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Motion Control of a Four-Wheel-Independent-Drive Electric Vehicle by Motor Imagery EEG Based BCI System

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Abstract: This paper proposed a control structure of Four-Wheel-Independent-Drive electric vehicles by motor imagery Electroencephalography (EEG) based BCI system. First work is the BCI system, Emotiv EPOC+ is used to acquire the raw EEG data, Independent Component Analysis (ICA) is used to preprocess the motor imagery EEG, then Common Spatial Pattern (CSP) is used to extract the features which is most related to the ERD/ERS. Last but not least, Back Propagation Neural Network (BPNN) is used to classify the left and right, at the meantime, subject's threshold value of average band power is calculated to classify the accelerate and brake. In the test, there is about 84% accuracy rate of accelerate and brake and 89.92% for left and right classification. The second work is that we design and construct a real model FWID electric vehicle with environmental perception subsystem, including ultrasonic wave radars and cameras, which can avoid the risk when BCI command is wrong. We also construct driving motor imagery sample data collector to get subjects' motor imagery data for classifier to improve the accuracy of BCI system.

Key Words: BCI, Four-Wheel-Independent-Drive Electric Vehicles, ICA, CSP, BPNN

1 Introduction

A brain computer interface (BCI) system permits encephalic activity to solely control computers or external devices. The basic goal of BCI systems is to provide communications capabilities to severely disabled people who are totally paralyzed, such as amyotrophic lateral sclerosis, brain stem stroke, or spinal cord injury [1]. So the BCI system makes it possible for the disabled to manipulate a vehicle, which highly enhances their life convenience.

Electroencephalography (EEG) is one of the key tools for observing brain activity. With respect to other data acquisition techniques, its main advantages are low costs, relative ease of use and excellent time resolution (millisecond scale temporal resolution) [2]. EEG is considered the only practical non-invasive brain imaging modality for repeated real-time brain behavioral analysis [3]. In this paper, EEG is used as the input brain imaging modality for BCI design rather than EOG, ECG or EMG.

Speaking of EEG signals, three most common used types are the P300, the SSVEP and the motor imagery. P300 and SSVEP are both EEG potentials that appear after external stimulation [4]. The motor imagery come out only when the subject makes the action or just imagine the action. Controlling a vehicle is an initiative action so the motor imagery is used in this paper as the most suitable EEG paradigm for brain controlled vehicle research.

Typically, a BCI is an artificial intelligence based system that can recognize a certain set of patterns in brain EEG signals via a number of consecutive phases; namely, signal acquisition for brain signals capturing, preprocessing or signal enhancement for preparing the signals in a suitable form for further processing, feature extraction for identifying discriminative information in the brain signals that have been recorded, classification for classifying the signals based on the extracted feature vectors, and finally the control interface phases for translating the classified signals into meaningful commands for any connected device, such as a wheelchair [5] or a vehicle [6].

Electrooculography (EOG) and electromyography (EMG) artifacts are considered among the most important sources of physiological artifacts in BCI systems. Due to the large number of unknown sources of neuronal and non-neuronal origins contributing to the recorded signal, it becomes a blind source separation (BSS) challenge to identify and remove artifacts on a single trial basis. The Independent Component Analysis (ICA), a BSS method, to remove blink (EOG), EMG and also line interference artifacts has its superiority over PCA and regressive methods. EEG signal changes according to the brain activity states. Depending on these states, we can distinguish several rhythms (waves) [7]: "mu" with a rate of change lies between 8 and 13 Hz, with 30–50 μV amplitude, "beta", the rate of change lies between 14 and 30 Hz, and usually has a low voltage between 5 and 30 μV. Beta is the brain wave usually associated with active thinking, active attention, and focus on the outside world or solving concrete problems. Furthermore, the mu and beta rhythms are associated with the event-related (de)synchronization (ERD/ERS), which are used as the feature extraction method in this paper. As for the classification, we use BP neural network to classify two motor imagery action: left and right, at the meantime, we

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calculate subject's threshold value of average band power to classify the accelerate and brake action.

In the research domain of EEG controlled vehicles, researches focus on driver vigilance detection for traditional fuel vehicles [8], and establish virtual vehicle control platform [9]. As for the processing of longitudinal motor imagery command, almost every researcher uses EOG or other ways indirectly related to the EEG, in the contrast, we calculate the average band power of motor imagery potentials. We also construct a real model Four-Wheel -Independent-Drive Electric Vehicle with environmental perception subsystem, including ultrasonic wave radars and cameras. We also construct driving motor imagery sample data collector to get subjects' motor imagery data for classifier to improve the accuracy of BCI system.

2 Brain-Computer Interface Based on Motor Imagery EEG Signals

The BCI system consists of five parts: signal acquisition, signal preprocessing, Feature Extraction, classification and command execution. The BCI system structure are as Fig.1.

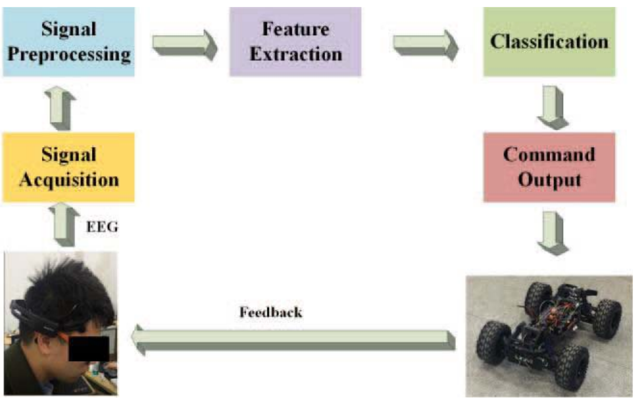

Fig 1: BCI system structure

The process of our EEG controlled FWID electric vehicle is as follows. A subject wears the EEG signal acquisition device and does driving motor imagery, then the device transfer to the computer via Bluetooth after signal amplification and power frequency filtering. Then we accomplish signal preprocessing to remove artifacts, after that, ERD/ERS based feature extraction and classification are done. Then control commands come from classifier are sent to microprocessor unit on the FWID electric car by wireless serial ports. Eventually, the environment perception system on the car work out the real-time safe and passable zone, only when the command fits the zone, will the vehicle execute the EEG processed command. The BCI system scene is illustrated as Fig.2.

Fig 2: BCI system scene

2.1 Signal Acquisition

We use the headset Emotiv EPOC+ to acquire subjects' EEG signals. The Emotiv EPOC+ has 16 electrodes, two of which are rubber reference electrodes fixed at P3(CMS) and P4(DRL). Other 14 gold-plated beryllium copper electrodes are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. The 16 channels' real-time potential signals are transferred to the signal sampling module, including preamplifier, high pass filter, 50 Hz notch filter and ADC. It has a lithium battery and uses 2.4GHz to transmit to the computer via a dongle. The Emotiv EPOC+ has a sampling rate of 128Hz and a bandwidth of 0.2-45Hz. The raw data as a double vector of the size 22 will be sent to the Simulink S-Function, the data vector contains elements in the following order: COUNTER, AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, GYROX, GYROY, TIMESTAMP, FUNC ID, FUNC VALUE, MARKER, SYNC SIGNAL. The Emotiv EPOC+ and electrode position are demonstrated as Fig.3 and Fig.4.

Fig3: Emotiv EPOC+

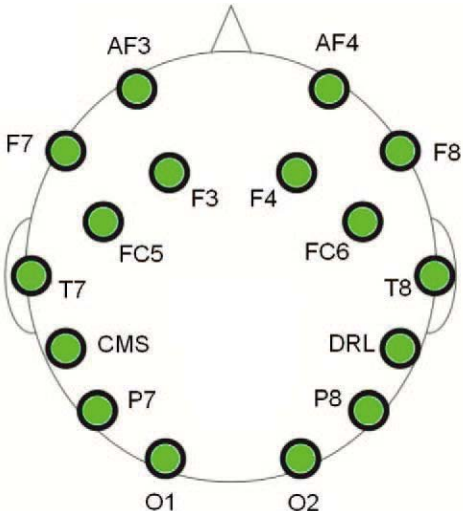

Fig.4: Electrode position

2.2 Signal Preprocessing

Although we get raw EEG data from the Emotiv EPOC+, there still exists artifacts such as electromyography (EMG), electrocardiogram (ECG) and electrooculogram (EOG). Independent component analysis (ICA) is applied to enhance event relate potential and remove artifacts and reconstruct the motor imagery EEG signals. The model of ICA can be written as (1) while $x=(x_1,x_{2,},...,x_n)^T$ denotes n dimensional random observation variables, $s=(s_1,s_2,...,s_m)^T$.

$$x = As(t) = \sum_{i=1}^{m} a_i s_i \tag{1}$$

Suppose A is a mixed matrix, the vector of row i is written as a_i . Seek whiten matrix V to get z as:

$$z = Vx = VAs \tag{2}$$

Then seek a reversible matrix W, which turns z into n dimensional vector of independent components.

The Fig.5 shows different components (ICA outputs) a_i obtained by projecting the input EEG data vector for each time instant along different ICA vectors.

In order to reconstruct the EEG matrix X , we must take frequency characteristics into consideration. It is proved that mu and beta rhythms are around 10Hz and 20 Hz, hence the coefficients must meet the frequency of motor imagery ICs.

2.3 Feature Extraction

Common spatial pattern (CSP) is used to extract the feature that maximize the differences between two classes of ERD/ERS in motor imagery EEG, the concrete process are as follows:

$X_d^i, d \in \{1,2\}$ denote the two kind sample signals, which are $N \times T$ matrixes, where N is the number of channels and T is the number of samples in every channel. Thus, the normalized spatial covariance matrix can be expressed by

$$R_d^i = \frac{X_d^i X_d^{iT}}{trace(X_d^i X_d^{iT})} \tag{3}$$

Where trace(x) means the sum of the spatial covariance. $R_d, d \in \{1,2\}$ denotes the average covariance of each kind, so the sum of two kind average covariance can be giving as

$$R_c = R_1 + R_2 \tag{4}$$

Seek eigenvalues of R_c

$$R_c = U_c \lambda_c U_c^T \tag{5}$$

While U_c is the eigenvector matrix, λ_c is eigenvalue matrix. U_c can be whiten by the whiten matrix P .

$$I = PR_c P^T \tag{6}$$

Where I is the identity matrix, also P can be expressed as

$$P = \sqrt{\lambda_c^{-1}} U_c^T \tag{7}$$

It can be seen that if R_1 and R_2 are processed by P

$$S_d = PR_d P^T, d \in \{1,2\} \tag{8}$$

The S_1 and S_2 have common eigenvectors, and the sum of corresponding eigenvalues equals 1. If

$$S_1 = B\lambda_1 B^T \tag{9}$$

$$S_2 = B\lambda_2 B^T, \ \lambda_1 + \lambda_2 = I \tag{10}$$

That means on the direction of the biggest eigenvalue of S_1 , the eigenvalue of S_2 is the smallest, and vice versa. So the difference between two kind signals reaches the maximum. Projection matrix can be giving as

$$W = B^T P \tag{11}$$

W is an $N \times N$ matrix, original signal X turns into Z through projection matrix W :

$$Z = WX \tag{12}$$

After the CSP process, the first m lines of W represent the best spatial filter of class 1, the other m lines represent the best spatial filter of class 2. After logarithm fetch and normalization to the variance of signals from 2m line spatial filter, final feature can be giving as

$$f_j = \frac{\lg\left[\operatorname{var}(Z_j)\right]}{\lg\left[\sum_{k=1}^{2m} \operatorname{var}(Z_k)\right]}, j = 1, \cdots, 2m \tag{13}$$

2.4 Classification

Back Propagation Neural Network (BPNN) is used in this paper to classify the left and right motor imagery. BPNN is a multi-layer feedforward neural network, including input layer, hidden layer and output layer. Fig. 6 is a classic three-layer BPNN structure.

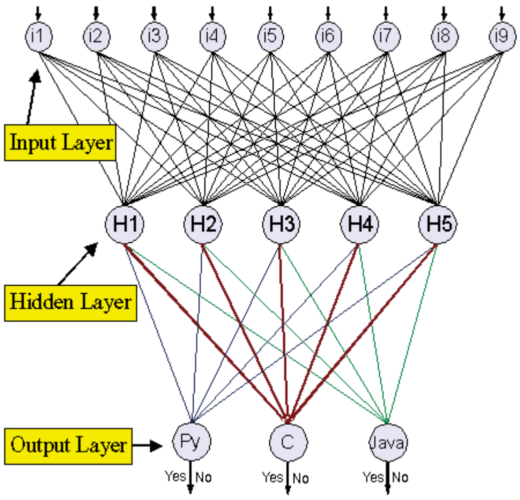

Fig. 6: Classic three-layer BPNN

The learning process of BPNN consists of forward calculation and error back propagation. During the forward calculation, input was calculated from the input layer to the hidden layer then to the output layer. Neuron of each layer can just influence the neuron of next layer. If output layer can't get expected output, then shift to error back propagation, error goes back the same way to adjust the weight and threshold value backwards layer by layer. These two steps continue to adjust weight and threshold values of every layer until network error meet the demand. Flow chart of BPNN algorithm is as follow.

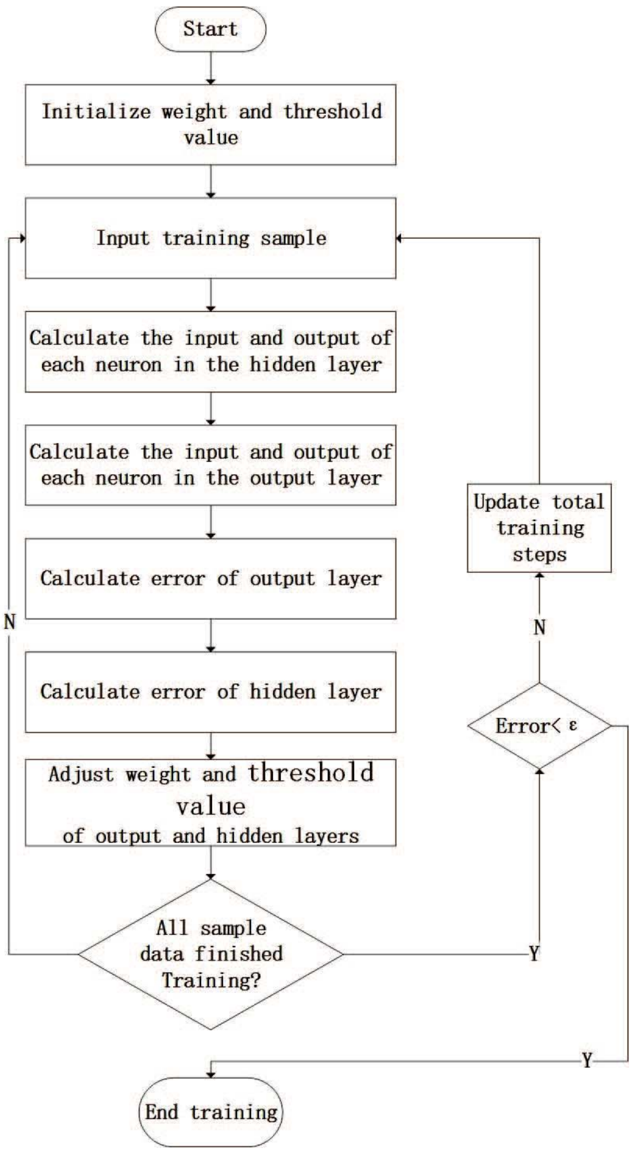

Fig. 7: Flow chart of BPNN algorithm

After that, we calculate subject's threshold value of average band power to classify the accelerate and brake action at the same time to realize the integrated four type classification.

2.5 BPNN Sample Data Collector Design

We use BP neural network to classify the EEG based motor imagery intention. In order to improve the accuracy of four classes: throttle, brake, left and right. We design training data collector as follow. We use serial port to get the angle of pedals and steering wheel, to attach corresponding EEG data as a supervised training label. Subjects wear Emotiv EPOC+ and think accelerate when press on the throttle pedal, think brake when press on the brake pedal, think left when turn the steering wheel left, think right when turn the steering wheel right. Repeatedly, we can collect enough sample training data.

Fig. 8: BPNN Sample Data Collector

3 Motion Control of a FWID Electric Vehicle

We construct a FWID Electric vehicle with multiple sensors, including four ultrasonic wave radars around the body and a camera on the top of the car. The vehicle has four independent actuating hub motor and can achieve high movement agility. Also, four ultrasonic wave radars detect obstacles' distance in four directions. Below is the vehicle.

Fig. 9: FWID Electric Vehicle

The high-definition camera captures road condition ahead. After image process procedure running in the on board DSP+ARM processor, obstacle information can be obtained. Below is camera based environment perception information.

Fig. 10: Camera based environment perception information

The control strategy of coordinating driving motor imagery BCI system and environmental perception system is that the environmental perception system has the priority. The environmental perception system keeps the vehicle in the safe movement status and safe environment. Only conforming to the passable judgement of environment perception system, can the command of BCI execute to assure the safety and avoid the EEG based command error. Below is the multi-senor information fusion system.

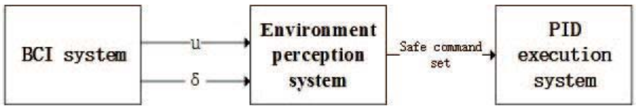

Fig. 11: multi-senor information fusion system

4 Experiments and Results

We use visualization software to demonstrate the effect of calculation of average band energy, picture is as follow.

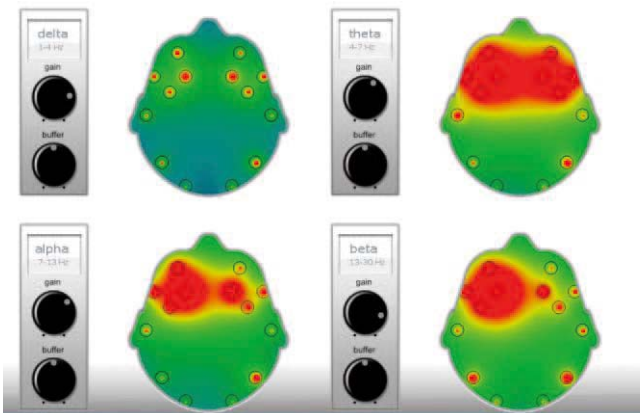

Fig. 12 effect of calculation of average band energy

By wearing Emotiv EPOC+, our three teammates all gather 160 sets of data on the sample data collector, 40 sets for left, 40 sets for right,40 sets for accelerate and 40 sets for brake. Table below is acceleration and brake test results by three subjects after calculating each person's average band power threshold value.

Table 1: Acceleration and brake test

Subject	Action	Accuracy
Jiayu Zhuang	Acceleration	85.23%
Jiayu Zhuang	Brake	83.34%
Deming Zhang	Acceleration	82.93%
Deming Zhang	Brake	81.29%
Lei Gong	Acceleration	86.48%

Lei Gong	Brake	83.62%

Number of neurons of input layer is 4, number of neurons of hidden layer is 21, number of neurons of output layer is 2, the result 0 represents left and 1represents right. Figure below is the test result of left and right by BPNN, achieving the accuracy rate of 89.92%.

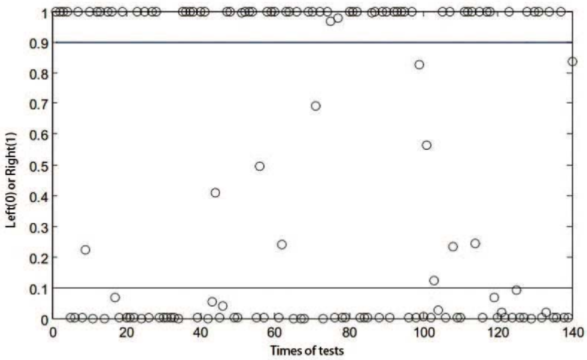

Fig. 12: BPNN classification results for left and right

5 Conclusion

We proposed a control structure of Four-Wheel-Independent-Drive electric vehicles by motor imagery Electroencephalography (EEG) based BCI system. We use Emotiv EPOC+ headset to acquire the raw EEG data, then use Independent Component Analysis (ICA) to preprocess the motor imagery EEG, then Common Spatial Pattern (CSP) is used to extract the features which is most related to the ERD/ERS. Last but not least, Back Propagation Neural Network (BPNN) is used to classify the left and right command, at the meantime, subject's threshold value of average band power is calculated to classify the accelerate and brake. In the test, there is about 84% accuracy rate of accelerate and brake and 89.92% for left and right classification. The second work is that we design and construct a real model FWID electric vehicle with environmental perception subsystem, including ultrasonic wave radars and cameras, which can avoid the risk when BCI command is wrong. We also construct driving motor imagery sample data collector to get subjects' motor imagery data for classifier to improve the accuracy of BCI system.

As for the perspective, there is a highly need to apply the deep learning to making the classifier more accurate and extracting further and deeper motor imagery features.

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