Available online at www.sciencedirect.com
ScienceDirect
Neurocomputing 70 (2006) 263–272
NEUROCOMPUTING
www.elsevier.com/locate/neucom

Quantitative measure of complexity of the dynamic event-related EEG data

Xiao-mei Pei*, Chong-xun Zheng, Wei-xing He, Jin Xu

Key laboratory of Biomedical Information Engineering of Education Ministry, Institute of Biomedical Engineering, Xi'an Jiaotong University, 710049, Xi'an, PR China

Received 27 June 2005; received in revised form 12 February 2006; accepted 13 February 2006
Communicated by S. Hochreiter
Available online 10 July 2006

Abstract

Currently, the quantification of event-related EEG is usually based on power feature with the classical band power method. In this paper, the method quantifying the complexity and irregularity of event-related EEG data in relation to hand motor imagery is presented. Two groups of the complexity indexes: Kolmogorov complexity (*Kc*) and Fourier spectral entropy (*FSE*) are discussed. The event-related desynchronization/synchronization (ERD/ERS) time course is analyzed and characterized by two parameters *Kc* and *FSE*, respectively. The percentage of EEG complexity during imagination of the unilateral hand movement relative to that during reference period is calculated for quantifying the complexity measure of ERD/ERS time course. The method is applied to two sets of movement-related EEG data recorded over the primary sensorimotor area from two subjects. In addition, the validity of the quantitative measure of complexity of the event-related EEG is testified by evaluating the performance of feature extraction and classification. The results show that both *Kc* and *FSE* can effectively describe the dynamic complexity of event-related EEG and also display the consistent and similar behaviors. The relative increase and decrease of event-related EEG complexity could be an indicator of ERD/ERS, which is also independent of the power changes. Thus, the dynamic complexity measure of event-related EEG quantified by *Kc* and *FSE* provides another evidence for ERD/ERS and can be meaningful for analyzing the event-related EEG.

Keywords: ERD/ERS time course; Complexity indexes *Kc* and *FSE*; Event-related EEG; Hand motor imagery

1. Introduction

Studies have shown that during imagining or preparing for unilateral hand movement, the amplitude of EEG rhythms within the specific frequency band (i.e. alpha and beta activity) attenuates over contralateral sensorimotor hand areas, which is called event-related desynchronization (ERD); while in certain cases, the amplitude of corresponding EEG rhythms increases over ipsilateral sensorimotor hand areas at the same time, which is called event-related synchronization (ERS) [12,13]. Based on ERD/ERS, the left- or right-hand motor imagery tasks are easily discriminated, which can be translated into binary output to control external devices. This technology is called Brain Computer Interface (BCI) [24].

In Refs. [3,13,14], the classical band power method for quantifying ERD/ERS was described by Pfurtscheller and his associates. The main idea is to compare the band power change of EEG recorded during hand motor imagery with that during reference period with brain resting state. Through the changed power percentage between the two different brain states, the ERD/ERS could be quantified. Other methods for analyzing ERD/ERS can be seen elsewhere including inter-trial variance method [3], autoregressive models and spectral decomposition [1], temporal spectral evolution method [21], task-related power increase and decrease method [3,14], etc., which were reviewed in [14]. Most of these methods are based on band power analysis. In this paper, analogous to classical band power method quantifying ERD/ERS, the analysis method of

*Corresponding author. Tel.: +86 029 82668774.
E-mail address: pei@zy165.com (X.-M. Pei).

0925-2312/$ - see front matter © 2006 Elsevier B.V. All rights reserved.
doi:10.1016/j.neucom.2006.02.011

quantifying the complexity measure of ERD/ERS is proposed. Two sets of movement-related data from two subjects are analyzed and two groups of complexity indexes including nonlinear measure *Kc* (Kolmogorov complexity) and the measure of information entropy *FSE* (Fourier spectral entropy) are discussed, respectively. The preliminary results suggest that with the amplitude attenuation of movement-related EEG, the corresponding EEG complexity measure increases, and vice versa. The dynamic complexity measures of event-related EEG quantified by *Kc* and *FSE* display the similar behaviors, but an inverse pattern as compared with the band power measure of ERD/ERS. Therefore, the complexity measure can be considered to characterize the dynamic change of event-related EEG.

2. The experimental data

Two sets of event-related EEG data from two subjects are analyzed, both of which were investigated in a feedback-guided motor imagery experiment. The *Subject* 1 performed the following task repeatedly in a series of sessions, in which each trial lasted 9 s. During the first 3 s reference period of each trial, the subject was asked to keep relaxed with eyes open, followed by an arrow pointing either to the right or left (cue stimulus) indicating motor imagery task of either with right- or left-hand till $t = 4.25$ s. The feedback bar, presented during the following period till $t = 9$ s, was moving horizontally towards the right or left boundary of the screen dependent on the on-line classification of the EEG signals, which directs the subject performing hand motor imagery. The feedback is the classification result obtained by the analysis of the preceding 1 s EEG. The details of experiment were provided in [9,16]. Three bipolar EEG channels were measured over the anterior and posterior of C3, C*z*, C4 with inter-electrode intervals of 2.5 cm. EEG was sampled with 128 Hz and filtered between 0.5 and 30 Hz. Both the train datasets and test datasets include 140 trials and the class labels, respectively, with the equal number of left- and right-hand motor imagery tasks.

Subject 2 performed the similar left- or right-hand motor imagery tasks to control the navigation in a virtual environment. The recordings were made with a bipolar EEG amplifier from g.tec. The EEG was sampled with 125 Hz and was filtered between 0.5 and 30 Hz with Notchfilter on. Each trial lasts 8 s. In the first 3 s, the subject is asked to keep relaxed, and then the subject is asked to imagine the movement of left or right hand until the end of trial. The details can be found in [7]. The train dataset include 320 trials and the class labels with also the equal number of left- and right-hand motor imagery tasks. In actual analysis, we only use 319 trials with exempting one trial containing NaN value. Both the two sets of data were provided by Graz University of technology available at the BCI2003 and BCI2005 competition website, respectively.

3. Methods

3.1. Kc measure

The complexity of EEG signal can be quantified by the *Kc*. As a nonlinear complexity measure, *Kc* can effectively reveal the regularity and randomness in a time varying EEG arising from the brain system and gain the information regarding the dynamics of the specific regional brain subsystem. According to Kolmogorov's definition, the complexity of a given string of zeros and ones is given by the number of bits of the shortest computer program which can generate this string [5]. Lempel and Ziv described the Kolomogorov complexity algorithm successfully. With the programs that allow copy and insert operations [5,8], they quantified the complexity of a given string $x \in [0, 1]$ by calculating a number $c(n)$, which is a useful measure describing the string with the length n and reflect the relative complexity of the string x. The details can be found in Refs. [5,8]. It has been shown by Lempel and Ziv that for almost all $x \in [0, 1]$, $c(n)$ tends to the same value [4]:

$$b(n) = \lim_{n\to\infty} c(n) \cong \frac{n}{\log_2 n}, \tag{1}$$

$b(n)$ gives the asymptotic behavior of $c(n)$ for a random string x; if normalize $c(n)$ by $b(n)$, the normalized complexity *Kc* is obtained [8]:

$$Kc = c(n)/b(n). \tag{2}$$

Obviously, $0 \leqslant Kc \leqslant 1$. $Kc = 1$ means the randomness of the signal reaching the maximum. Some studies showed that the complexity measure may be useful in tracking short-term and long-term changes in brain functions such as anesthetized depth [23], drug effects [20]. Also, the parameter *Kc* can be used to characterize dynamic complexity of event-related EEG [10].

Before calculating *Kc* complexity of the data, EEG is to be transferred into a symbol sequence $x \in [0, 1]$. Here, binary symbol sequences were constructed by partitioning about the mean.

3.2. FSE measure

The complexity of EEG signal also can be characterized by *FSE*, which was introduced and applied to quantify the EEG irregularity by Inouye et al. [2]. *FSE* calculates the entropy of EEG spectrum within a specific frequency range so that it actually characterizes the uniformity degree of EEG power distribution within different frequency band. By analyzing the distribution of the EEG spectrum in specific frequency band, *FSE* can effectively describe the EEG structural complexity. For the EEG spectrum within a specific frequency band, the narrower spectrum peak and the smaller the peak number is, the smaller the spectral entropy is, the more regular the corresponding EEG signal is, and vice versa. Different from the *Kc* complexity, *FSE* was defined by the Shannon entropy, which describes the EEG structural complexity from the frequency domain.

If we let $X(k), k = 1, 2 \ldots N$ denote the complex *FFTs* of the EEG signal $x(k)$, where N is the number of EEG sample points, then the corresponding EEG power spectrum can be obtained as follows [2]:

$$P(k) = \left|X(k)\right|^2. \tag{3}$$

The frequency of the kth spectral sample is

$$f_k = \frac{kf_s}{N}, \tag{4}$$

where f_s is the sampling frequency. For a specific frequency band, for example, $f_k \in [f_p \sim f_q]$ Hz, $k_r = Nf_r/f_s$, $(r = p, q)$, where k_r denotes the integer part of (Nf_r/f_s); assuming that $f_q > f_p$and setting $k \in [k_p, k_q]$, then the normalized signal power p_j, which reflects the percentage of EEG spectrum at each frequency to the total spectrum within $f_p \sim f_q$, could be defined as follows:

$$p_j = P(k) / \sum_{k=k_p}^{k_q} P(k), \tag{5}$$

where $\sum_j p_j = 1$.

And then the corresponding *FSE* of EEG within $f_p \sim f_q$ can be calculated as follows:

$$FSE = -\sum_j p_j \ln(p_j). \tag{6}$$

For EEG oscillations in different frequency bands such as delta (0–4 Hz), theta (4–7 Hz), alpha (8–13 Hz) and beta (14–30 Hz), the complexity measure *FSE* of the corresponding EEG rhythms could be flexibly quantified by selecting f_p and f_q.

From the above analysis, it can be seen that both *Kc* and *FSE* could measure the EEG complexity and irregularity. Therefore, it's reasonable to expect that the event-related EEG time courses characterized by two complexity measures of *Kc* and *FSE* should show the consistent behaviors. The movement-related EEG appears mainly within alpha and beta band. Here, *FSE* and *Kc* of EEG within 8–30 Hz are studied, respectively.

To describe the time-dependent EEG complexity changes, EEG is divided into many 1-s segments to extract the complexity for each segment. Then slide time window stepped by one sample to calculate the complexity of the next segment. The process is made until the EEG complexity of the last 1-s segment is calculated. And the continuous EEG complexity time course can be obtained.

3.3. The quantitative measure of complexity of ERD/ERS

The complexity method for quantifying event-related EEG is similar to the band power method proposed by Pfurtscheller [3,13,14]. The difference between the two methods is the different EEG feature to be selected. The classical band power method to quantify ERD/ERS is based on EEG power feature, i.e. the squared amplitude. Complexity method is based on EEG complexity feature. The procedure of quantifying the complexity measure of ERD time course by *Kc* and *FSE* can be as follows:

(1) Computing of the complexity time course of event-related EEG within the specific frequency band.
(2) Squaring of the *Kc* complexity sample to obtain the squared *Kc* complexity; there is no need to square*FSE* for it calculates the Shannon entropy of the squared EEG amplitude.
(3) Averaging of the complexity samples (*FSE* or squared *Kc*) across all trials.
(4) Calculating of EEG complexity percentage during hand motor imagery relative to the complexity during the reference period.
(5) Averaging over time samples to smooth the data and reduce the variability.

As a comparison, the algorithm of the classical inter-trial variance method is described simply as the following four steps: bandpass filter, squaring the inter-trial amplitude, averaging over trials, averaging over time. The details could be found in [3,14].

3.4. Performance evaluation

Different from the classical band power method, the quantitative complexity measure of the event-related EEG can reveal the complexity information of the time varying EEG signals arising from the specific brain system. Especially for the *Kc* parameter, as a nonlinear complexity measure, it directly reflects the dynamics of the brain sensorimotor subsystem underlying electrodes C3 and C4.

To demonstrate the validity of complexity measure for quantifying the event-related EEG, as an example, we select *Kc* extracting the complexity features of EEG combined with the power features extracted by classical FFT method to discriminate the left- and right-hand motor imagery tasks. Here, Fisher discriminant analysis is used to realize the classification of two classes of EEG patterns. Firstly, according to the above analysis, the two kinds of features of event-related EEG within 8–30 Hz from the electrodes C3 and C4 over the left and right hemispheres for the train data and test data are calculated to construct the four-dimensional time-dependent feature vectors $F_{\text{train}-t}$, and $F_{\text{test}-t}$, respectively. By learning the training vectors, the time-dependent weight coefficients W_t and threshold b_{0t} in Fisher discriminant are obtained. The time-variant Fisher discriminant is obtained as follows:

$$D_t = W_t * F^{\mathrm{T}}_{\text{test}-t} - b_{0t}, \tag{7}$$

where D_t is the classification margin, which reflects the confidence degree of classification at each time point t. For one specific trial, the class label of each time point is deterministic. To derive the continuous classification at a certain time t_0, we can incorporate the prior knowledge from all the preceding time points $t \leqslant t_0$, leading to an information accumulation across time about the Fisher discriminant distance so that the binary decision could be better made. Here, the accumulative Fisher discriminant distance is defined as follows:

$$Dc_{t_0} = \sum^{t_0} D_t, \tag{8}$$

where Dc_{t_0} is the sum of the classification margin preceding time points $t \leqslant t_0$, which reflects the overall confidence degree of classification incorporating the previous information. For the test feature vector $F_{\text{test}-t_0}$ at time point t_0, by the symbol Dc_{t_0}, the class label can be determined as follows:

$$\begin{aligned} &F_{\text{test}-t_0} \in \text{left}, Dc_{t_0} < 0, \\ &F_{\text{test}-t_0} \in \text{right}, Dc_{t_0} > 0, \\ &\textit{nondecisive}, Dc_{t_0} = 0. \end{aligned} \tag{9}$$

Two sets of dataset are from the BCI competition, and therefore the performance indexes for evaluating BCI system are introduced. Currently, there are two major indexes, i.e. classification accuracy and mutual information (MI) for evaluating the classification results and the performance of BCI system. The classification accuracy reflects the ability of BCI system identifying the brain consciousness tasks correctly. If we regard BCI as a direct communication channel between brain and external environment, the information transfer performance of BCI is also to be considered. The information transferred by a BCI system is the effective information contained in brain consciousness, which can be translated into the effective control order over external environment. Thus, MI reveals how much the correct brain motor imagery information is contained in the classification results. In [22], Schlogl proposed that the parameter MI could be used to quantify the information transfer of BCI system. According to Shannon communication theory, signal-noise ratio (*SNR*) and MI between BCI input and output are derived during the imagination of left- or right-hand movement:

$$SNR_{t_0} = \frac{2 \operatorname*{var}_{i \in \{L,R\}} \{Dc_{t_0}^{(i)}\}}{\operatorname*{var}_{i \in \{L\}} \{Dc_{t_0}^{(i)}\} + \operatorname*{var}_{i \in \{R\}} \{Dc_{t_0}^{(i)}\}} - 1, \tag{10a}$$

$$I_{t_0} = 0.5 \log_2(1 + SNR_{t_0}), \tag{10b}$$

where SNR_{t_0} is the signal-noise ratio, i stands for the ith trial, var{•} represents calculating variance for all the trials i, $Dc_{t_0}^{(i)}$ is the accumulative discriminant distance in the ith trial, $\{L\}$, and $\{R\}$ are the sets of left and right trials, and I_{t_0} is the MI between BCI input and output. The details can be found in Ref. [22]. Both classification accuracy and MI also can reflect the separability of features for classification of two classes of EEG patterns and therefore can be used to evaluate the contribution of the different EEG features.

4. Results

4.1. The analysis of complexity measure time course

The complexity measures of two sets of movement-related EEG data from *Subject* 1 and *Subject* 2 are analyzed by two parameters *Kc* and *FSE*. The movement-related EEG from the electrodes C3 and C4 are studied during left- or right-hand motor imagery task. Firstly, the complexity measure (*Kc*,*FSE*) of EEG within 8–30Hz in the first second time window is calculated. Then the time window slides to the next 1 s stepped by one sample until the complexity of EEG data in the last second time window is calculated so that the complexity time course of event-related EEG could be obtained. According to the above procedure presented in Section 3.3, the percentage of EEG complexity during the imagination of hand movement relative to that during the reference period is computed. The complexity measure time courses of ERD/ERS for *Subject* 1 and *Subject* 2 quantified by *Kc* and *FSE* are presented in Fig. 1(c–f) and 2(c–f), respectively. As a comparison, ERD and ERS time courses quantified by inter-trail variance band power method [3] are also given in Fig. 1(a,b) and 2(a,b), in which the 0.5–1.5 s epoch is defined as the reference period. In complexity measure of ERD time course quantified by *Kc* and *FSE* measure, the 0–2.5 s epoch containing the complexity changes of 0.5–1.5 s EEG data is used as reference period.

Let's begin with the complexity analysis of event-related EEG for *Subject* 1. From Fig. 1, it can be seen that ERD and ERS appear over the contralateral and ipsilateral brain hand areas, respectively, which correspond to the pronounced decrease and increase of EEG power in Fig. 1(a,b), and correspond to the increase and decrease of complexity measure shown in Fig. 1(c–f). The complexity measure time courses of event-related EEG quantified by both *Kc* and *FSE* display consistent behaviors with each other, but they show the opposite patterns compared with ERD/ERS time course by band power method. For example in Fig. 1(a), during the imagination of left-hand movement, a pronounced power decrease over electrode C4 occurred at the imagination onset, that is at about $t = 3$ s which is known as ERD, and the corresponding complexity measures obviously increase during $t = 4$–5 s in Fig. 1(c,e), while the increased power of ERS over electrode C3 corresponds to the decreased complexity measures. The similar EEG changes for right-hand motor imagery are illustrated in Fig. 1(b,d,f). Because the complexity at time t is obtained from the 1-s data segment prior to the time t, the complexity changes of the event-related EEG delay 1 s relative to the EEG power changes. From Fig. 1, it can be seen clearly that with the EEG power dropping, the corresponding complexity increases corresponding to ERD, and vice versa.

Next, let us look at the complexity measure time course of event-related EEG for *Subject* 2. In Fig. 2(a,b), it can be

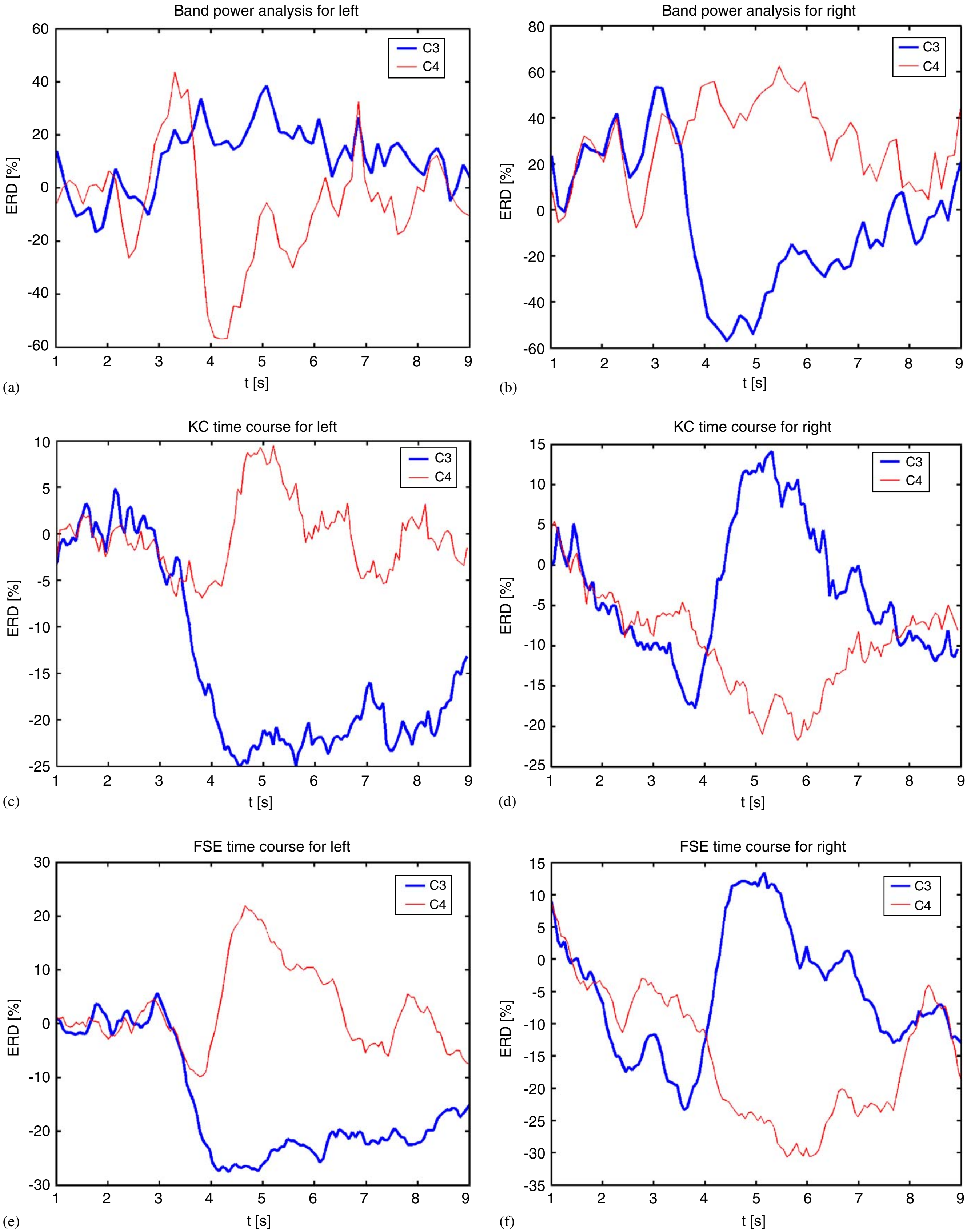

Fig. 1. Quantification of ERD time course of event-related EEG with inter-trial band power and with the complexity analysis method, respectively, for *Subject* 1; (a) and (b) describe ERD time course with band power method during imagination of left- and right-hand movement, respectively; (c) and (d) quantify the complexity measure of ERD by *Kc* corresponding to (a) and (b); (e) and (f) quantify the complexity measure of ERD by *FSE*; the thick and thin lines correspond to the analysis of the event-related EEG over electrodes C3 and C4; the left and right columns describe event-related EEG time courses for left- and right-hand motor imagery.

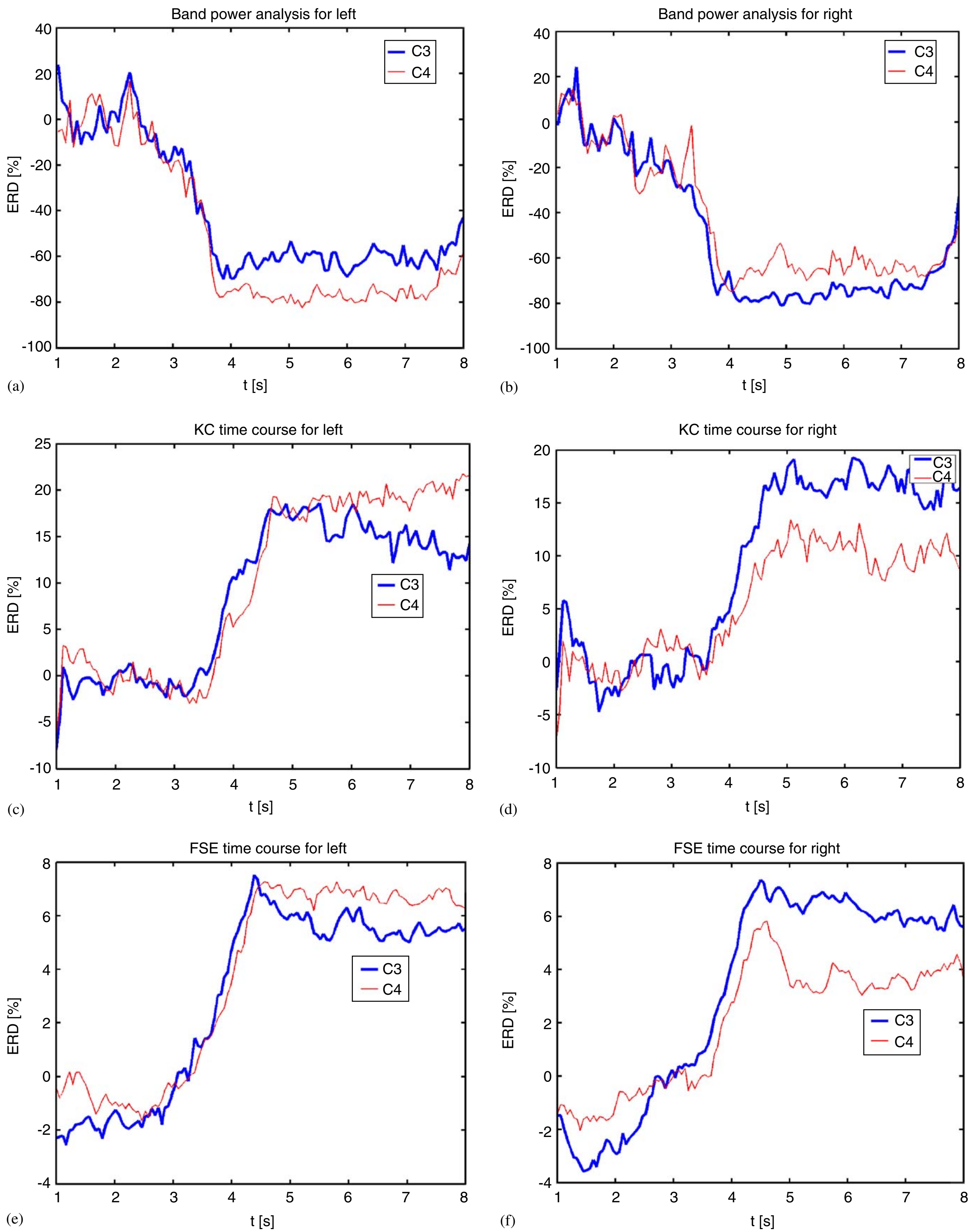

Fig. 2. Quantification of ERD time course of movement-related EEG for *Subject* 2; (a) and (b) describe ERD time course with band power method for left- and right-hand motor imagery tasks, respectively; (c) and (d) quantify ERD time course by *Kc* measure corresponding to (a) and (b); (e) and (f) quantify ERD time course by *FSE* measure; the thick and thin lines correspond to the analysis of the event-related EEG over electrodes C3 and C4; the left and right columns describe event-related EEG time courses for left- and right-hand motor imagery.

seen that different from *Subject* 1, ERD appears bilaterally over both contralateral and ipsilateral brain hand areas, but with the more decreased power over contralateral cortex area than that over ipsilateral cortex area during *Subject* 2 imagined the movement of left or right hand. Accordingly, the complexity measures of the event-related EEG quantified by *Kc* and *FSE* increase remarkably over two hemispherical hand areas, with the more increased complexity over contralateral cortex area than that over ipsilateral cortex area. Although ERD/ERS patterns appear differently over contralateral and ipsilateral areas between *Subject* 1 and *Subject* 2, there still exist the similar ERD/ERS behaviors between the complexity measure *Kc* and *FSE*, and the opposite ERD/ERS patterns between the complexity measure and band power. ERD corresponds to the desynchronized EEG processes, which would result in the increased EEG irregularity so that the corresponding EEG complexity increases. ERS corresponds to the synchronized EEG processes which would result in the increased EEG regularity so that the EEG complexity decreases. For *Subject* 2, the more enhancement of ERD over contralateral hand area reflects the stronger desynchronized EEG process than that over ipsilateral hand area, which also is consistent with the more enhancement of complexity measure of event-related EEG.

The number of single trials for *Subject* 1 and *Subject* 2 is different, but it will not affect the analysis results, because the analysis data of *Kc*, *FSE* and the band power are calculated by the averaged corresponding parameters across all the trials to show the statistical mean behaviors.

According to Figs. 1 and 2, we can also see that *Kc* and *FSE* quantifying the complexity measure time courses of event-related EEG have a very similar pattern. In contrast, they exhibit somewhat different behaviors between the left- and right-hand motor imagery tasks. For example, the curve over C3 in Fig. 1(c), corresponding to the ERD for left-hand motor imagery, displays the slightly different behavior from the curve over C4 in Fig. 1(d) also corresponding to ERD but for right-hand motor imagery. The similar case also occurs between the curves over C3 and C4 in Fig. 1(e,f). This slightly different behavior of complexity measure of event-related EEG between left- and right-hand motor imagery tasks possibly may result from the asymmetry of two brain hemispheres.

In general, the two parameters *Kc* and *FSE* quantifying the complexity measure of ERD time courses show the consistent behaviors, which indicates that the complexity measure changes of EEG recorded over left and right sensorimotor hand cortex areas can characterize the event-related EEG data during the imagination of the unilateral hand movement.

4.2. Classification accuracy and MI time courses

To testify the validity of quantitative complexity measure of event-related EEG, the complexity features are used to realize classification of left- and right-hand motor imagery and the two evaluation indexes including classification accuracy and MI are introduced in Section 3.4. In this Section, we will give the classification results for the two subjects. Firstly, we obtained the band power feature and the complexity feature of EEG within 8–30 Hz extracted by classical FFT and *Kc* method, respectively. Then the two kinds of features are combined to distinguish the left- and right-hand motor imagery tasks. By the method described in Section 3.4, the two indexes including classification accuracy and MI time course for *Subject* 1 *and Subject* 2 are calculated and shown in Fig. 3. Here, for *Subject* 1, we obtain the classification results of 140 test dataset by learning the 140 train dataset. For *Subject* 2, the train dataset include enough large amount of dataset with 319 single trials. To simplify the problem, only the train dataset are analyzed to evaluate the classification performance by leave-one-out (LOO) cross-validation.

From Fig. 3(a,b), we can see that for *Subject* 1, the maximum classification accuracy and MI appear at about $t = 7$ s with 88.57% and 0.5965 bit, respectively. *Subject* 2 reaches the maximum value with the classification accuracy 90.60% and with MI 0.6195 bit. The two indexes are gradually increased with time changing because the accumulated information preceding time are applied in classifier design. The satisfactory classification results show that both the complexity feature and band power feature of event-related EEG make contributions.

To compare the contribution of the complexity feature with that of the band power feature, the two kinds of features are separately extracted to discriminate the left- and right-hand motor imagery tasks. Table 1 gives the comparison of two evaluation indexes, i.e. the maximum classification accuracy and MI by using the band power features extracted by FFT, complexity features extracted by *Kc* and the combined features, respectively, for *Subject* 1 *and Subject* 2.

From Table 1, we can see that only by combining with the two kinds of features, i.e. the band power features and complexity features, could the best classification results be obtained. Any single kind of feature cannot give satisfactory results. For the two subjects, the feature of the band power and the complexity contributes to the classification results differently. Even if the single complexity feature gives the lower classification results for *Subject* 2, it does improve the performance when combined with power features. For *Subject* 1, the single complexity features give the better classification accuracy than the single band power feature. *Kc*, as a nonlinear complexity measure, quantifies the regularity and randomness in the event-related EEG and reveals the information regarding the dynamics of the specific brain system. Thus, *Kc* measure of event-related EEG carries the information independent of that by the band power method, which helps to improve the classification accuracy when combined with the band power features.

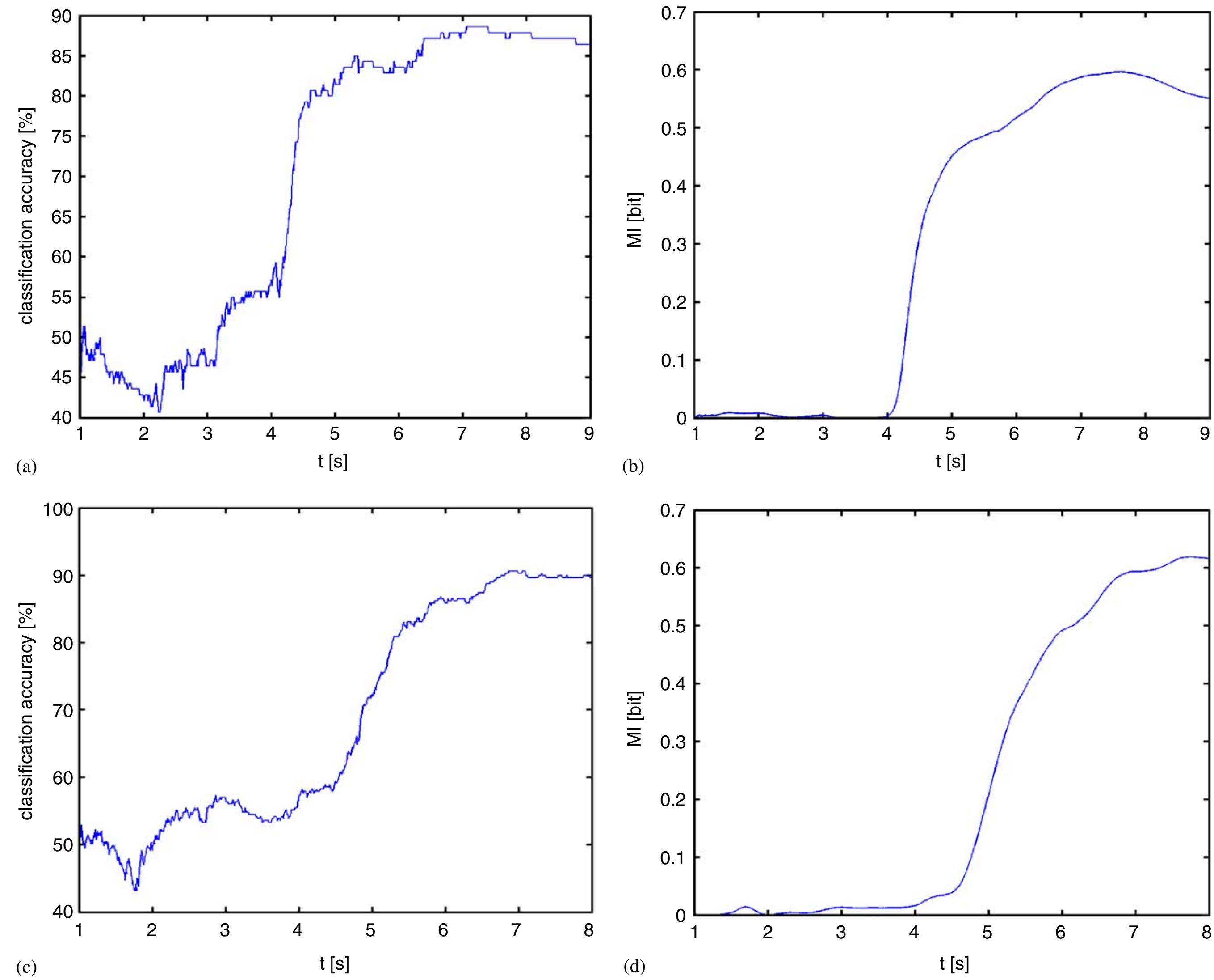

Fig. 3. Classification results for *Subject* 1 *and Subject* 2; (a, b) classification accuracy and the corresponding MI time courses by combining the power feature and complexity feature of event-related EEG within 8–30 Hz extracted by FFT and *Kc* method, respectively, for *Subject* 1; (c, d) classification accuracy and the corresponding MI time courses for *Subject* 2.

Table 1
Comparison of the classification results with different EEG features for *Subject* 1 and *Subject* 2

Features	Max classification accuracy (%)		Max MI (bit)	
	Subject 1	*Subject* 2	*Subject* 1	*Subject* 2
Complexity	86.43	70.0	0.5256	0.138
Power	85.71	89.9	0.5422	0.598
Power, Complexity	88.57	90.6	0.5965	0.6195

5. Discussions

In Ref. [15], Pfurtscheller showed that motor imagery is closely related to the primary sensorimotor areas activation. A desynchronized EEG indicates excited cell assemblies ready or prepared for sensory, motor or cognitive processing [15]. EEG desynchronization is induced by information input which implies a lesser coordination between the ongoing EEG processes and more independent neural processes contribute to complex brain dynamics [11,15] so that the desynchronized EEG shows the more irregular behavior. A synchronized EEG within specific frequency band correlated of deactivated cortical areas marks specific cortical areas at rest or an idling state [11,18], which implies a more coordination between the ongoing processes so that the synchronized EEG shows the more regular behavior. The fact that the increase of event-related EEG complexity quantified by *Kc* and *FSE* corresponds to ERD over the activated brain areas, and the complexity decrease corresponds to ERS over the deactivated brain areas for *Subject* 1 can provide another evidence for the above viewpoints. For *Subject* 2, although the ERD appears over both hemispheres, it can be seen that the degree of ERD over the contralateral hand area is more than that of ERD over the ipsilateral hand area.

It was reported that the complexity of EEG during open eyes increases relative to that during closed eyes, which suggests that more independent, parallel, functional processed activities are involved during open eyes than during closed eyes [6]. Studies on single-channel EEG correlation dimension also found increase after eye opening [19]. Motor imagery as well as eye opening involves information processing, and the corresponding brain state changes are similar. The complexity increase of EEG resulting from hand motor imagery is also in accordance with the above findings.

When calculating *Kc* of EEG, it would be overestimated for a shorter data segment [23]. In this paper, the data length to be analyzed is short with only 1 s data segment. However, the quantitative measure of the complexity of ERD time course by *Kc* actually reflects the ratio of complexity between the two different periods i.e. motor imagery period and reference period for the same length data segments. The complexity time course quantified by *Kc* can be understood in a relative sense. So the short length data makes no difference for the analysis results.

Kc measures the complexity of event-related EEG in time domain. *FSE* characterizes the structural complexity of EEG in frequency domain by calculating the uniformity degree of EEG signal power distribution within the specific frequency band [2]. There are two considerations to quantify ERD/ERS time course by the parameter *FSE*. On the one hand, for the investigated event-related EEG within 8–30 Hz, it contains alpha (8–13 Hz) and beta (14–30 Hz) rhythms, which would show different behaviors during hand motor imagery. Furthermore, studies on the functional dissociation of lower and upper frequency mu rhythms of movement-related EEG showed that the lower frequency component (8–10 Hz) results in a widespread movement-type nonspecific ERD pattern, whereas the upper frequency component (11–13 Hz) shows a more focused and movement-type specific pattern [17]. Within 8–30 Hz, there exist at least three different frequency band EEG oscillations in relation to hand motor imagery, which show inconsistent behaviors with one another. It is reasonable to expect that the different distributive information of EEG components within the three separate frequency bands must have great effects on the complexity measure of event-related EEG quantified by*FSE*. Therefore, *FSE* within 8–30 Hz reflect not only the distributive information of the power in three separate bands but also the distributive information of the power at each frequency. On the other hand, the imagination of left- or right-hand movements results in different spatial ERD patterns over contralateral and ipsilateral sensorimotor hand cortex areas. The synchronized EEG would result in the concentrated distribution of signal power, and vice versa. By *FSE*, we could characterize how concentrated or widespread the power spectrum of event-related EEG signal can be.

Different from the classical band power method, *Kc* and *FSE* characterize the complexity of the event-related EEG and reflect the desynchronized and synchronized processes from another viewpoint. Although the complexity features extracted by only *Kc* measure are applied to classify left- and right-hand motor imagery tasks and the corresponding classification results are evaluated in Section 4.2, however, the fact that the complexity features extracted by *Kc* improve the classification performance when combined with band power features at least can show that the complexity information is independent of the power changing in the event-related EEG. Therefore, the complexity measure *Kc* and *FSE* of the event-related EEG can be regarded as another indicator of ERD/ERS.

In general, based on the analysis of two sets of event-related EEG and the performance evaluation from two subjects, we can conclude that the two parameters *Kc* and *FSE* can well quantify the complexity measures of the dynamic event-related EEG. Moreover, the complexity indexes *Kc* and *FSE* quantifying the complexity measures of ERD/ERS not only show the very consistent and similar behaviors with each other, but also display an inverse pattern as compared with the band power measure of ERD/ERS by classical band power method. The results suggest that the time-dependent complexity measure quantified by *Kc* and *FSE* can be meaningful in analyzing the event-related EEG.

Acknowledgments

This work is funded by National Nature Science foundation of China (#30370395 and #30400101). The authors would like to thank Graz University of Technology for providing the data and really appreciate the anonymous reviewers for the valuable comments on the paper.

References

[1] G. Florian, G. Pfurtscheller, Dynamic spectral analysis of event-related EEG data, Electroenceph. Clin. Neurophysiol. (95) (1995) 393–396.
[2] T. Inouye, K. Shinosaki, H. Sakamoto, S. Toi, et al., Quantification of EEG irregularity by use of the entropy of the power spectrum, Electroenceph.Clin. Neurophysiol. (79) (1991) 204–210.
[3] J. Kalcher, G. Pfurtscheller, Discrimination between phase-locked and non-phase-locked event-related EEG activity, Electroenceph. Clin. Neurophysiol. (94) (1995) 381–384.
[4] F. Kaspar, H.G. Schuster, Easily calculable measure for the complexity of spatiotemporal patterns, Phys. Rev. A (36) (1987) 842–848.
[5] A.N. Kolmogorov, Three approaches to the definition of the concept of quantity of information, Probl. Inform. Transm. 1 (1) (1965) 1–7.
[6] I. Kondakor, D. Brandeis, J. Wackermann, et al., Multichannel EEG fields during and without visual input: frequency domain model source locations and dimensional complexities, Neurosci. Lett. (26) (1997) 49–52.
[7] R. Leeb, R. Scherer, F. Lee, H. Bischof, G. Pfurtscheller, Navigation in virtual environments through motor imagery, in: Ninth Computer

Vision Winter Workshop, CVWW'04, 4–6 February 2004, Piran, Sloveria; Proceedings of the CVWW'04, 2004, pp. 99–108.
[8] A. Lempel, J. Ziv, On the complexity of finite sequence, IEEE Trans. Inform. Theory (22) (1976) 75–81.
[9] C. Neuper, A. Schlogl, G. Pfurtscheller, Enhancement of left-right sensorimotor EEG differences during feedback-regulated motor imagery, J. Clin. Neurophysiol. 16 (4) (1999) 373–382.
[10] Pei Xiaomei, Zheng Chongxun, He Weixing, Dynamic complexity analysis of event-related EEG data, Biomed. Tech. (Suppl. 1) (2004) 87–88 (Second International BCI Workshop & Training Course 2004, 17–18 September, Graz, Austria).
[11] G. Pfurtscheller, Event-related synchronized (ERS): an electrophysiological correlate of cortical areas at rest, Electroenceph. Clin. Neurophysiol. (83) (1992) 62–69.
[12] G. Pfurtscheller, A. Aranibar, Event-related cortical desynchronization detected by power measurement of scalp EEG, Electroenceph. Clin. Neurophysiol. (42) (1977) 817–826.
[13] G. Pfurtscheller, A. Aranibar, Evaluation of event-related desynchronisation (ERD) preceding and following voluntary self-paced movement, Electroenceph. Clin. Neurophysiol. (46) (1979) 138–146.
[14] G. Pfurtscheller, F.H. Lopes da Silva, Event-related EEG/MEG synchronization and desynchronization: basic principles, Clin. Neurophysiol. (110) (1999) 1842–1857.
[15] G. Pfurtscheller, Ch. Neuper, Motor imagery activates primary sensorimotor area in humans, Neurosci. Lett. (239) (1997) 65–68.
[16] G. Pfurtscheller, Ch. Neuper, A. Schlogl, et al., Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters, IEEE Trans. Rehab. Eng. 6 (3) (1998) 316–325.
[17] G. Pfurtscheller, C. Neurper, G. Krausz, Functional dissociation of lower and upper frequency mu rhythms in relation to voluntary limb movement, Clin. Neurophysiol. (111) (2000) 1873–1879.
[18] G. Pfurtscheller, A. Stancak Jr, Ch. Neuper, Event-related synchronization (ERS) in the alpha band—an electrophysiological correlate of cortical idling: a review, Int. J. Psychophysiol. (24) (1996) 39–46.
[19] P.E. Rapp, T.R. Bashore, J.M. Martinerie, et al., Dynamics of brain electrical activity, Brain Topogr. (2) (1989) 99–118.
[20] P.E. Rapp, I.D. Zimmermean, E.P. Vining, N. Cohen, A.M. Albano, et al., The algorithmic complexity of neural spicke trains increases during focal seizures, J. Neurosci. 14 (1995) 4731–4739.
[21] R. Salmelin, M. Hamalainen, M. Kajola, R. Hari, Functional segregation of movement-related rhythmic activity in the human brain, Neuroimage (2) (1995) 237–243.
[22] A. Schlogl, C. Neuper, G. Pfurtscheller, Estimating the mutual information of an EEG-based brain-computer interface, Biomed. Tech. 47 (1–2) (2002) 3–8.
[23] Shaw Fu-Zen, Chen Ruei-Feng, Tsao Hen-Wai, Yen Chen-Tung, Algorithmic complexity as an index of cortical function in awake and pentobarbital-anesthetized rats, J. Neurosci. Methods (93) (1999) 101–110.
[24] J.R. Wolpaw, N. Birbaumer, McFarland, et al., Brain-computer interfaces for communication and control, Clin. Neurophysiol. (113) (2002) 767–791.

Xiaomei Pei received the MS degree from School of Automatic control and information of Xi'an University of Technology, Xi'an, China, in 2003. And now she is a candidate for PhD degree in Institute of Biomedical Engineering of Xi'an Jiaotong University, Xi'an, China. Her research interests include brain-computer interface, event-related EEG analysis, pattern recognition, biomedical signal processing.

Chongxun Zheng was born in China in 1939. He received the diploma in Electrical Engineering from Xi'an Jiaotong University, China, in 1962. He worked in the Department of Electrical Engineering and then in the Department of Information and Control Engineering, Xi'an Jiaotong University, from 1962 to 1981. He was as a Visiting Scholar in King's College of London and Brunel University, UK, from 1981 to 1983. Then he joined the Department of Information and Control Eng., Xi'an Jiaotong University, until 1991, where he was an Associate Professor and then a Professor. He currently is the Director of the Research Institute of Biomedical Engineering at the same university. His research interests include biomedical signal processing and applications, brain-computer interface, image processing, cardiac electrophysiology, neuroscience.

Wei-Xing He received the BS degree from Xi'an Jiaotong University, Xi'an, China, in 1982, the MS degree from Tongji University, Shanghai, China, in 1993, both in Automatic Control Engineering. Since 1985, he has been working in Jiangsu Unverisity, Zhenjing, China, and obtained an associate professor position in the same university in 1995. He is currently working on his PhD degree in biomedical engineering at Xi'an Jiaotong University. His main research interests include signal processing, device research and development, automatic control and fault detection.

Xu Jin received the MS degree from Xi'an Institute of Optics and Precision Mechanics of Chinese Academy of Science in 1999. She is now an associate professor in the Institute of Biomedical Engineering of Xi'an Jiaotong University, Xi'an, China, and is working towards Ph.D. degree. She has been engaged in the neuro-electrophysiology signal collection and processing.