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Multi-channel linear descriptors for event-related EEG collected in brain computer interface

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Abstract

By three multi-channel linear descriptors, i.e. spatial complexity (Ω), field power (Σ) and frequency of field changes (Φ), event-related EEG data within 8–30 Hz were investigated during imagination of left or right hand movement. Studies on the event-related EEG data indicate that a two-channel version of Ω, Σ and Φ could reflect the antagonistic ERD/ERS patterns over contralateral and ipsilateral areas and also characterize different phases of the changing brain states in the event-related paradigm. Based on the selective two-channel linear descriptors, the left and right hand motor imagery tasks are classified to obtain satisfactory results, which testify the validity of the three linear descriptors Ω, Σ and Φ for characterizing event-related EEG. The preliminary results show that Ω, Σ together with Φ have good separability for left and right hand motor imagery tasks, which could be considered for classification of two classes of EEG patterns in the application of brain computer interfaces.

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Studies at Graz University of Technology have shown that unilateral hand motor imagery results in signal amplitude attenuation of alpha and beta rhythmic activities over the contralateral hand area, which is called event-related desynchronization (ERD) and, in certain cases, in conjunction with an increased amplitude of the rhythmic activities over the ipsilateral hand area, which is called event-related synchronization (ERS) [1, 2]. Based on the antagonistic ERD/ERS patterns, the left and right hand motor imagery tasks could be identified. Motor imagery is transformed into control signals, which can be applied in brain computer interfaces (BCI) [3]. A BCI with satisfactory classification accuracy depends not only on the good performance of the classifier but also on the choice of proper parameters characterizing EEG signal features [4]. Thus studies on event-related EEG are meaningful for choosing EEG features for the classification of certain mental tasks. Currently, ERD/ERS is often quantified for the single-channel event-related EEG by the classical band power method [2]. For the antagonistic ERD/ERS pattern, a hypothesis has been proposed about 'focal ERD/surround ERS' reflecting a thalamo-cortical mechanism to enhance focal cortical activation by simultaneous inhibition of other cortical areas [5]. Whatever the brain state of the mid-central region is, it would be reasonable to expect some different functional interaction between the contralateral and mid-central regions, and between the ipsilateral and mid-central regions. This paper assesses the usefulness of the three multi-channel linear descriptors (spatial complexity Ω, local field power Σ and the frequency of field changes Φ) for the analysis of the ERD/ERS time course over the left and right brain hemispheres. The three multi-channel linear descriptors for characterizing the overall brain macrostates of the specific regions are investigated and furthermore three kinds of EEG features are extracted for the discrimination of the left and right hand motor imagery tasks. Preliminary results show that Σ, Ω together with Φ could well reflect the antagonistic ERD/ERS patterns over the contralateral and ipsilateral areas and thus may provide new parameters for the classification of left and right hand motor imagery tasks in BCI.

2. Material and method

2.1. Experimental data

Event-related EEG changes were investigated in a feedback-guided motor imagery experiment [6, 7]. The subject 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, and this was followed by an arrow pointing either to the right or left (cue stimulus) indicating the motor imagery task for either the right or left hand till $t = 4.25$ s (t stands for time). 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 [6–8]. The feedback is the classification result obtained by an analysis of the preceding 1 s EEG.

Three bipolar EEG channels were measured over the anterior and posterior of C3, Cz, C4 with inter-electrode intervals of 2.5 cm. The EEG was sampled with 128 Hz and filtered between 0.5 and 30 Hz. The datasets used here were obtained from the BCI2003 competition website provided by Graz University of Technology [9]. An EEG was collected from a normal subject, who is a 25 year old woman and seated in a relaxing chair with armrests. The MATLAB data files, x_train.mat, y_train.mat, are train datasets and the files x_test.mat, y_test.mat are test datasets, which both include 140 trials and the class label, respectively. The details could be found in the relevant BCI2003 competition website and in [7–9].

2.2. Multi-channel linear descriptors

Wackermann proposed a Σ–Φ–Ω system for describing the comprehensive global brain macrostate [10, 11]. Firstly, let us review the definition of the three linear descriptors. Consider N EEG samples in the observed time window at K electrodes to construct the voltage vectors $\{u_1, \ldots, u_N\}$, where each u_i ($i = 1, \ldots, N$) has K dimensions and corresponds to the state vector representing the spatial distribution of EEG voltage over the scalp at the ith sample. The data are assumed to have been already centered to zero mean and transformed to the average reference. Then Σ, Ω and Φ can be calculated as follows [10, 11]:

$$m_0 = \frac{1}{N}\sum_i \|u_i\|^2 \qquad (1a)$$

$$m_1 = \frac{1}{N}\sum_i \left\|\frac{\Delta u_i}{\Delta t}\right\|^2 \qquad (1b)$$

where $\Delta u_i = u_i - u_{i-1}$, $\Delta t = 1/f_s$; f_s is sample frequency;

$$\sum = \sqrt{m_0/K} \qquad (2a)$$

$$\Phi = \frac{1}{2\pi}\sqrt{\frac{m_1}{m_0}}. \qquad (2b)$$

The covariance matrix is constructed as

$$C = \frac{1}{N}\sum_n u_n u_n^T. \qquad (3a)$$

The eigenvalues $\lambda_1, \ldots, \lambda_K$ of matrix C are calculated; then complexity Ω can be obtained:

$$\log\Omega = -\sum_i \lambda_i' \log\lambda_i', \qquad (3b)$$

where λ_i' is the normalized eigenvalue [9, 10].

In the Σ–ϕ–Ω system, K-dimensional voltage vectors constructed from the simultaneous EEG measurements over K electrodes with the time changing are regarded as the trajectories in the K-dimensional state space. By the three linear descriptors, the physical properties of the EEG trajectory and then the brain macrostates are characterized. The number of electrodes K determines the dimension of the state space and the K electrodes array sites determine the brain region of interest Λ to be studied. Σ describes the field strength of the specific brain region Λ [μV]; Φ reflects the mean frequency of the corresponding field changes [Hz]; Ω measures the spatial complexity of the brain region Λ, which decomposes the multi-channel EEG data into spatial principal components and then quantifies the degree of synchrony between the distributed EEG by an extension along the principal axes; a larger value of Ω corresponds to low synchrony, and vice versa. It can be seen that the three linear descriptors can describe the different brain macrostate features of the brain regions of interest. The details can be found in [10, 11].

2.3. Linear descriptors for the event-related EEG

For the EEG data presented here, the analysis proceeded as follows: the three-channel EEG data over C3, Cz and C4 were first zero-centered in the time domain. There is no influence from reference derivation and no need to transform the data to the average reference because EEG was recorded by bipolar derivation acting as a spatial high-pass filter to allow local cortical activity to be measured [12, 13]. Different EEG signal powers within different channels would have effects on Ω complexity, which was discussed in [14]. Before calculating Ω, we normalized the EEG signal by the maximum signal amplitude of each channel to reduce its influence on Ω. Then for the left and right hand motor imagery, Σ, Ω and Φ from electrode arrays (C3, Cz) and (C4, Cz) were calculated, respectively. Therefore the number of electrodes K in equation (2a) is 2 and the multi-channel linear descriptors are reduced to two-channel Ω, Σ and φ, which are defined as TCC (two-channel complexity), TCFP (two-channel field power) and TCPHI (two-channel frequency of field change) respectively. Ω complexity quantifies the amount of spatial synchrony [10, 11] so that TCC reflects the degree of synchronization of two spatially distributed brain processes over the contralateral, ipsilateral and mid-central regions, respectively; TCFP reflects the corresponding regional field power; TCPHI characterizes the speed of regional field changes between the contralateral and mid-central regions, and between the ipsilateral and mid-central regions, respectively.

To obtain the time course of Ω, Σ and Φ, a 1 s segment is extracted to calculate Ω, Σ and Φ. By shifting the segment sample by sample from start to end of the trial and calculating the averaged Ω, Σ and φ across all the same label of trials for each segment, the time sequences of Ω, Σ and Φ are obtained. In an event-related paradigm, each trial is repeated a number of times with the same experimental situation controlled. So Σ, Ω and Φ calculated from the ensemble of trials recorded for each repetition of the event can yield information which reveals the short time changes in parameters due to the left or right hand motor imagery involved [15].

There are two considerations for studying TCC, TCFP and TCPHI from only C3 and Cz, C4 and Cz, respectively. On the one hand, the unilateral hand motor imagery results in an antagonistic ERD/ERS pattern over the contralateral and ipsilateral areas. EEG over the mid-central region (close to Cz) could not show the identical changes between left and right hand motor imagery for the asymmetry of the two brain hemispheres. It is reasonable to expect that there would be pronounced differences in EEG features between the contralateral and mid-central, and between the ipsilateral and the mid-central regions. So not only the antagonistic ERD/ERS patterns over contralateral and ipsilateral areas but also the interrelation between different brain regions is effectively characterized. On the other hand, although Σ, Ω and Φ of the EEG from the combined C3 and C4 or from the combined three channels C3, C4, Cz are also interesting, they are not discussed in this paper because they make little contribution to the classification of left and right hand motor imagery.

2.4. Classification of left and right hand motor imagery tasks

To demonstrate the validity of TCC, TCFP and TCPHI for characterizing the event-related EEG, the features described by the three two-channel linear descriptors are extracted 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 three kinds of features of event-related EEG within 8–30 Hz from the left and right hemispheres for the train data and test data are calculated to construct the time-dependent feature vectors $F_{\text{train-}t}$, $F_{\text{test-}t}$ respectively. By learning the training vectors, the time-dependent weight coefficients W_t and threshold b_{0t} in the Fisher discriminant are obtained. The time-variant Fisher discriminant is obtained as follows:

$$D_t = W_t * F_{\text{test-}t}^T - b_{0t} \quad (4)$$

where D_t is the classification margin, which reflects the confidence degree of classification at each time point t. For one specific trial lasting 9 s, 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 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:

$$Dc_{t_0} = \sum^{t_0} D_t \quad (5)$$

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, using the symbol Dc_{t_0}, the class label can be determined as follows:

$$\begin{cases} F_{\text{test-}t_0} \in \textit{left}, Dc_{t_0} < 0 \\ F_{\text{test-}t_0} \in \textit{right}, Dc_{t_0} > 0 \\ \text{non-decisive}, Dc_{t_0} = 0. \end{cases} \quad (6)$$

There are two major indexes, i.e. classification accuracy and mutual information (MI), for evaluating the classification results and the performance of a BCI system. The classification accuracy reflects the ability of a 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 the external environment. Thus MI reveals how much the correct brain motor imagery information is contained in the classification results. In [16], Schlögl *et al* proposed that the parameter MI could be used to quantify the information transfer of a BCI system. According to the Shannon communication theory, the SNR and MI between BCI input and output are derived during the imagination of left or right hand movement:

$$\text{SNR}_{t_0} = \frac{2 * \underset{i\in\{L,R\}}{\text{var}} \left\{Dc_{t_0}^{(i)}\right\}}{\underset{i\in\{L\}}{\text{var}} \left\{Dc_{t_0}^{(i)}\right\} + \underset{i\in\{R\}}{\text{var}} \left\{Dc_{t_0}^{(i)}\right\}} - 1 \quad (7a)$$

$$I_{t_0} = 0.5 * \log_2(1 + \text{SNR}_{t_0}), \quad (7b)$$

where SNR_{t_0} is signal-to-noise ratio; i stands for the ith trial; $\text{var}\{\bullet\}$ represents the calculating variance for all the trials i; $Dc_{t_0}^{(i)}$ is the accumulative discriminant distance in the ith trial. $\{L\}, \{R\}$ are the sets of left and right trials; I_{t_0}: mutual information between BCI input and output. Both classification accuracy and MI also can reflect the separability of features for classification of two classes of EEG patterns. The details can be found in [16].

3. Results

Figure 1 summarizes the analysis results of the event-related EEG data within 8–30 Hz during left or right hand motor imagery, which shows the ensemble averages of the three features TCC, TCFP and TCPHI time courses. The four rows refer respectively to ERD/ERS time courses quantified by the classical power method [2] in figures 1(a) and (b), TCC time course including Cc3z, Cc4z from C3 and Cz, C4 and Cz in figures 1(c) and (d), TCFP time course (FPC3z, FPC4z) in figures 1(e) and (f), and TCPHI time course (PhC3z, PhC4z)

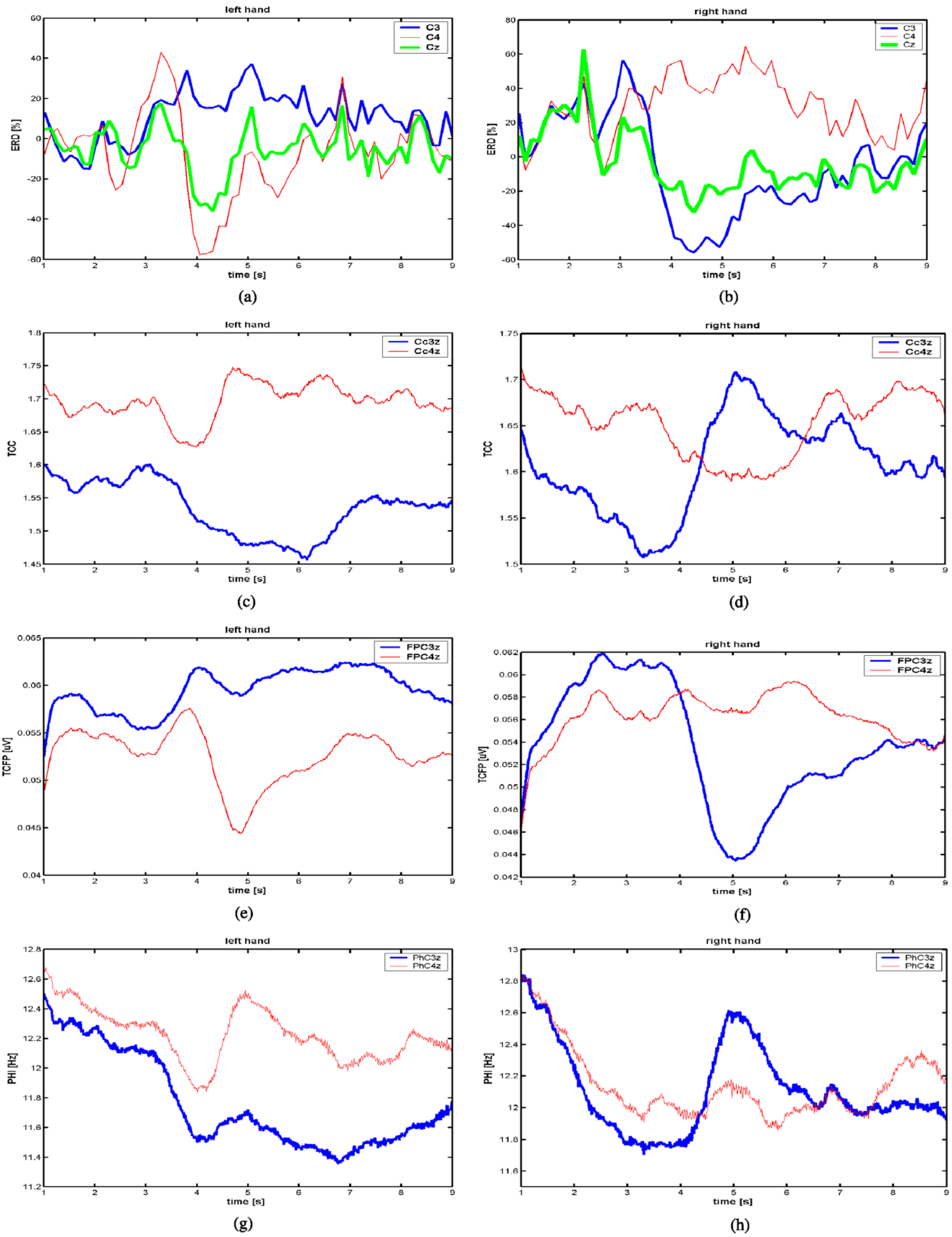

Figure 1. ERD/ERS time course in (a) and (b); spatial complexity Cc3z, Cc4z time courses in (c) and (d); and the regional field power FPC3z, FPC4z time courses in (e) and (f); PhC3z, PhC4z time courses in (g) and (h). The left and right panels correspond to left and right hand motor imagery respectively.

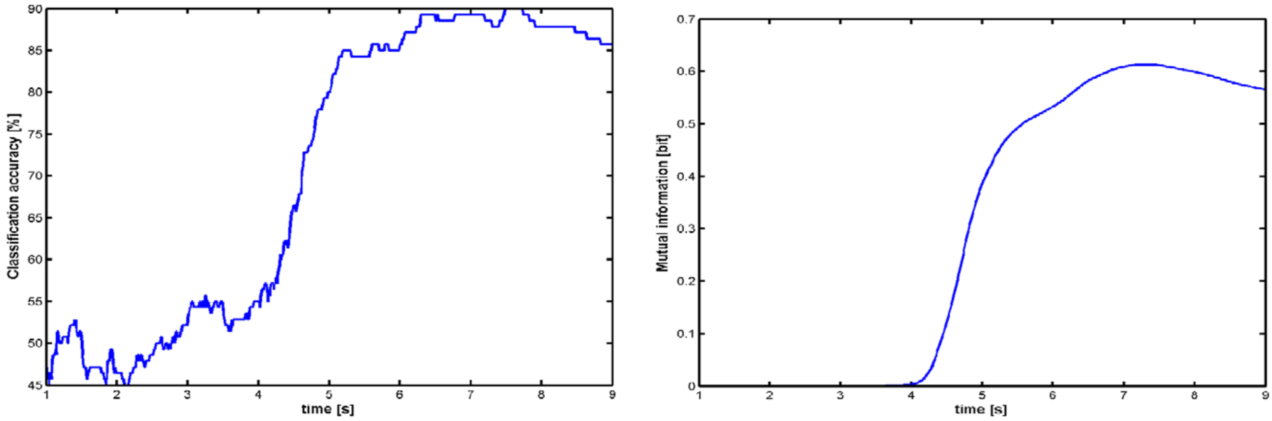

Figure 2. Classification accuracy time course in (a) and MI time course in (b).

in figures 1(g) and (h). From figures 1(a) and (b), a pronounced decrease in signal power corresponding to ERD occurs not only over the contralateral hand area but also over the mid-central region close to Cz, simultaneously accompanied by a little increase in signal power corresponding to ERS over the ipsilateral hand area at the onset of imagination. Here, the reference interval was defined as 0.5–1.5 s and ERD time course was computed as the percentage changes of the inter-trial variance related to the reference interval [2, 13].

3.1. TCC time course analysis

During the unilateral hand motor imagery, the event-related EEG signals within 8–30 Hz covering the alpha and beta rhythms over the contralateral and mid-central regions were desynchronized when each of the underlying brain areas becomes active and then the degree of synchrony between the rhythms is decreased [15]. A dynamic complexity analysis of the single-channel event-related EEG also suggests that ERD/ERS correspond to the increase and decrease of EEG complexity [17]. Ω complexity characterizes the spatial complexity and the degree of synchrony between EEG signals distributed over different brain regions. Therefore in figures 1(c) and (d) an increase with TCC (Cc3z for right; Cc4z for left) corresponding to the contralateral hemisphere occurs at the onset of imagination. In contrast, in association with ERS over the ipsilateral hand area and simultaneous ERD over the mid-central region, a decrease with TCC (Cc3z for left; Cc4z for right) appears. The enhancement of TCC over the contralateral area and the mid-central region during unilateral hand motor imagery suggests there are stronger independent, parallel, functional active processes between the two regions, which is just in accordance with the fact that ERD appears over these two regions. This result is also similarly consistent with the findings of Andrew *et al* [15].

3.2. TCFP time course analysis

ERD/ERS correspond to the signal amplitude attenuation and increase. The desynchronized functional processes underlying the two brain areas result in a total power attenuation of EEG signals. Thus the field power quantified by TCFP from the two desynchronized regions would decrease, which is reflected by a pronounced decrease of the field power TCFP from the contralateral and mid-central regions (FPC3z for right and FPC4z for left in figures 1(e) and (f)). In contrast, ERS with the amplitude enhancement appears over the ipsilateral area so that the field power TCFP between the ipsilateral and mid-central region shows a little increase (FPC3z for left and FPC4z for right). It is clearly seen that the field power TCFP of the contralateral region changes much more than that of the ipsilateral region at the onset of imagination.

3.3. TCPHI time course analysis

TCPHI reflects the speed of the field changes. From figures 1(g) and (h), for both left and right hand motor imagery, a pronounced decrease occurs with TCPHI in the first 3 s, which describes the phase of the relaxed brain state of the subject gradually getting stable at the beginning of the trial. Then at the onset of imagination, the speed of field change TCPHI over the contralateral hemisphere (PhC3z for right; PhC4z for left) increases faster than that over the ipsilateral hemisphere (PhC3z for left; PhC4z for right), which characterizes that the signal power change resulting from the ERD over the contralateral region is much larger than that of ERS over the ipsilateral region. This result is just consistent with the field power TCFP time course.

By the above analysis of the three linear descriptors, the dynamic change of the event-related EEG and antagonistic ERD/ERS patterns over the contralateral and ipsilateral areas are well characterized from the three kinds of brain macrostates. The two different stages of brain states including the relaxed state and the imagination of the left or right hand movement could be clearly reflected from the time course of the three linear descriptors. Also the time courses of the parameters Cc3z, Cc4z, FPC3z, FPC4z, PhC3z, PhC4z show good separability between the left and right hand motor imagery tasks. So applying these features of the event-related EEG to discriminate the left and right hand motor imagery tasks, it is reasonable to expect satisfactory classification results.

Table 1. A comparison of the classification results with different features.

Features	Max classification accuracy (%)	Max MI (bit)
TCC	80.71	0.3349
TCFP	85.71	0.5586
TCPHI	84.29	0.4534
TCC, TCFP, TCPHI	90.00	0.6134

3.4. Classification accuracy and mutual information time courses

Σ, Ω and Φ of the event-related EEG within 8–30 Hz from C3 and Cz, C4 and Cz, i.e. the combination of the six features Cc3z, Cc4z, FPC3z, FPC4z, PhC3z, PhC4z, are extracted to discriminate left and right hand motor imagery for the test dataset. By the method described in section 2, the classification accuracy and MI time courses are obtained and shown in figures 2(a) and (b), respectively. The maximum classification accuracy reaches 90% at about $t = 7.5$ s. And the maximum mutual information reaches 0.6134 bit. This result is a little better than that obtained by the winner of the BCI2003 competition, in which the band power features within the subject-specific frequency band were extracted by wavelet transformation [18]. The satisfactory classification accuracy and MI time course both show that TCC and TCFP together with TCPHI could well characterize the effective EEG features with good separability for left and right hand motor imagery.

For a comparison, the three kinds of features Σ, Ω and Φ of the event-related EEG within 8–30 Hz, i.e. Cc3z, Cc4z, FPC3z, FPC4z, PhC3z, PhC4z, are separately extracted to discriminate left and right hand motor imagery for the test dataset. Table 1 gives a comparison of two evaluation indexes including the maximum classification accuracy and MI by using the different features.

From table1, we can see that only by combining the three kinds of parameters TCC, TCFP and TCPHI could the best classification results be obtained. Any single feature cannot give satisfactory results. Also the feature of the field power TCFP contributes the most to the classification results, then does the feature of TCPHI, and at last that of TCC.

4. Discussions

In the previous studies reported, Σ, Ω and Φ of at least 19 channels of EEG data are used to characterize global brain macrostates for different purposes such as sleep and wakefulness, sensory and motor processes, etc [11, 19, 20]. The above analysis of event-related EEG data demonstrates that the two-channel linear descriptors (TCC, TCFP and TCPHI) are also sensitive to local brain macrostate changes. Two-channel linear descriptors TCC, TCFP and TCPHI could be regarded as the simplest case of the multi-channel Ω, Σ and Φ, which makes the former keep the good property similar to the latter. The lower number of electrodes also meets the requirements of BCI applications. In addition, TCC, TCFP and TCPHI reflect more information including not only EEG features over the contralateral and ipsilateral sensorimotor areas but also EEG features over the mid-central region, so that our method presented here achieves a satisfactory result, which is as good as the winner's results in the BCI2003 competition. The preliminary results suggest that Σ, Ω together with Φ can characterize the event-related EEG and thus can be considered as EEG features for classification of left and right imagination tasks in BCI.

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