique, which employs higher-order statistics, is appropriate. However, ICA separated sources are, in its nature, in random order and random direction. This has prevented a quantitative analysis on ICA separated sources. In this paper, we present a method of fixing the orders and the directions of ICA separated sources, then show how to remove artifacts from brain sources followed by extraction of two features, ERD and FD. ERD is featured by the absence of the specific frequency component appeared when the subject prepares limb movement while FD is featured by the temporal complexity of the EEG signal.

These extracted features constitute input vectors of the LVQ neural network that will be trained for inferring the volitions of the subjects.

BCI System

Fig. 1 shows a block diagram of the proposed BCI system. Cue generator generates left or right cues in

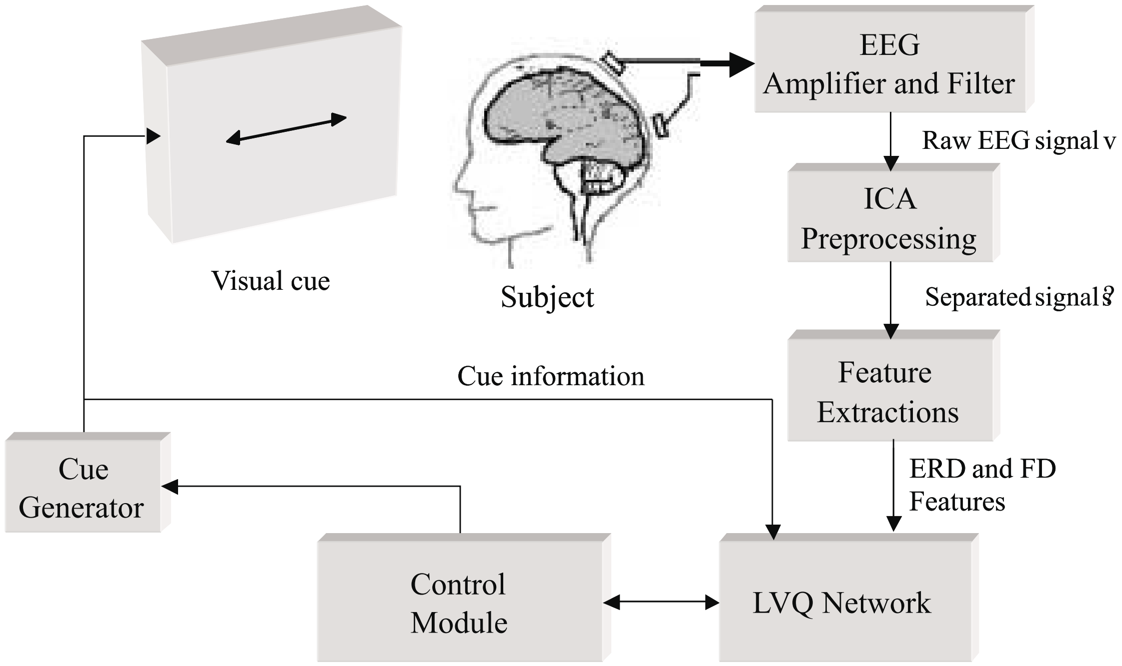


Fig. 1. Block diagram of the proposed BCI system.

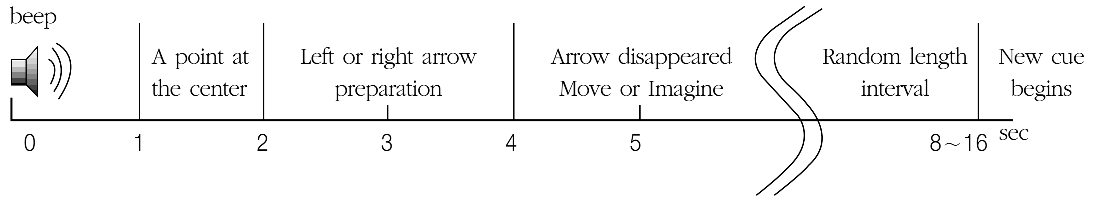


Fig. 2. Signal sequence of the cue.

pseudo-random order which are appeared as arrows on the monitor.

Constitution of the cue is depicted in Fig. 2 Each cue is started with short warning tone (beep). After one second, a point was displayed at the center of the monitor then it changed into arrow of left or right direction. The subject was instructed to prepare the movement while arrow is shown. As soon as the arrow disappeared, subject moves or imagines moving his/her index finger of the hand that arrow points. Random length interval is attached to the end of each cue.

Eight channel EEG amplifier of Biopac MP 100 series acquires raw EEG signals at eight selected electrodes from international 10-20 system in a sampling rate of 256 Hz. Built-in analog filters, 1 Hz HPF and 35 Hz LPF, are used and no digital filters are further utilized since we observed that the ICA successfully took the place of them. Raw EEG signal is preprocessed by the ICA to separate brain sources and exclude artifacts, then two features, ERD and FD, are extracted. The input vector from extracted features and the target vector from cue information make up a training set of LVQ neural network. These on-line EEG signal procedures are programmed in National Instrument LabVIEW.

ICA algorithm

ICA is a higher-order statistical method that aims to separate sources in the linear mixture of signals without any knowledge about sources and mixture model. We suppose that there are M unknown brain sources, $\mathbf{s}(t)$ that may include some artifacts. By also unknown linear mixture model, $\mathbf{A}$, the sources are mixed and what we can observe are N signals, $\mathbf{v}(t)$ i.e.

$$\mathbf{v}(t) = \mathbf{A}\mathbf{s}(t), \tag{1}$$

where $\mathbf{s}(t) = [s_1(t)\ s_2(t) \cdots s_M(t)]$ and $\mathbf{v}(t) = [v_1(t)\ v_2(t) \cdots v_N(t)]$, The followings are basic assumptions on applying ICA. Components $s_i(t)$ are zero mean and statistically independent. Distributions of each source are nongaussian or there is only one gaussian source. For convenience, unknown mixing matrix, $\mathbf{A}$, is square, i.e. $M=N$.

The problem of estimating the matrix $\mathbf{A}$ in Eq. (1) can be simplified[4] if we perform a preliminary sphering or prewhitening of the $\mathbf{v}(t)$ as

$$\mathbf{x}(t) = (\mathbf{\Phi}\mathbf{\Lambda}^{-\frac{1}{2}})^T \mathbf{v}(t) = \mathbf{M}\mathbf{v}(t), \tag{2}$$

where $\mathbf{\Phi}$ is the orthogonal matrix of eigenvectors of $E\{\mathbf{v}(t)\mathbf{v}(t)^T\}$, the covariance matrix, and Λ is the diagonal matrix of its eigenvalues. Each $x_i(t)$ from $\mathbf{x}(t) = [x_1(t)\ x_2(t) \cdots x_N(t)]$ are mutually uncorrelated and have unit variances. After the whitening we have

$$\mathbf{x}(t) = \mathbf{M}\mathbf{v}(t) = \mathbf{M}\mathbf{A}\mathbf{s}(t) = \mathbf{B}\mathbf{s}(t). \tag{3}$$

Since $E\{\mathbf{x}(t)\mathbf{x}(t)^T\} = \mathbf{I}$, it holds $E\{\mathbf{x}(t)\mathbf{x}(t)^T\} = \mathbf{B}E\{\mathbf{s}(t)\mathbf{s}(t)^T\}\mathbf{B}^T = \mathbf{B}\mathbf{B}^T = \mathbf{I}$ This implies that B is orthogonal, i.e. $\mathrm{B}^{-1}=\mathrm{B}^{\mathrm{T}}$. Now sources can be expressed as

$$\mathbf{s}(t) = \mathbf{B}^{-1}\mathbf{x}(t) = \mathbf{B}^T\mathbf{x}(t). \tag{4}$$

A single layer neural network with weight matrix

$\mathbf{W}$ is adopted so that it can be trained to estimate source signals as

$$\hat{\mathbf{s}}(t) = \mathbf{y}(t) = \mathbf{W}\mathbf{x}(t)\,. \tag{5}$$

$\mathbf{W}$ is trained in a way that nongaussianity of $\hat{s}_i(t)$are maximized or minimized, become more dissimilar from gaussian distribution. Commonly used measures for nongaussianity are kurtosis[3, 4, 5] and negentropy[5]. In[3], gradient ascent rule to train $\mathbf{W}$ with kurtosis measure is established as

$$\Delta\mathbf{W}(t) \propto [\mathbf{W}(t)^T]^{-1} + (1-2\mathrm{y}(t))\mathrm{x}(t)^T \tag{6}$$

Although this rule is widely applied in blind source separation problem, it converges too slowly and performance is crucially dependent on the learning rate. In [4], fixed-point ICA algorithm, which takes expectation on the kurtosis based weight update equation and finds a fixed weight point, is introduced. Each row vector, $\mathbf{w}_i$, of $\mathbf{W}$ can be found by applying the following equation several times.

$$\mathbf{w}_i = scalar \times (E\{\mathbf{x}(\mathbf{w}_i^T\mathbf{x})^3\} - 3\|\mathbf{w}_i\|^2\mathbf{w}_i) \tag{7}$$

This algorithm leads to reasonably faster convergence without dependency on learning parameters. The proposed BCI system adopts this fixed-point ICA algorithm with some modifications.

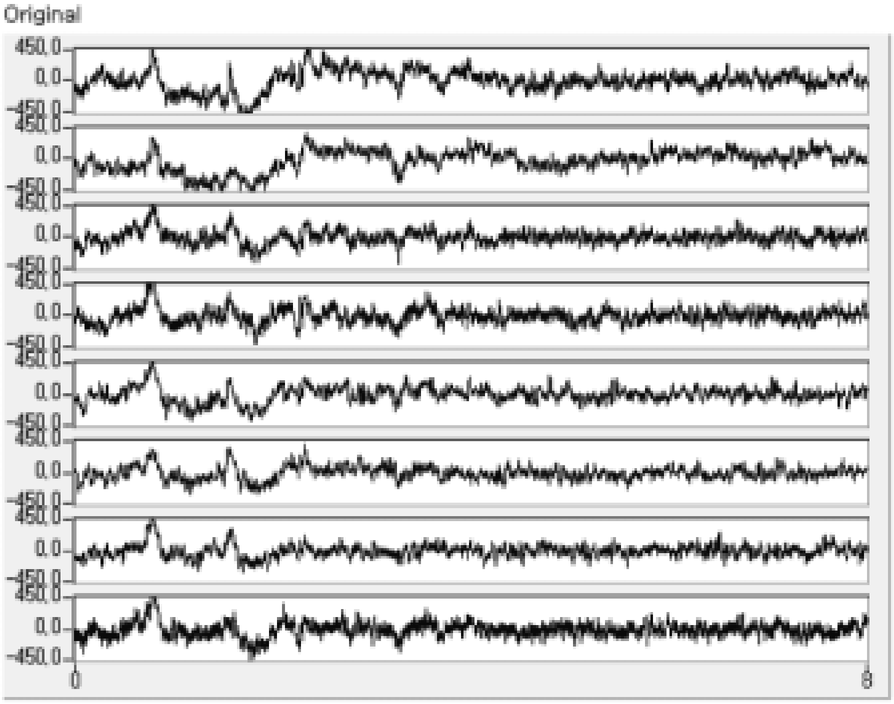
Whenever ICA is applied upon the same mixed signals, the orders and directions of the separated independent sources are not same because $\mathbf{w}_i$ is initialized to random before Eq.

(7) is evaluated and this $\mathbf{w}_i$ is converged to the nearest fixed-point. If this is the case, we can distinguish each separated source by conjecture, but systematical analysis of separated sources is impractical. Many studies on ICA analysis of EEG signal so far have provided merely vague discrimination on the sources. In order to fix the order of sources, proposed BCI system evaluates the norms of row vectors of unmixing matrix $\mathbf{W}$, then permute the rows of $\mathbf{W}$ to arrange them by the size of the norm. For directions, the sign of the first element in is multiplied to every element in $\mathbf{w}_i$ order to fit the first element to be nonnegative. These will make ICA separate sources in same orders and directions. In addition, initial values of $\mathbf{w}_i$ can be set in order that they start converging from the basin of predefined attraction points. In doing this, initializing $\mathbf{W}$ with previously evaluated one for separating different mixtures with similar environments will have effects of fast convergence and consistent orders among separated sources.

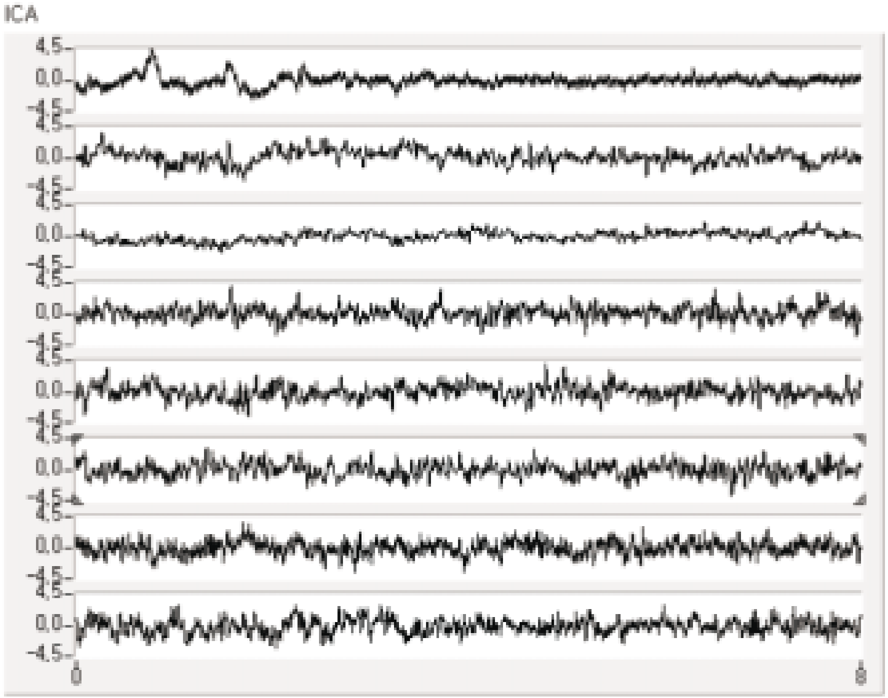
Fig. 3 shows an example of ICA separation of EEG signals from electrodes configured in Table 1. As can be seen, low frequency artifact, which is caused by muscle activity, is dominant all over the electrodes in original signals. However, ICA clearly separates this artifact from other meaningful brain sources and it is localized in the first channel. We also noticed that 60 Hz power line noise is also contained in the first channel. We cannot explain why this happens. We observed that if we eliminated one of the ICA separated sources which has the highest frequency component at 60 Hz, we also have chance to eliminate the low frequency artifact. Thus, seven out of eight sources are used for feature extractions.

Feature extractions

Two features, event-related desynchronization(ERD) and fractal dimension(FD), are extracted from ICA separated EEG sources. A phenomenon called ERD is observed when human prepares to move, or just imagines moving, his/her limbs[1]. This is a sudden attenuation of subject' s mu-rhythm (8-12 Hz EEG) on the electrodes near C3 and C4. To detect a moment that relative frequency component of 8-12 Hz is minimum, FFT is performed during two seconds of data, one second before and after the arrow on the monitor is disappeared, by utilizing one second length



(a)



(b)

Fig. 3. (a) Original EEG signals acquired at eight electrodes and (b) ICA separated EEG sources.

Table 1. Electrode configurations.

Channels	Electrodes of International 10-20 System
1	Fp1
2	Fp2
3	C3
4	C4
5	O1
6	O2
7	P3
8	P4

window with 1/4 second length sliding step. For EEG data of 1-second length window, power spectrum is evaluated as

$$S_{xx}(f)=\left(\frac{|FFT(x(\tau))|}{L}\right)^2, \tag{8}$$

where L is 256, the number of data points in 1-second length window, and τ is defined between time points $t-L$ and t. We calculate frequency component of 8-12 Hz as

$$\mu(t)=\sum_{f=8}^{12} S_{xx}(f), \tag{9}$$

then, relative power spectrum at eight time points, each 1/4 second sliding step during 2 seconds, are given

$$R_\mu(t)=\frac{\mu(t)}{\sum_{i=1}^{8}\mu(t_0-s\times i)\Big/8}, \tag{10}$$

where s is 64, the number of data points along the sliding step, t_0 and is the time when the arrow is shown. In one trial, eight time series of relative power spectrums are generated at seven channels and the minimal value is marked with its time index. For ERD feature, the minimal values and time indices at seven channels, up to 14 elements, constitutes LVQ input vector.

Since ERD is a basically frequency analysis, it does not adequately reflect the variations of each person's time-related brain activity. As a complementary feature, we adopt fractal dimension(FD) estimated by Higuchi's algorithm[6]. FD refer to a non-integer or fractional dimension of any object. Higuchi's algorithm utilizes temporal approach of FD, in contrast to the phase space analysis. It estimates the dimension of a time varying signal directly in the time domain, which saves significant computational burdens. Consider $x(1)$, $x(2)$, $\cdots$, $x(N)$ the time series to be analyzed. k new time series is constructed as

$$X_m^k=\left\{X(m),X(m+k),X(m+2k),\cdots,X\left(m+\left\lfloor\frac{N-m}{k}\right\rfloor k\right)\right\}, \tag{11}$$

for, $m=1, 2, \cdots, k$, where m indicates the initial time value, and k indicates the discrete time interval between points. For each curve, X_m^k its length is calculated by

$$L_m(k)=\left(\sum_{i=1}^{\left\lfloor\frac{N-m}{k}\right\rfloor}\left|X(m+i\times k)-X(m+(i+1)\times k)\right|\right) \times\frac{N-1}{\left\lfloor\frac{N-m}{k}\right\rfloor\times k}. \tag{12}$$

The average of k values of $L_m(k)$ is calculated by

$$L(k)=\frac{\sum_{m=1}^{k}L_m(k)}{k}. \tag{13}$$

We set the value of $k_{\min}$ and $k_{\max}$, then calculate $L(k)$ for each k, $k_{\min}\le k\le k_{\max}$. For the points of $\ln(L(K))$ versus $\ln(1/k)$, the slope of the least-squares linear best fit is the estimate of the FD. FD has the values range from 1 to 2 and higher value indicates more complex signal[6, 7]. We observed that FD has a tendency to rise before the preparation of the movement. Thus, the way extracting the FD feature is similar to that of the ERD. First, two seconds of FD values before the arrow is shown are estimated, with the same window and sliding step as ERD, for average. Then, with the data of one second before and after the disappearance of the arrow, series of relative FD are estimated as the FD values divided by the average. The maximal relative FD is marked with its time index. In this way, another 14 elements constitutes LVQ input vector. There are total of 28 elements in one LVQ input vector.

Decision module

Learning vector quantization 2 (LVQ 2) neural network[8] is used for the decision module of the proposed BCI system. LVQ has a simple architecture but overcomes the linear separable problem by combining several subclasses into one class. It effectively associates input and target vectors with competitive and supervised learning. Input vector constitutes of 28 elements extracted from ERD and FD analyses. The input vector is normalized with inverse of the sigmoid like functions to enhance the effect of the elements that has distinctively large or small values. Input vector is applied to the LVQ then, the first layer that performs competitive learning indicates a subclass that the input belongs. The second layer, further combines selected subclasses into one class and it is compared to the target vector to train the weights of the first layer. Two classes are assigned for the left and the right cases and three subclasses are allocated for each class.

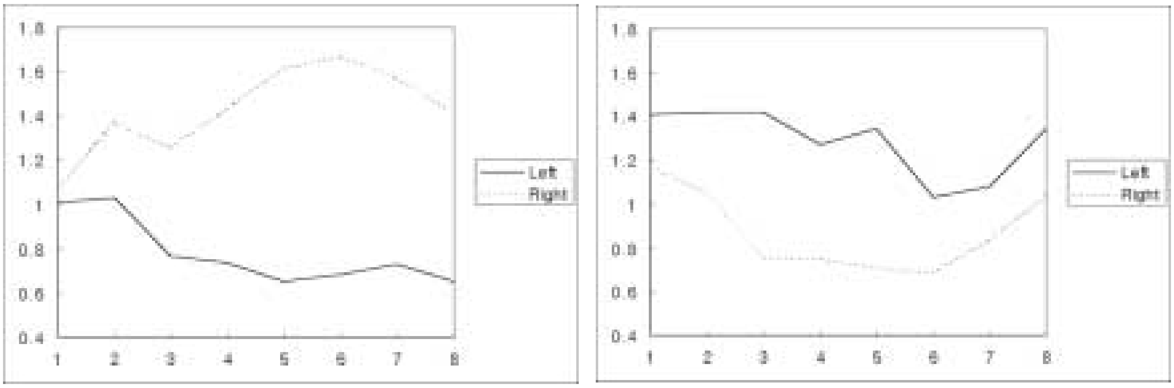
Experiments

Three male graduate students participated in the experiment. Four sessions were held at each subject and each session was proceeded with ten left and ten right cues. The first two sessions were accompanied by real hand movements and the last two sessions by imagery movements. During the experiments, illuminations of the chamber were maintained dim. The unmixing matrix for ICA was evaluated for each subject from eight seconds of the data at session 1, and then it was used throughout the remaining sessions. In the sessions 1, 2 and 3, the accuracies of the BCI system's inference were evaluated off-line. The session 1 utilized its own input and target vectors for training and testing. The LVQ, which had been trained from session 1, was further altered for training new sets from the session 2 then was tested with input vectors of the session 2, and so on for the session 3. In off-line training, each training set was applied to the LVQ 10 times with random order. In the session 4, the accuracies were evaluated on-line. For the LVQ trained up to the session 3, the input vectors of the session 4 were applied just one time and the results were promptly calculated. Fig. 4 shows averaged ERD features of subject A during session 2. ERD features with left and right cues are averaged separately and among others channel 3 and 5 well describe ERD characteristics for left and right cases. Similarly, averaged FD features of channel 6 and 2 are shown in Fig. 5. The accuracies evaluated throughout the sessions are summarized in Table 2.

The session 2 provided better accuracies than the session 1 for all subjects because it started training from the state that had already been trained by the previous session. In session 3, however, the accuracies for the subject A and C had fallen. This is due to the fact that the sessions 3 and 4 were accompanied by imagery hand movements. For the session 4, the accuracies were evaluated on-line but the subjects A and B had shown lower accuracies compared to the previous session due to the lacks of the training sets. The effectiveness of applying ICA in the proposed BCI system can be justified when we compare the accuracies in Table 2 with Table 3 that are obtained with raw EEG signals.

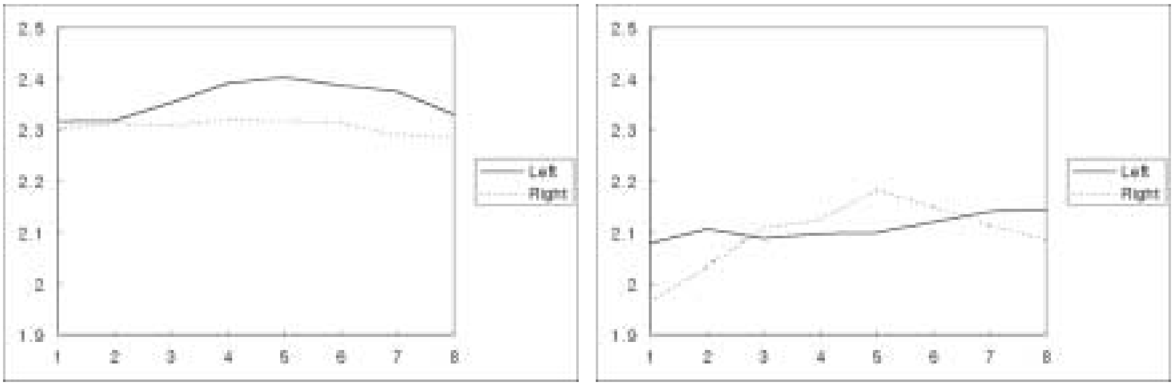
Conclusions

We developed a BCI system that aims for inferring



(a) (b)

Fig. 4. ERD features of subject A during session 2 which are averaged separately into left and right cases. The x-axis denotes eight time points in 2 seconds at which features for LVQ are evaluated. (a) In channel 3 left case has lower ERD and (b) in channel 5 right case has lower ERD.



(a) (b)

Fig. 5. FD features of subject A during session 2 which are averaged separately into left and right cases. The x-axis denotes eight time points in 2 seconds at which features for LVQ are evaluated. (a) In channel 6 left case has higher FD and (b) in channel 2 right case has higher FD.

the intentions of the subjects. By using effective ICA algorithm, the brain sources are consistently separated from the artifacts and the acquired unmixing matrix can be used from session to session for the same subject.

Definitely, we cannot count the exact number of brain sources nor separate them entirely.

However, for EEG signals from noninvasive scalp electrodes, it is observed that ICA statistically separates significant brain sources among others. Thus, utilizing features extracted from these separated sources provided a new insight on the development of BCI system. We believe that both ERD and FD are meaningful features and have complementary relationships. We estimated ERD and FD features from all the ICA separated brain sources, and then used them for input vectors because we do not know how many sources are involved in constituting the designated features. Although we normalized the input elements with inverse of the sigmoid function to

Table 2. Accuracies of the proposed BCI system tested on three subjects at four sessions.

			Subjects		
Sessions	Training	Movement	A	B	C
1	off-line	Actual	70	55	65
2	off-line	Actual	80	60	70
3	off-line	Imagery	75	65	65
4	on-line	Imagery	70	60	65

Accuracies [%]

Table 3. Accuracies evaluated without applying ICA.

			Subjects		
Sessions	Training	Movement	A	B	C
1	off-line	actual	60	50	60
2	off-line	actual	75	55	65
3	off-line	imagery	70	65	55
4	on-line	imagery	65	60	60

Accuracies [%]

lessen the effects from irrelevant sources, studies should be concerned on actual elimination of the irrelevant sources in order to increase the accuracies. In addition, tuning the band of mu-rhythm in accordance with each subject's responses rather than fixing its range to 8-12 Hz should be accomplished in order to obtain more reliable ERD feature.

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