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Applications of Event-Related-Potential-Based Brain Computer Interface to Intelligent Transportation Systems

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Abstract *In this paper, an event-related-potential (ERP) -based brain computer interface (BCI) is proposed for the application of intelligent transportation systems (ITS). It consists of a virtual-reality (VR) motion simulation platform and an electroencephalographic signal detection and analysis system. The goals are to demonstrate the feasibility of detecting and analyzing multiple streams of ERP signals that organize operators' cognitive states and responses to task events, and to develop an ERP-based brain computer interface to meet the requirements of public security of intelligent transportation systems. We setup detailed experimental procedures to perform the cognitive tasks and collect high-fidelity ERP signals in the well-controlled VR-based laboratory environments. The independent component analysis (ICA) algorithms are applied to separate and get noise-free ERP signals from the multi-channel measured signals. Experimental results show that the separated ERP signals achieve a satisfactory result and can be further classified and transformed as the control/monitoring signals of safety-driving system for ITS.*

Keywords: brain computer interface, event-related brain potential, virtual reality, independent component analysis, intelligent transportation system.

1. Introduction

During the past years, the public security has become an important issue, especially, the safe manipulation and control of various vehicles in intelligent transportation systems (ITS) [1-4]. Many researches have focused on the training and censoring of operators relying on the actual machines, which has high demands in space, time and cost. To tackle the above dilemma, a virtual-reality (VR) based simulation platform is suitable to provide various dynamic driving environments and to reduce the development cost.

Another important interesting issue of safely driving is to detect the drivers' cognitive states as well as environmental conditions, and to awake or give proper warnings to drivers. The brain computer interface (BCI) technology provides the users the communication and control channels, which can provide feedbacks to engage the user's perceptive and reactive capacities. It may demand the access of the brain activities using a non-invasive device and require determining the corresponding electroencephalographic (EEG) signals for the desired actions.

A way to realize the relationship of human cognitive response to different stimulus is the use of event-related brain potential (ERP) signals. An ERP signal will be observed with some latency (e.g., P300) as the stimulus event is given or removed to a subject. The key point for measuring correct ERP signals is whether or not the subject can clearly recognize the stimulus. That is, the subject's cognitive state may change accompanying correct, incorrect and absent responses in attention-demanding cognitive tasks under the same stimulus.

In this paper, we construct a VR-based environment and design a detailed experimental procedure to detect, acquire, and analyze ERP signals as well as perception of human brain activities in a single trial mode such that it is capable of applying to on-line human-machine interface. We also use an applicable method for removing a wide variety of artifacts from ERP records based on blind source separation by independent component analysis (ICA).

Our results demonstrate that the ERP signals can be measured correctly through the VR stimulus and the ICA algorithm can effectively detect, separate, and remove contaminations of the artificial sources in ERP records. This results and know-how can also be generalized to other events naturally and the separated ERP signals through ICA algorithms can be further classified and transformed as control signals of safety-driving system through the brain computer interfaces for monitoring intelligent transportation systems.

2. System Architectures

The first step of constructing BCI is to design and setup an experiment for fundamental studies of neural correlates between cognitive states and event perceptions. In this paper, we focused on the detecting and analyzing of the responses of brain activities to the traffic-light events (Red-Green-Yellow) since they are the most frequently happened events when driving on the roads. Fig. 1 shows the flowchart and hardware setup of the VR-based BCI development environment. The system consists of three major parts. Detailed setup for this experimental are listed below:

(1) In the VR scene development, we develop a preliminary VR scene by the widely used software, Coryphaeus, in a high-performance SGI workstation. First, we create models (such as traffic-light, road, car, building, and tree, etc.) for the scene. Second, we create terrain by reading satellite terrain data. At last, we setup position, attitude and other relative parameters. In the beginning of our research, a VR scenario is used to give three kinds of traffic-light signals (R-G-Y). The VR-based traffic-light stimulus sequences contain 150 events as shown in Fig. 2, and the length of one experimental sequence is about 400 seconds. The event allotment ratios are R:30%, G:60%, and Y:10%, and they appeared randomly with random intervals between {1.7, 2.1 2.3 (sec)}. The on-off duration of each traffic-light event is 300 ms.

(2) The second part of the experiment setup is a car-driving simulator based on six-degree-of-freedom (6-DOF) Stewart platform. The Stewart platform is a parallel manipulator. It has a lower base platform and an upper payload platform connected by six extensible legs with ball joints at both ends. The 6-DOF platforms can provide different virtual driving conditions with position control coupled with VR scenario.

(3) The third part is the EEG measurement system with 36-channel EEG head mounted sensors to detect the brain activities as shown in Fig. 3. The measured EEG signals were amplified and recorded in the data-storing server with 1KHz sampling rate. The design of ERP-measured experiment needs the subject to do some reactions according to different stimuli in order to confirm and establish the relationship between measured EEG signals and stimuli. The subject is asked to decelerate/stop the car by pressing the right button of a joystick using right hand when he/she detected a red light, to accelerate the car by pressing the left button using left hand when he/she saw a yellow light, and do nothing (keep constant speed) when he/she saw the green light.

3. Analysis of EEG Signals

Independent Component Analysis was originally proposed in 1994 and is highly effective at performing source separation problems. Comon [5] defined the concept of ICA as maximizing the degree of statistical independence among outputs using contrast functions approximated by Edgeworth expansion of the Kullback–Leibler divergence. Bell and Sejnowski [6] derived a simple neural network algorithm based on information maximization that can blindly separate super-Gaussian sources. The important fact used to distinguish a source, s_i , from mixtures, x_i , is that the activity of each source is statistically independent of the other sources, i.e., the mutual information between any two sources, s_i and s_j , is zero. The task of ICA algorithm [7-10] is to recover a version, $U = WX = WAS$ of the original sources S by finding a square matrix W that inverts the mixing process linearly and save the identical scale and permutation.

For EEG analysis, the rows of the input matrix X are the EEG signals recorded at different electrodes, the rows of the output data matrix $U=WX$ are time courses of activation of the ICA components, and the columns of the inverse matrix W^{1} give the projection strengths of the respective components onto the scalp sensors. The scalp topographies of the components provide information about the location of the sources (e.g., eye activity should project mainly to frontal sites, etc.). "Corrected" EEG signals can then be derived as $X'=W^{1}U^{T}$, where U^{T} is the matrix of activation waveforms U [11-12].

In our experiment, we assume that the multi-channel EEG recordings are mixtures of underlying brain sources and artificial signals. We suppose that the number of sources is the same as the number of sensors by assuming that the source numbers contributing to the scalp EEG are statistically independent, that is, if there are N sensors, the ICA algorithm can separate N sources. The conduction of the EEG sensors is assumed to be instantaneous and linear such that the measured mixing signals are linear and the propagation delays are negligible. We also assume that the signal source of muscle activity, eye, and, cardiac signals are not time locked to the sources of EEG activity which is regarded as reflecting synaptic activity of cortical neurons. Therefore, the time courses of the sources are assumed to be independent.

4. Experimental Results

In our experiment, a subject was driving a car in the VR-based ERP experimental system designed in Section 2. The objective of this experiment is to detect and analyze cognitive responses of the driver to traffic-light events by analyzing the measured multi-channel EEG signals. The continuous EEG signals measured from 36-channel EEG sensors are firstly separated into several epochs/trials where only 31-channel data are used (four EOG channels and one reference channel are removed). An epoch or a trial contains the sampled date from –200 ms to 1000 ms when a light event was given at 0 ms. The subject is asked to press the right button of the joystick when he saw the red event. Fig. 4 shows the measured time-domain overlap-added averaged red-light-event ERP signals of all 31 channels.

The topographic maps of the variations of ERP in a single epoch (red-light event) are also shown in Fig. 5. Both N150 and P300 could be observed clearly. The time -domain overlap-added averaged ERP signals of three kinds of stimulus events in Pz channel are shown in Fig. 6. We can find that the average ERP signal in our ERP experiment is similar to the general visual ERP signal where P100, N150, and P300 could be clearly observed. It can also be found that EEG response of three events are very different and can be used as the features for further classification. This observation demonstrates the correctness of our experimental setup.

The ERP signals at Fz channel and Pz channel corresponding to red-light event are further shown in Fig 7(a) and 7(b), respectively. The amplitude of P300 at Pz is larger than that at Fz because Pz is more closed to the vision zone of the brain. We can compare the ERP signals caused by different events in the same channel in Fig. 7(b) and 7(c). The amplitude of P300 caused by red-light event is higher than the amplitude of P300 caused by green-light event because adding a pressing-button action can attract the subject's attention and get higher EEG magnitude.

The measured ERP signals are further analyzed using ICA algorithm trained in single trials. The topographic maps of the obtained 31 ICA components after training are shown in Fig. 8. We can observe that component 1 contributes most ERP signals in the vision zone. The ERP signal measured by each channel can be composed as:

$$ERP_i = w_{i,1}S_1 + w_{i,2}S_2 + \cdots + w_{i,j}S_i + \cdots + w_{i,31}S_{31}$$

where ERPi means the ERP signal measured by at i^{th} channel; w_{ij} is the weighting factor trained by the ICA algorithm; S_i is the obtained i^{th} ICA component. Fig. 9(a) shows the ERP signals contributed by component 1 at Pz channel compared to the contribution of component 16 shown in Fig. 9(b). We can find that the component 1 contributed strong ERP signal and the component 16 was a noisy EEG signal. The same phenomenon could also be observed at other channels. Therefore, component 1 can be regarded as the major source of visual ERP signals to analyze human's perception of traffic-light events. Comparing Fig. 7(b) with Fig. 9(a), we can also find out that the ERP signal obtained from the analysis of ICA algorithm in single trial is more clear and noise-free than that obtained from traditional time-domain overlap-added method. This experimental result encourages us to design an on-line application for the brain-computer interface.

5. Conclusions

In this paper, an event-related-potential (ERP)-based brain computer interface (BCI) is proposed for the application of intelligent transportation systems (ITS). It consists of a virtual-reality (VR) motion simulation platform and an electroencephalographic signal detection and analysis system. We proposed a detailed experimental setup for measuring and analyzing ERP signals. The experimental results show that the proposed experimental setup can measure ERP signals correctly by using time-domain overlap-added method. In addition, after the analysis of ICA algorithms, we obtained a correct, clear, and noise-free ERP signals in single trials. We can further classify and transform these ERP signals as the control/monitoring signals of on-line brain computer interfaces for safety-driving system. Based on experimental results, we will perform more experiments on VR-based driving dynamic simulator and also study brain dynamics corresponding to kinesthetic stimuli to develop brain-computer interfaces for the intelligent transportation systems.

Acknowledgement

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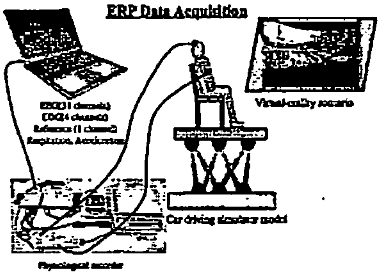

Fig. 1: The VR-based mental-and-physical signal measurement system.

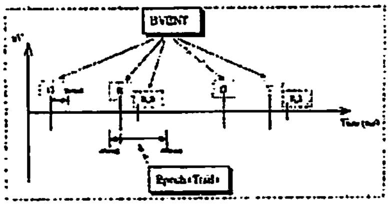

Fig. 2: The traffic-light stimulus sequences.

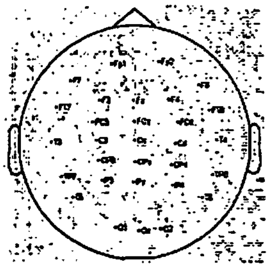

Fig. 3: The channel locations of head mounted EEG measurement system with 36-channel EEG sensors.

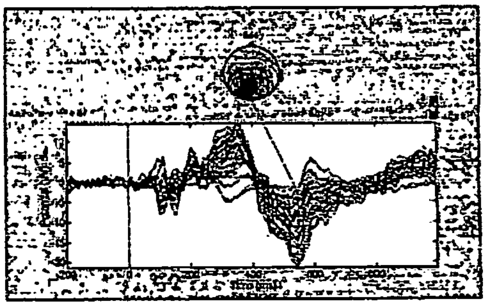

Fig. 4: The measured red-light-event ERP signals of all 31 channels.

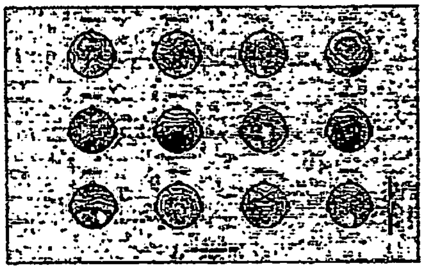

Fig. 5: The spatial maps of the variations of ERP in a single trial.

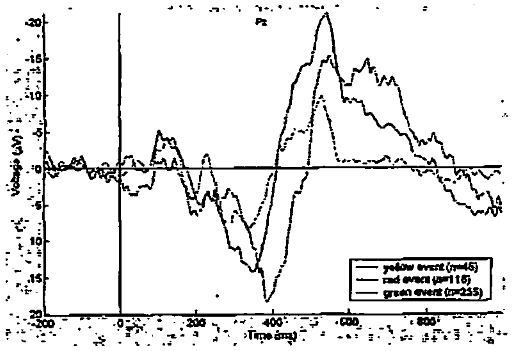

Fig. 6: A time-domain overlap-added averaged ERP signal at Pz channel for three kinds of stimuli. P100, N150, and P300 could be clearly observed in our ERP experiments.

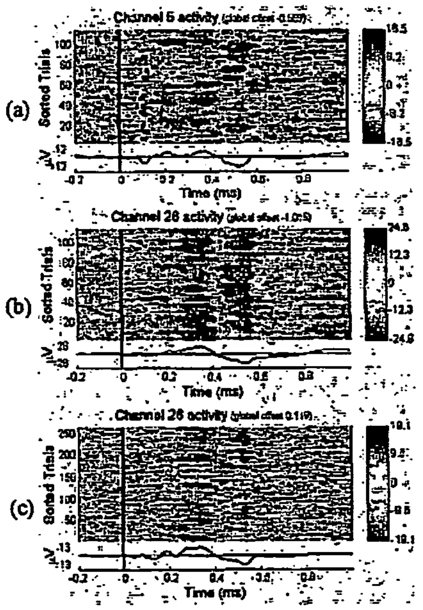

Fig. 7: Single-trial ERP signals: (a) red-light event at Fz (5th) channel, (b) red-light event at Pz (26th) channel, and (c) green-light event at Pz (26th) channel.

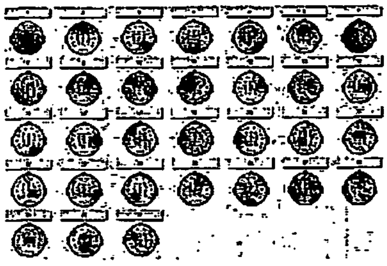

Fig. 8: Spatial maps of the 31 ICA components.

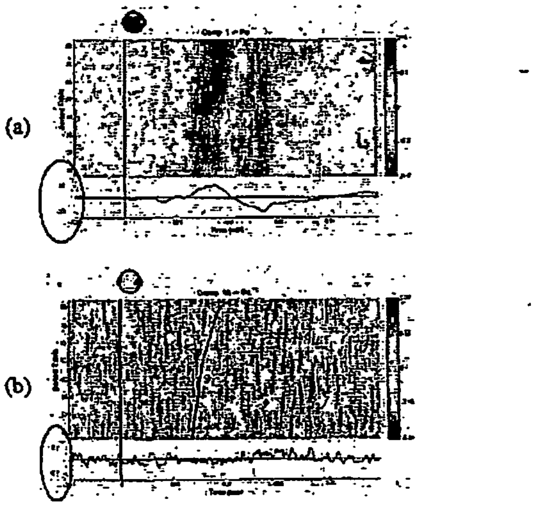

Fig. 9: The ERP signals: (a) contributed by component 1 at channel Pz and (b) contributed by component 16 at channel Pz.