A Novel HCI System Based on Real-Time fMRI Using Motor Imagery Interaction

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Abstract. Real-time functional resonance imaging (rtfMRI) provides an emerging human-computer interaction (HCI) technology with relatively high spatial resolution. The motor imagery is widely used for sports training of athletes and motor ability rehabilitation of patients, which is a common interaction approach for EEG-based and fMRI-based BCI. An appropriate method of interaction can improve the performance of BCI. In this paper, we implemented a novel HCI system based on rtfMRI using motor imagery interaction. The user interacted with the system by regulating blood oxygenation level dependent (BOLD) signal intensity of the region of interest (ROI) in motor areas using motor imagery, which was presented by the running speed of a virtual human in an animation. The ROI was chosen according to the motor network resulted from the real-time independent component analysis (rtICA). Through the interaction with the HCI system, the user could learn the effectiveness of his motor imagery.

Keywords: HCI system, real-time fMRI, motor imagery, animation interaction.

1 Introduction

The emerging intelligent human-computer interaction (HCI) technology based on cognitive neuroscience is a promising tool to provide more novel interactive experience [1, 2]. Brain-computer interfaces (BCI) based on Electroencephalography (EEG) have been used for volitional regulation of electrical brain activity [3, 4]. However, the regional specificity of self-regulation is limited to the relatively low spatial resolution of EEG. The BCI based on real-time functional resonance imaging (rtfMRI) is another non invasive BCI with comparatively high spatial resolution, which has been broadly used in the novel neuroscience investigations [5, 6] and potential clinical applications [7, 8].

Motor imagery [9] has been used for sports training of athletes and motor ability rehabilitation of patients, which is a common interaction approach in the EEG-based BCI [3, 4] and fMRI-based BCI [10-12]. As known in fMRI studies, motor imagery will lead to the activation of motor areas in brain, among which the motor areas such

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as primary motor cortex (M1) can be self-regulated through rtfMRI [5, 6]. Besides, an appropriate method of interaction can effectively improve the performance of BCI. Generally, the animation presentation can largely avoid the dull interactions (e.g. word, number) that are unattractive to the user.

In this paper, we implemented a novel HCI system based on rtfMRI using motor imagery interaction. The user interacted with the system by regulating blood oxygenation level dependent (BOLD) signal intensity of the region of interest (ROI) in motor areas using motor imagery, which was presented by means of the running speed of a virtual human in an animation. The ROI was chosen according to the motor network resulted from the real-time independent component analysis (rtICA) [13, 14]. Through interaction with the HCI system, the user could learn the effectiveness of his motor imagery and try different strategies to adjust his brain.

2 Methods

2.1 The HCI System

The HCI system based on rtfMRI consists of hardware and software (Fig. 1). The MRI scanner scans the user's whole brain every repetition time (TR). Within one TR, the software has to finish the data preprocess and statistical analysis, and control the interactive presentation in the projector displayed to the user. The data preprocess includes head motion correction and spatial smooth, which is to reduce the noise in signal. The method of statistical analysis is sliding-window rtICA [14], which can result in the task-related brain network. The interactive control is to compute the running speed in the animation of a virtual human running (Fig. 2) in accordance with the BOLD signal originating from the corresponding motor areas.

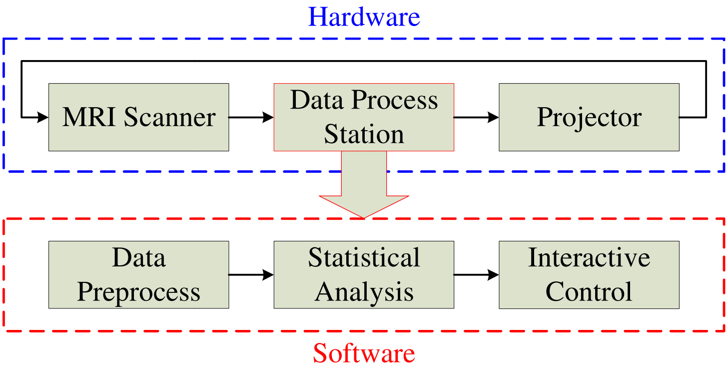

Fig. 1. The HCI system based on rtfMRI

Fig. 2. The 12 frames of pictures in the running animation

2.2 The Experiment Design

We carried out an experiment in block design on one subject (female, age 21 years), which was performed in a 3.0-T Siemens MRI scanner. The 32 axial slices were acquired in an interleaved order using a single-shot T2*-weighted gradient-echo EPI (echo-planar imaging) sequence (TR/TE/flip angle = 2000ms/40ms/90°, matrix size = 64×64, voxel size = 3.1×3.1×4.8 mm^3, slice thickness = 4 mm, slice gap = 0.8 mm).

The experiment included three sessions. The first session was for ROI functional localization, in which the subject was instructed to tap his right hand fingers. The following two sessions were for animation interaction, in which the subject regulated the running speed using motor imagery. Here, we took the first-person motor imagery that included both visual and kinesthetic imagery compared with the third-person motor imagery [15, 16].

In the ROI functional localization session, a motor network was resulted from the rtICA, in which the supplemental motor area (SMA) was chosen as the ROI for self-regulation. The entire session was made up of five 30s rest blocks and four 30s task blocks. Each block consisted of fifteen trials and each trial lasted 2s. During the rest blocks, a text cue "rest" was presented to the subject, and during the task blocks, a text cue "task" was presented.

The interaction session was made up of eight 30s rest blocks and seven 30s task blocks. Each block consisted of fifteen trials and each trial lasted 2s. During the rest blocks, a green cross was presented in the center of the monitor and the subject was instructed to take a rest and think nothing. During the task blocks, the running interactive animation was presented and the subject was requested to adjust the speed as fast as possible. It was allowed that the subject could try different motor imagery strategies (e.g., playing basketball, playing piano) to reach a high running speed.

2.3 The Interactive Control

In the animation, one complete virtual human running action is made up of twelve frames of pictures (Fig. 2). The animation is performed by changing the frame rate (FPS) with the ROI activation intensity (S). The running speed is termed by the number (N) of complete actions in one second. The formulation of FPS and N can be described as follows:

$$FPS = N \times 12 \tag{1}$$

The average signal intensity of the ROI in the last rest block is taken as a baseline (B). The ROI activation intensity (S) is the signal intensity in one scan of the current task block, and the signal change (C) is $S - B$. Thus, the N can be determined as follows:

$$N = N_{baseline} + \frac{0.5 N_{\max}}{C_{\max}} \times C \tag{2}$$

In practice, the maximum $N\left(N_{\max}\right)$ is chosen as two to prevent the running speed from getting too fast for the user. The baseline of $N\left(N_{baseline}\right)$ is chosen as one when

C is zero, and the bottom of N is zero. Since the signal change in real motion is generally stronger than that in motor imagery, we choose the maximum C in the first localization session as the $C_{\max}$ for the follow interaction sessions.

3 Results

In the ROI functional localization session, the motor network was automatically derived from the rtICA, which mainly included the left M1, pre-motor cortex and SMA (Fig. 3). The SMA was chosen as the ROI for the next two interaction sessions.

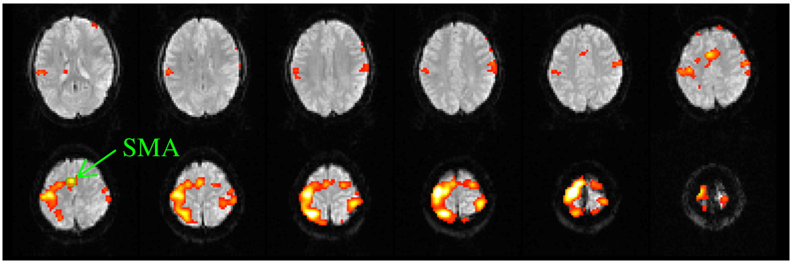

Fig. 3. The brain network derived from the sliding-window rtICA. The green rectangle was the chosen ROI (SMA).

In the second interaction session, the running speed of the animation was computed from the signal change of the target ROI by the formulations above (Fig. 4). In most of the task blocks, it could be seen that the signal intensity arose at the beginning of the block, and then turned fluctuant. The running speed changed with the signal intensity, and was faster than baseline as a whole in majority of the task blocks.

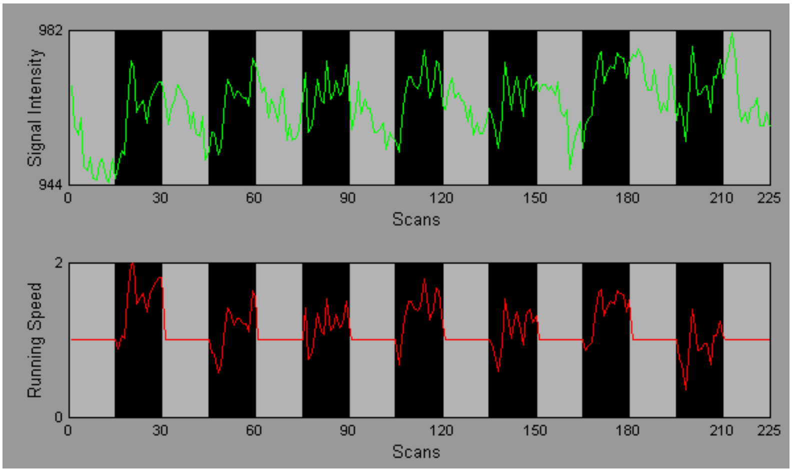

Fig. 4. The average signal intensity change of ROI (up, green curve) and the running speed change of the animation (down, red curve) along with the scans in the second interaction session. The black blocks were task blocks and the gray ones were rest blocks. Besides, the baseline of running speed is one as shown in the straight line in the rest blocks (down).

4 Discussion

We successfully applied the HCI system in an interactive motor imagery experiment. After the experiment, the subject reported that the running speed could be basically controlled by his motor imagery at the task blocks, which was in accord with the Fig. 4. It was hard for the subject to concentrate on the task all the time, so the speed would fall down or be out of control at times when he was distracted. Nevertheless, the subject still expressed that the animation was very interesting and novel. It could be seen that the experience of observing and controlling one's own brain activity might bring more fun in the interactive process.

As a new way to BCI technology, rtfMRI-based motor imagery could be used to control the movement of a cursor turning left or right through a maze [11] and the movement of a robotic arm [12]. In our system, the running speed depending on the intensity of SMA could also serve as a control signal to manipulate real machines. This showed the feasibility to extend this online system.

Compared with the previous studies on rtfMRI which mainly focused on the ROI activated by the task, our work also provided a new way to assess and control the activation of the task related network. In the component derived from the ICA (Fig. 3), as an important node in motor network [17], SMA was chosen as the target ROI to be regulated as well as the regulation of motor brain network. The whole component could also be chosen as the target to be regulated. Thus, the system using ICA method might have a potential for interaction based on brain network activities.

After all, the experiment was performed on only one subject, so the result was very preliminary. The effectiveness of motor imagery interaction has to be further investigated in a larger sample size with more sessions to allow for the conclusions on the efficiency of this HCI system.

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