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ScienceDirect

Procedia Computer Science 107 (2017) 256 – 261

Procedia Computer Science

International Congress of Information and Communication Technology (ICICT 2017)

Evaluation of motor training performance in 3D virtual environment via combining brain-computer interface and haptic feedback

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Abstract

Brain-computer interfaces (BCIs) based on virtual reality (VR) mostly integrate visual and/or auditory feedback. Haptic feedback which has the potential on improving the feasibility and operability of VR-based BCI systems is rarely explored in previous studies. In this article, we present a novel framework of BCI system based on both visual and haptic feedback, in which users can learn to manipulate the haptic device's stylus for motor training. The effects of motor training with and without haptic feedback are evaluated by detecting and analysing the changes of electroencephalogram (EEG). The preliminary experimental results indicate that haptic feedback may influence the modulation of the beta rhythms over left and right sensorimotor cortex during hand movements. This study can be easily replicated to evaluate the existing systems with haptic feedback and used to develop new applications for motor training.

Keywords:Haptic feedback, brain-computer interface (BCI), Electroencephalogram (EEG), event-related spectral perturbation (ERSP), virtual reality (VR);

Peer-review under responsibility of the scientific committee of the 7th International Congress of Information and Communication Technology
doi:10.1016/j.procs.2017.03.096

1. Introduction

Virtual reality (VR) has become a state-of-the-art technique in simulating and training the moving ability of users with multiple input and output interface devices. It can improve the efficiency of training system and shorten the training cycle by providing immersive environment integrated with visual, auditory and/or haptic feedback[1]. Current VR systems are requiring multi-modal interaction channels. One promising type is brain computer interface (BCI). It is a new type of human-computer interaction technology, which establish interactive channel through human brain and external electronic devices independent of peripheral nerve and muscle output path[2]. BCIs are able to identify user's intention directly through electrophysiological (EEG) or other signals of the brain, and to translate into corresponding commands to control external devices[3].

In previous studies, BCIs based on VR have been realized with the high integration of visual and/or auditory feedback[4,5]. Haptic feedback as an important component of VR system has attracted more and more attention[6]. The feasibility and operability of VR-based BCI systems could be improved by employing haptic interface[7]. The evidence has suggested that an accurate assessment of the effects of haptic feedback could be very beneficial for user training strategy and system design. To evaluate interactive training system usually relies on questionnaires or behavioural measures (e.g., reaction time or accuracy rate). However, although these techniques have been successful in former researches, they still suffer from some limitations. They cannot provide and harness mental states for understanding users' experience. Recently, it has been suggested that the detection of EEG signals may offer an alternative way to quantitatively assess users' motor-cognitive training task[8]. So far few studies have investigated on the changes of metal states associated with haptic feedback during motor training tasks. Some studies have found that users' brain activities caused by haptic feedback can be detected in motor cortex and sensory cortex in a brain[9-11]. However, neither of these studies state explicitly on how haptic feedback affects brain activity. Moreover, they usually explore the effects of visual and/or haptic feedback in two-dimensional simulation scenarios, but mostly the applications combined with haptic feedback have been implemented in 3D virtual environment, such as virtual surgery, rehabilitation training system, VR game and so on.

In this study, we preliminarily study on the changes of brain activity induced by haptic feedback in 3D virtual environment. We build a framework of BCI system based on both 3D visualization and haptic guidance, where users could learn to manipulate the haptic device to move. The effect of motor training with and without haptic feedback is evaluated by detecting and analysing the brain activities in the sensorimotor area. The framework of the system proposed in this study would be easily replicated to evaluate the existing systems with haptic feedback and used to develop new applications.

2. Method

2.1. Subjects

Five subjects (2 males and 3 females; 22-26 years old) were recruited for the experiments, all of them were healthy without neurological disease, and were accustomed to use their right hand. Each subject had no experience with BCI and haptic feedback, and the details of the entire process of experiment were provided to subjects prior to the experiment. At the beginning of the experiment, the subjects sat on a comfortable armchair 50cm from the computer screen. Following a task cue in the virtual environment, they were asked to use their right hands to control a haptic device to perform the experiments of tracking task.

2.2. Experimental environment

The general process of the experiment was illustrated in Fig.1 (A). We implemented a 3D virtual environment for motor training through visual stimulation and haptic simulation, then analyzed the EEG signals in haptic and non-haptic feedback scenarios respectively. The major experimental equipment included a haptic device to provide high fidelity force feedback output (Geomagic Touch X) and an EEG acquisition system with 32 Ag/AgCl electrodes (BioSemi ActiveTwo), as indicated in Fig.1 (B).

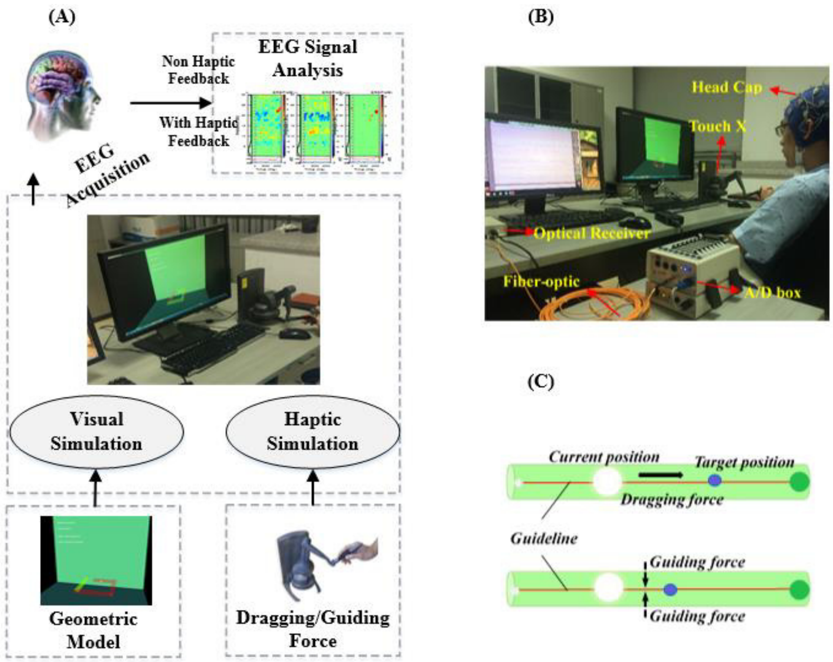

Fig.1. The experimental environment based on VR system and EEG recording system. (A) The EEG signals acquisition process in both with and without haptic feedback scenarios. (B) The hardware components of the experimental environment. (C) Two types of haptic feedback (dragging force and guiding force) generated when subjects move the haptic device's stylus in 3D virtual environment.

During the experimental task, each subject learned to control the movement of the haptic device's stylus in 3D virtual environment. This movement process was guided in real time by visual and haptic feedback simultaneously, as shown in the Fig.1 (C). The white ball and green ball signified the current position and the target position of the haptic device's stylus respectively. The blue ball moving at a constant velocity indicated the location of trace point. The system of 3D virtual environment also provided two types of force feedback to the subjects: dragging force and guiding force. Subjects manipulated the stylus to trace the blue ball along the centre line (the red guideline) of the green tube. If the current position of stylus deviated from the guideline and exceeded the green tube, guiding forces were generated to pull the white ball back to the guideline while the tube turned red. The above simulation system was implemented by using the C# and Open Graphics Library (OpenGL) on a computer with Intel Xeon E5-1620 3.5GHz CPU, 32GB RAM and NVIDIA Quadro K2200 display card.

Fig2 (A) indicated a Biosemi ActiveTwo system with 32 Ag/AgCl electrodes for collecting EEG signals, and the sampling frequency was set to 256 Hz. The offset of each electrode did not exceed $\pm$25 mV. The electrodes of interest (C3 and C4) were mainly around the area of the sensorimotor cortex[12]. Trigger signals were also recorded to label the event for continuous EEG signals.

2.3. Experimental paradigm

To investigate the effects of haptic feedback on brain activity during hand movement, each subject performed the tracking task with or without haptic feedback. During the experimental process, each single-trial tracking task included four starting position marking the different directions, in which composed of a baseline cycle of 1 seconds and a movement cycle of about 6 seconds. Each subject needed to complete two experimental tasks with haptic and non-haptic feedback, each of which was repeated 5 times. In the last, the above experimental procedure was totally copied for 10 runs. In between each run, the subjects were given 1-3 min short breaks to relieve the fatigue of their arms. Altogether, each subject was asked to perform 100 trials divided equally into haptic and non-haptic feedback. The entire experiment took about one hour for each subject.

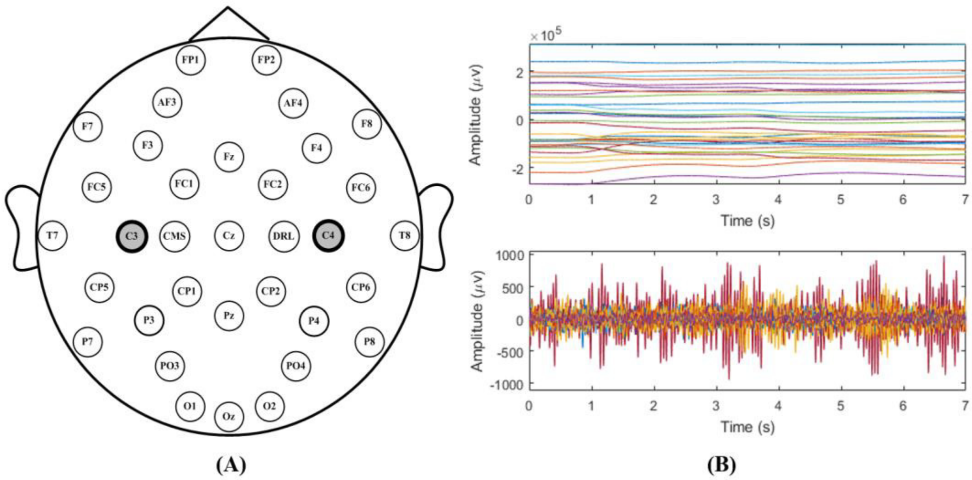

Fig.2. (A) The electrode positions of the EEG acquisition system with 32 Ag/AgCl electrodes, and the gray-marked electrodes represent the sensorimotor area. (B) Each trial of raw EEG signals (upper panel) was re-referenced by using CAR method, and then bandpass filtered in 8-26Hz (lower panel).

2.4. Data preprocessing

For analyzing the EEG signals in both haptic and non-haptic feedback scenarios, each trial involved 1 second before the tracking task and 6 seconds after the execution that was first extracted from continuous EEG data utilizing the trigger signals. Then the means of common average reference (CAR)[13] was used to re-reference the EEG signals of these trials and reduce the noise in the signal, where the average value of the entire electrode was subtracted from every single electrode. With a fifth order Butterworth filter, the re-referenced EEG data were 8-25Hz band-pass filtered over the alpha and beta rhythm bands[14], which were associated with the execution of hand movement. A single trial of raw EEG signals with 32 electrodes and the corresponding filtered signal are shown in Fig2. (B).

2.5. Time-frequency analysis and statistical analysis

All of EEG signal processing steps were performed by using MATLAB and the open source toolbox EEGLAB. In the study, we employed the approach of time-frequency analysis proposed by Makeig et al.[15], which allowed to measure average dynamic changes in the power spectrum with respect to the experimental event. To calculate the event-related spectral perturbation (ERSP), we first computed the power spectrum of each trial over a sliding latency window. We then normalized spectral estimate via respective average baseline spectra of each trial. In the end, we averaged the estimates over these trials[16]. For n trials, $F_k(f,t)$ represented its spectral reckon of a single trial k at a given frequency f and the time t relative to a pre-event baseline. In the study, we calculated $F_k(f,t)$ by using the approach of short-time Fourier transform (STFT). The formula is shown below:

$$ERSP(f,t) = \frac{1}{n}\sum_{k=1}^{n} \left|F_k(f,t)\right|^2 \quad . \tag{1}$$

The aboved features of all trials were divided into two conditions with and without haptic feedback. For each scenarios, significant changes in ERSP, i.e., increase or decrease of time-frequency features from baseline power, were assessed by employing a bootstrap statistical method (hereafter, we set the level of significance at $p<0.05$). The reliability of these differences across the two conditions was also computed and estimated through a non-parametric statistical analysis. The null hypothesis was that there was no difference among the conditions.

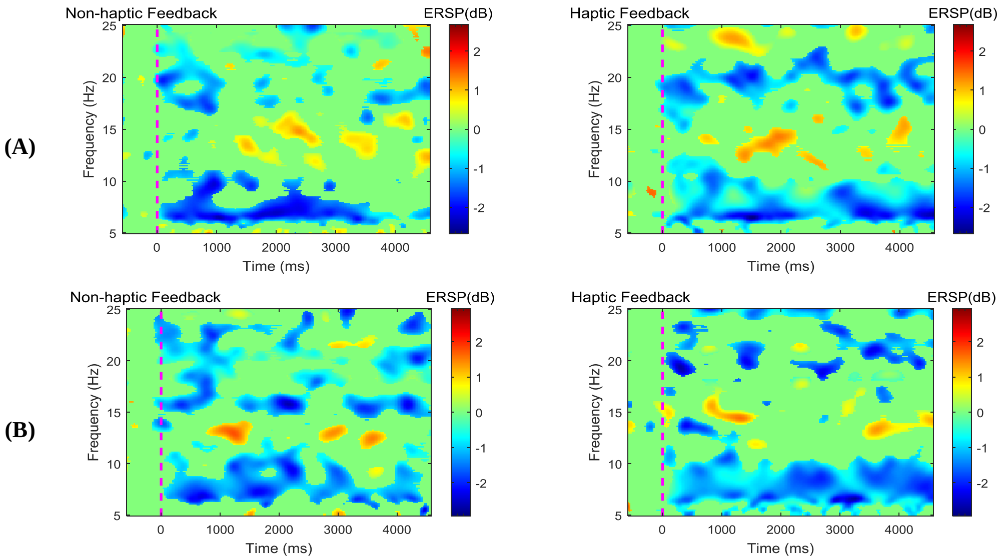

Fig.3.Statistically significant (p<0.05) ERSP-values. The x-axis denotes the time of trials, and the onset is plotted vertically as a dashed line. The y-axis labels frequency 5-25Hz with alpha (8-13Hz) and beta (18-25Hz) band. Blue represents significant power reduction with respect to baseline before stimulation and red represents significant power increase (p<0.05). (A) The ERSP-values of C3 electrodes with non-haptic and haptic feedback respectively. (B) The ERSP-values of C4 electrodes with non-haptic and haptic feedback respectively.

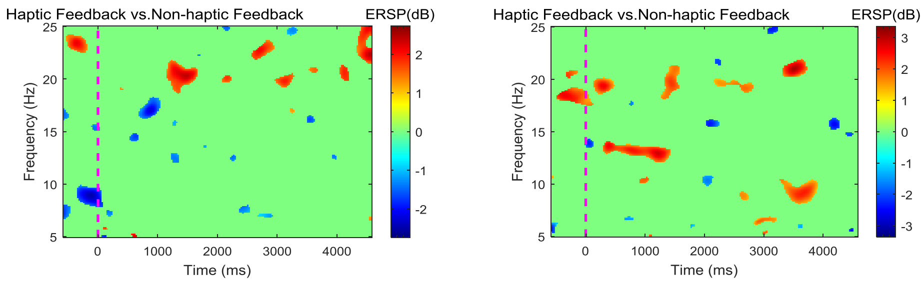

Fig.4. Time-frequency contrast statistical plots of the haptic feedback vs. non-haptic feedback. Red represents significant power increase of the statistical contrast plot and blue represents significant power reduction of the statistical contrast, green represents nonsignificant change of the plots. Left panel displays time-frequency contrast statistical plots of haptic feedback vs. non-haptic feedback at C3 electrodes, and right panel displays that of at C4 electrodes.

3. Experimental Results

The ERSP images of C3 and C4 electrodes are computed and plotted respectively to compare the differences between the trials from two experimental scenarios (haptic feedback vs. non-haptic feedback). The average change of the power spectrum (in 'dB') in the experimental EEG signal, relative to 1 second prior to movement-onset (plotted vertically as a dashed line), as shown in Fig.3. Blue represents significant power decreasing with respect to baseline before stimulation and red represents significant power increasing with respect to the baseline ($p<0.05$). Non-significant time/frequency are colored in green. For both non-haptic and haptic feedback scenarios, the ERSP of signals locate at the C3 and C4 electrodes simultaneously exhibit the statistically significant ($p<0.05$) power suppression near 8Hz or 20Hz associated with the range of alpha and beta rhythms respectively.

Moreover, it is observed in the left panel of Fig.4 that at C3, the reduction of the power spectrum around 20 Hz in haptic feedback scenario is more obvious than that of without haptic feedback, while the results are similar in the right panel of Fig.4 that at C4. These results are statistically significant ($p<0.05$). The preliminary experimental results indicate that haptic feedback may influence the modulation of the beta rhythms over left and right sensorimotor cortex during hand movements.

4. Conclusion

This paper presented a novel framework for evaluating motor training performance by combining haptic device and BCI in 3D virtual environment. We found that users' brain activity occurred in a significant change after haptic stimulation. The preliminary experimental results indicated that EEG signal exhibited significant beta rhythm power suppression in the left and right sensorimotor cortex regions with haptic feedback. The results certified the haptic feedback could influence the EEG rhythm in the sensorimotor area of the brain. In the future, the effects of haptic feedback on other brain cortex regions would be studied. Furthermore, the proposed evaluation framework could be employed on assessing users' training skill of virtual surgery or rehabilitation systems.

Acknowledgements

This work was partly supported by grants from The National Natural Science Foundation of (No.: 61305097 and 81601576), a grant from The Key Laboratory for Robot and Intelligent System of Guangdong Province (No. : ZDSYS20140509174140672), a grant from Ministry of Science and Technology of Peoples Republic of China under Singapore-China 9th Joint Research Programme (No.: 2013DFG12900), a grant from Shenzhen Fundamental Research and Discipline Layout Project (No.: JCY20150925163244742), a grant from the Guangdong Natural Science Foundation (No. 2016A030313047), and a grant from Hong Kong Polytechnic University (G-YBKX).

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