Motor imaginary-based BCI for controlling a remote car

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Abstract: This paper presents the application of an effective electroencephalogram (EEG) based brain-computer interface (BCI) for controlling a remote car in a practical environment. The BCI uses the motor imaginary to translate the subject's motor intention into a control signal through classifying EEG patterns of different imaginary tasks. The system is composed of a remote car, a digital signal processor and a wireless data transfer module. The performance of the BCI was found to be robust to distract motor imaginary in the remote car controlling and need a short training time. The experimental results indicate that the successful ternary-control by using motor imaginry may be practicable in an uncontrolled environment.

Key words: electroencephalogram (EEG); brain-computer interface (BCI); motor imaginary; online classification

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Great progress has been made in brain-computer interface (BCI)[1] over the last decade and continues to attract new researchers from multiple disciplines. The most practical and widely applicable BCI solutions are those based on noninvasive electroencephalogram (EEG) measurements recorded from the scalp. These generally utilize either event-related potentials (ERPs) such as P300[2], visual evoked potential (VEP)[3] and steady-state visual evoked potentials (SSVEPs) measures[4], or self-regulatory activity such as slow cortical potentials[5] and changes in cortical rhythms[6,7]. The former design, being reliant on natural involuntary responses, has the advantage of requiring no training, whereas the latter design normally demonstrates effectiveness only after periods of biofeedback training, which needs the subject to learn to regulate the relevant activity in a controlled way. Such systems were recently reported to achieve the control accuracy of 82% averaged on four subjects in a cursor control of two dimensional eight targets[7] by adaptively updating the parameters of a linear function online. BCI systems employing imagined movements of hands, feet or tongue have been mainly introduced by Pfurtscheller et al. in Austria[6]. One BCI solution that has seen considerable success in optimizing this performance measure relies on motor imaginary (MI), a mechanical-hand orthosis was controlled by ongoing EEG activity based on a synchronous BCI design and two types of motor imaginary. After a number of training sessions with varying types of motor imaginary strategies over a period of several months, motor imaginary of foot movement versus right hand movement achieved a classification accuracy of close to 100%[8]. However, in the classical approach, the majority of BCI research was performed by long training periods for the users of BCI[7,9]. Subjects had to undergo weeks or months of training to adjust their brain signals to the use of the BCI. The need for online model training is acknowledged[10], but to date there are few existing real-time adaptive BCI systems. Some BCIs are capable of online model training using supervised learning with correct information on the subject's intent[11]. However, when users autonomously control an application, correct class labels are not available. The need for adaptive systems is obvious but a challenging task, especially as class information is difficult to infer from noisy and nonstationary EEG signals.

In this paper, a novel application of the MI-based BCI design for a real-time car control is addressed. We propose a method which combines common spatial pattern (CSP) and support vector machine (SVM) to classify the EEG of mental tasks online for left-hand, right-hand and foot movement imagination corresponding to three-class control commands in a BCI system. Fig.1 shows the framework of our BCI system.

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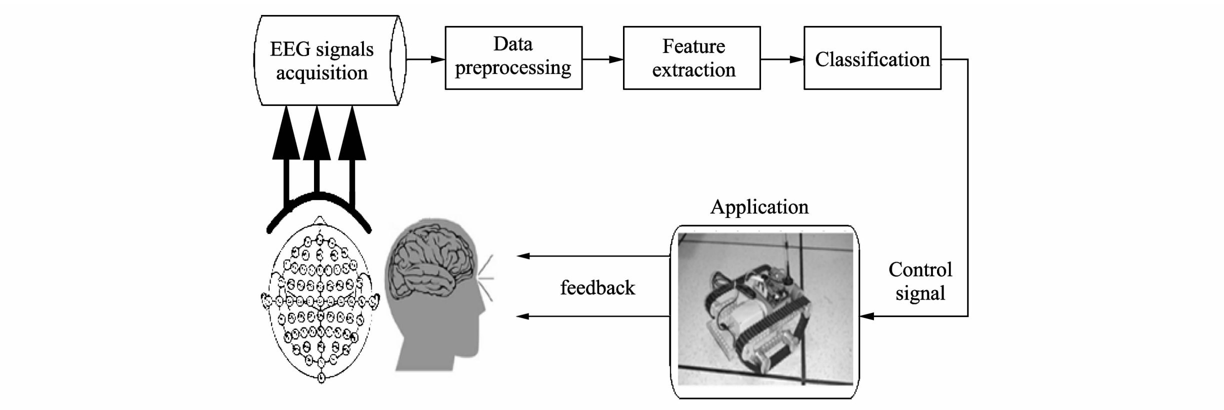

Fig. 1 BCI system

1 Preliminary analysis

1.1 Subjects

Subjects participated in the preliminary study were three male students of Tongji University and they were aged between 21 and 30, right-handed. All subjects had normal or corrected-to-normal vision.

1.2 EEG recordings

Subjects were asked to sit in an armchair, with two hands relaxing, and looked at a 17-inch computer monitor approximately 1 m in front of the subject at their eye level. 13 channels of EEG signals were recorded by a 16-channel high-performance and high-accuracy biosignal amplifier and acquisition/processing system (g. USBamp, GTEC) in our Lab using the following channels located at the positions of the 10-20 international electrode-positioning standard[12]: FC3, FCZ, FC4, C5, C3, C1, CZ, C2, C4, C6, CP3, CPZ and CP4. Skin-electrode junction impedances were maintained below 5 kΩ. Signals were digitized at a sampling frequency of 500 Hz and bandpass filtered between 8 Hz and 30 Hz. The data collection procedure has three stages: 1) Subject preparation; 2) Training data collection; 3) Test data collection. The paradigm required the subject to control a cursor moving on the monitor by imagining the movements of his right hand, left hand or foot for 2 s with a 4-s break between trials. For each subject, the data were collected over two sessions with a 15-min break in between. The first session was conducted without feedback, and 60 trials (20 trials for each class) obtained in this session were used for training and analysis. 150 trials (50 trials for each class) in the next session were taken as testing data to give online feedbacks.

1.3 Data pre-processing

Excluding contamination of EEG activity (e. g. eye movements, blinks, cardiac signals, muscle activity and line noise) is a serious problem for EEG classification and analysis. One way of dealing with this problem is to simply reject segments of EEG with unacceptable amounts of noise. However, this may result in an unacceptable amount of data loss. Independent component analysis (ICA) is a good method for blind source separation, which is shown to outperform the principal component analysis (PCA) in many applications[13]. In particular, it has been applied in the extraction of ocular artifacts from the EEG, where PCA could not separate eye artifacts from brain signals, especially when they have comparable amplitudes.

The ICA model can be stated as

$$\boldsymbol{X}(i) = \boldsymbol{A}S(i), \tag{1}$$

where $\boldsymbol{X}(i)$ represents the observed n-dimensional data vector, $\boldsymbol{A}=[anm]$ represents the mixing matrix and $\boldsymbol{S}(i)=[S_1(i)\cdots S_m(i)]$ represents the independent source signals. Both $\boldsymbol{A}$ and $\boldsymbol{S}(i)$ are unknown. Other conditions for the existence of a solution are (a) $n=m$ (there are at least as many mixtures as the number of independent sources), and (b) up to one source may be Gaussian. Under these assumptions, the ICA seeks a solution of the form:

$$\boldsymbol{Y}(i) = \boldsymbol{BX}(i), \tag{2}$$

where $\boldsymbol{B}$ is called the separating matrix, and $\boldsymbol{Y}(i)$ is the estimation of $\boldsymbol{S}(i)$.

Recent experiments have developed new methods for removing a wide variety of artifacts based on ICA[14-17]. In this work, we will apply cICA[17] for the artifact rejection in EEG signal analysis.

1.4 Feature extraction

The traditional CSP algorithm can handle only binary classification, so multi-class classification needs to extend CSP algorithm to multi-class CSP.

Multi-class extensions of CSP algorithm can be obtained from the following three strategies[18]:

1) Using CSP within the classifier (IN)

This algorithm reduces a multi-class classification problem to several binary problems, calculating the spatial patterns extracted by CSP method, and then combining all the spatial patterns as the multi-class spatial patterns. This algorithm results in high dimension of feature extraction coefficient by translating N-class classification problem to $N(N-1)/2$ binary problems.

2) Simultaneous diagonalization (SIM)

In the binary case, the CSP algorithm finds a simultaneous diagonalization of both covariance matrices whose eigenvalues sum to one. Thus a possible extension to many classes, i. e. many covariances $(\sum_i)_{i=1,\cdots,N}$ is to find a matrix $\boldsymbol{R}$ and diagonal matrices $(\boldsymbol{D}_i)_{i=1,\cdots,N}$ with elements in $[0,1]$ and with $\boldsymbol{R}\sum_i\boldsymbol{R}^{\mathrm{T}} = \boldsymbol{D}_i$ for all $i = 1,\cdots,N$ and $\sum_{i=1}^{N}\boldsymbol{D}_i = \boldsymbol{I}$. But this method can be done exactly for $N=2$; for $N>2$, in general, only approximate solutions can be obtained.

3) One versus the rest CSP (OVR)

By computing spatial patterns for each class against all others, it translates N-class problem into N new two-class problems. The OVR approach appears rather similar to the IN approach, but there is in fact a large practical difference. OVR does multi-class classification on all projected signals ereas IN does binary classification on the CSP patterns according to the binary choice. Compared with the IN and SIM algorithm, OVR method requires to choose much less patterns. In this work, we will use OVR method to improve the BCI performance. Fig. 2 shows the three - class extensions of CSP algorithm by OVR approach.

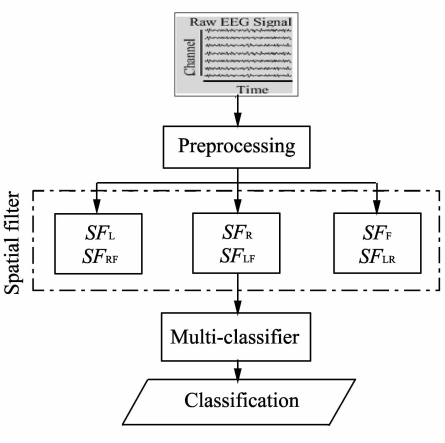

Fig. 2 Three-class extensions of CSP algorithm by OVR approach

Details of the algorithm are described as follows with the example of discriminating left hand vs. right hand imaginary. Let $\boldsymbol{S}_{\mathrm{L}}$ and $\boldsymbol{S}_{\mathrm{R}}$ denote the corresponding EEG matrices under two conditions (left hand and right hand) with dimensions $N\times M$, where N is the number of selected channel, M is the number of samples in each trial. The normalized spatial covariance of the EEG can be calculated as

$$\boldsymbol{X}_{\mathrm{L}} = \frac{\boldsymbol{S}_{\mathrm{L}}\boldsymbol{S}_{\mathrm{L}}^{\mathrm{T}}}{tr(\boldsymbol{S}_{\mathrm{L}}\boldsymbol{S}_{\mathrm{L}}^{\mathrm{T}})},\ \boldsymbol{X}_{\mathrm{R}} = \frac{\boldsymbol{S}_{\mathrm{R}}\boldsymbol{S}_{\mathrm{R}}^{\mathrm{T}}}{tr(\boldsymbol{S}_{\mathrm{R}}\boldsymbol{S}_{\mathrm{R}}^{\mathrm{T}})}, \tag{3}$$

where $tr()$ is the trace operator that sums up the diagonal elements of a matrix, T denotes the transpose operator of a matrix. The final spatial covariances $\bar{\boldsymbol{X}}_{\mathrm{L}}$ and $\bar{\boldsymbol{X}}_{\mathrm{R}}$ are respectively computed by averaging over the trials under each condition. The composite spatial covariance matrix is defined as

$$\boldsymbol{X} = \bar{\boldsymbol{X}}_{\mathrm{L}} + \bar{\boldsymbol{X}}_{\mathrm{R}}. \tag{4}$$

As $\boldsymbol{X}$ is a symmetrical matrix, it can be factored into its eigenvectors by SVD

$$\boldsymbol{X} = \bar{\boldsymbol{X}}_{\mathrm{L}} + \bar{\boldsymbol{X}}_{\mathrm{R}} = \boldsymbol{R}_0\boldsymbol{\lambda}_0\boldsymbol{R}_0^{\mathrm{T}}, \tag{5}$$

where $\boldsymbol{R}_0$ is the matrix of eigenvectors and $\boldsymbol{\lambda}_0$ is the diagonal matrix of eigenvalue. Note that the eigenvalues are assumed to be sorted in descending order.

The whitening transformation matrix is

$$\boldsymbol{P} = \sqrt{\boldsymbol{\lambda}_0^{-1}}\,\boldsymbol{R}_0^{\mathrm{T}}. \tag{6}$$

By $\boldsymbol{P}$, the individual covariance matrices $\bar{\boldsymbol{X}}_{\mathrm{L}}$ and $\bar{\boldsymbol{X}}_{\mathrm{R}}$ are transformed to

$$\boldsymbol{U}_{\mathrm{L}} = \boldsymbol{P}\bar{\boldsymbol{X}}_{\mathrm{L}}\boldsymbol{P}^{\mathrm{T}},\ \boldsymbol{U}_{\mathrm{R}} = \boldsymbol{P}\bar{\boldsymbol{X}}_{\mathrm{R}}\boldsymbol{P}^{\mathrm{T}}, \tag{7}$$

where $\boldsymbol{U}_{\mathrm{L}}$ and $\boldsymbol{U}_{\mathrm{R}}$ share common eigenvectors and the sum of corresponding eigenvalues for the two matrices will always be one

$$\begin{gathered}\boldsymbol{U}_{\mathrm{L}} = \boldsymbol{U}\boldsymbol{\lambda}_{\mathrm{L}}\boldsymbol{U}^{\mathrm{T}},\ \boldsymbol{U}_{\mathrm{R}} = \boldsymbol{U}\boldsymbol{\lambda}_{\mathrm{R}}\boldsymbol{U}^{\mathrm{T}},\\ \boldsymbol{\lambda}_{\mathrm{L}} + \boldsymbol{\lambda}_{\mathrm{R}} = \boldsymbol{I},\end{gathered} \tag{8}$$

where $\boldsymbol{I}$ is the identity matrix. Since the sum of two corresponding eigenvalues is always one, the eigenvector with largest eigenvalue for $\boldsymbol{U}_{\mathrm{L}}$ has the smallest eigenvalue for $\boldsymbol{U}_{\mathrm{R}}$ and vice versa. This property makes the eigenvectors $\boldsymbol{U}$ useful for classification of the two distributions. The projection of whitened EEG onto the first and last eigenvectors in $\boldsymbol{U}$ will give feature vectors that are optimal for discriminating two populations of EEG in the least squares sense.

With the projection matrix $\boldsymbol{W}=\boldsymbol{U}^{\mathrm{T}}\boldsymbol{P}$, the decomposition (mapping) of a trial $\boldsymbol{E}$ can be transformed into uncorrelated components

$$\boldsymbol{Z} = \boldsymbol{W}\boldsymbol{E}, \tag{9}$$

where $\boldsymbol{Z}$ is EEG source components including common and specific components of different tasks. The original EEG $\boldsymbol{E}$ can be reconstructed by

$$E = W^{-1} Z, \tag{10}$$

where W^{-1} is the inverse matrix of W. The columns of W^{-1} are the common spatial patterns and can be seen as time-invariant EEG source distribution vectors.

1.5 Classification

SVM was used as the classifier model in this work because of its good classification performance and its speed of training[19-21]. SVM is essentially a linear classifier and can be described as

$$\frac{1}{2} \| \boldsymbol{w} \|^2 + C \sum_{i=1}^{N} \xi_i^2, \text{ subject to}$$
$$y_i (\boldsymbol{w}^{\mathrm{T}} \boldsymbol{x}_i + \boldsymbol{b}) \geqslant 1 - \xi_i^2, \ (i = 1, \cdots, N), \tag{11}$$

where $C > 0$ is a regularization parameter and ξ_i is the slack variable, $\boldsymbol{w}$ is the weight vector and $\boldsymbol{b} \in \boldsymbol{R}$ is the offset, $\boldsymbol{x}_i$ is the support vector of training data and $y_i \in \{-1, 1\}$ is their corresponding class label. The SVM is based on the idea of separating the training data $\boldsymbol{x}_i$ with labels y_i by means of a linear hyperplane, such that the minimal distance of each point from the hyperplane, i.e. the so-called margin, is maximized. The regularization parameter C controls the tradeoff between two objectives: a smaller C will result in a larger margin around the hyperplane, but may cause a higher error on the training data. A larger C will decrease the training error, but possibly reduce the generalization error by enlarging the margin. In this study, we used a SVM with a radial basis function (RBF) kernel with $\gamma = 0.1$. The SVM was trained with regularization parameter $C = 0.8$, which places an upper bound on the fraction of error examples and lower bound on the fraction of support vectors[22].

2 Online training and controlling

The object of the BCI is to gain ternary control of the moving direction of a remote car using only the player's EEG. The system is composed of a remote car, a digital signal processor and a wireless data transfer module as shown in Fig. 3. Another wireless data transfer module is connected to PC through the RS232 port. The commands issued by the user are sent to the remote car through the RS232 port of the digital signal processor. These commands are translated by retrieving the information pre-stored in the memory and then sent to the device to be controlled by the user. In the training, we suppose that left/right hand imaginary means turn to the left/right and foot imaginary means go forward (Fig. 4). The control begins with a brief classifier training period. The training process consisted of the repetitive epoches of triggered movement imaginary trials. Each trial started with the full black screen, and at 3 s, a visual cue was displayed at the center of the monitor for 5 s, representing the mental task to perform. Depending on the symbols (left arrow, right arrow, down arrow) presented, the subject was instructed to perform different tasks: imaging a movement of left hand, right hand and foot. The trail was ended after 5 s imagination and a blank screen was shown until the beginning of the next trial. The mental tasks represented by visual cue were chosen randomly to avoid adaptation. During this training period, feedback is presented in order to ensure compliance.

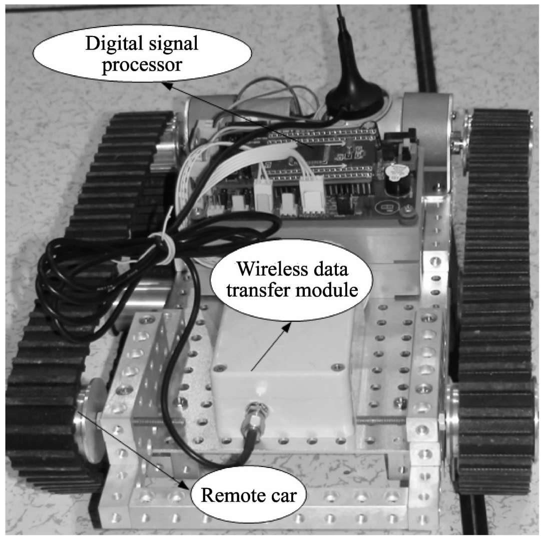

Fig. 3 Composition of the remote car

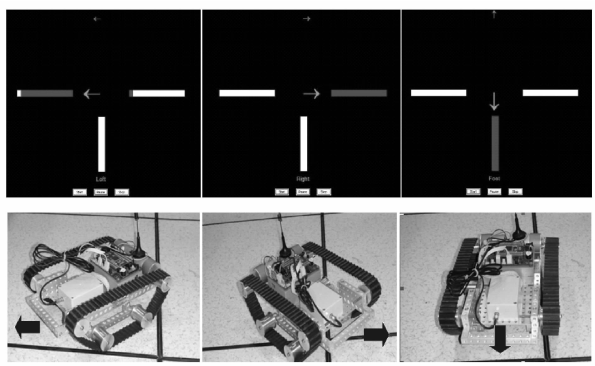

Fig. 4 Online feedback paradigm of the three-class motor imagery tasks and car's movement during the controlling

Three male subjects aged between 21 and 30 participated in the following test procedure to assess performance of the online controlling. All subjects had normal or corrected to normal vision. When the remote car was controlled the EEG was analyzed by the CSP and SVM method described above for the online data.

3 Results and discussion

We utilize a novel method of on-line classification based on multi-class CSP for feature extraction and SVM as a classifier. The best classification results for three subjects are 86.3%, 91.8% and 92%. The results suggest that the event-related (de)synchronization (ERD/ERS) elicited by MI can be successfully used to make decisions in a real time BCI-controlled environment. The problem we frequently encountered in a BCI system is that the performance is normally difficult to be maintained when the system runs from offline training sessions to online operation. One could suspect this to be caused by bad model selection strategies which could in principle choose overly complex classification models that overfit the EEG data. When using online training it is difficult to select when the model should be trained and when it should be kept static. It is also difficult to know when the training should be done by the user and when by the model, and what happens if both earn simultaneously. Longer experiments are needed to address this question. Furthermore, choosing the correct speed for adapting the classifier in a supervised framework is crucial since too quick updates can produce false results and erroneous feedback.

4 Conclusion

This paper presents the application of an effective EEG based BCI for controlling a remote car in a practical environment, which is able to translate the user's control intentions during online experiments, so that online training and adaptation of the motor imaginary in BCI can be effectively used. The experimental results show that the successful ternary-control using MI may be practicable in an uncontrolled environment.

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