Towards intelligent environments: an augmented reality–brain–machine interface operated with a see-through head-mount display

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INTRODUCTION

The brain–machine interface (BMI) or brain–computer interface (BCI) is a new interface technology that uses neurophysiological signals from the brain to control external machines or computers. This technology is expected to support daily activities, especially for persons with disabilities. To expand the range of activities enabled by this type of interface, here, we added augmented reality (AR) to a P300-based BMI. In this new system, we used a see-through head-mount display (HMD) to create control panels with flicker visual stimuli to support the user in areas close to controllable devices. When the attached camera detects an AR marker, the position and orientation of the marker are calculated, and the control panel for the pre-assigned appliance is created by the AR system and superimposed on the HMD. The participants were required to control system-compatible devices, and they successfully operated them without significant training. Online performance with the HMD was not different from that using an LCD monitor. Posterior and lateral (right or left) channel selections contributed to operation of the AR–BMI with both the HMD and LCD monitor. Our results indicate that AR–BMI systems operated with a see-through HMD may be useful in building advanced intelligent environments.

Keywords: BMI, BCI, augmented reality, head-mount display, environmental control system

MATERIALS AND METHODS

SUBJECTS

Fifteen subjects were recruited as participants (aged 19–46 years; 3 females, 12 males). All subjects were neurologically normal and strongly right-handed according to the Edinburgh Inventory (Oldfield, 1971). Our study was approved by the Institutional Review Board.
Review Board at the National Rehabilitation Center for Persons with Disabilities. All subjects provided written informed consent in accordance with institutional guidelines.

**EXPERIMENTAL DESIGN**

Augmented reality techniques were combined with a BMI (Figure 1). The AR–BMI system consisted of an HMD (LE750A, Liteye Systems, Inc., Centennial, CO, USA) or LCD monitor (E207WFPC, Dell Inc., Round Rock, TX, USA), a PC, USB camera (QCAM-200V, Logicool, Tokyo, Japan), EEG amplifier (g.USBamp, Guger Technologies OEG, Graz, Austria), and EEG cap (g.EEGcap, Guger Technologies OEG). We used the ARToolKit C-language library for the system (Kato and Billinghurst, 1999). When the camera detects an AR marker, the pre-assigned infrared appliance becomes controllable. The AR marker’s position and posture were calculated from the images detected by the camera, and a control panel for the appliances was created by the AR system and superimposed within sight of the subject. We prepared a TV and a desk light as controllable devices. AR markers for the control panels for the TV and desk light were prepared (Figure 2).

We prepared green/blue flicker matrices (Takano et al., 2009b) as control panels. The duration of intensification/rest was 100/50 ms. All icons flickered in random order, creating a sequence. One classification was carried out per 15 sequences (Figure 2). Subjects were required to send five commands to control both the TV and desk light. We asked the subjects to focus on one of the icons.

**EEG RECORDING AND ANALYSIS**

Eight-channel (Fz, Cz, Pz, P3, P4, Oz, Po7, and Po8) EEG data were recorded using a cap. All channels were referenced to the Fpz and grounded to the AFz. Electrode impedance was under 20 kΩ. The EEG data were amplified/digitized at a rate of 128 Hz using a gUSBamp. The gUSBamp internal digitization rate was higher than 128 Hz, so the data were down-sampled. The digitized data were filtered with an eighth-order high-pass filter at 0.1 Hz and a fourth-order 48–52 Hz notch filter.

In the analyses, recorded EEG data were filtered with a first-order band-pass filter (1.27–2.86 Hz); 120 digitization points of ERP data were recorded according to the timing of the intensification. Data from the first 20 points (before intensification)
were used for baseline correction. The remaining 100 points (after intensification) were down-sampled to 25.6 Hz and used for classification.

In training sets, we recorded EEG data to create a feature vector beforehand. Subjects were required to focus on one of the target icons, and four target icons were used. Sixty (4 trials × 15 intensifications) sets of digitization points were recorded as the target data set, and 600 (4 trials × 15 intensifications × 10 non-target icons) sets of digitization points were recorded as the non-target data set. Each data set included 100 digitization points per each EEG channel, and these data sets were down-sampled to 20 digitization points per each EEG channel. In total, 160 dimension-feature vectors (20 dimensions per EEG channel) were calculated using the segmented data for each subject. Feature vectors were derived for each experimental condition (LCD and HMD).

In testing sets, using the feature vectors, target and non-target icons were discriminated using Fisher’s linear discriminant analysis. The result of the classification, as the maximum of the summed scores, was used to determine the icon to which the subjects were attending.

RESULTS

ONLINE PERFORMANCE AND OFFLINE EVALUATION

In the current study, we prepared an AR–BMI to control system-compatible devices. We used both a see-through HMD and an LCD monitor to further evaluate the effect of different types of visual stimuli on the AR–BMI.

Online performance was evaluated and the mean accuracy rate for the TV control panel was 88% (SD = 3.20) with the LCD monitor, compared to 82.7% (SD = 2.63) with the HMD; however, these results were not significantly different (Figure 3). In contrast, a significant difference was noted in an offline evaluation [two-way repeated ANOVA $F(1,420) = 13.6, p < 0.05$; Tukey–Kramer test, $p < 0.05$]. The mean accuracy rate for light control was 84% (SD = 3.40) with the LCD monitor, compared to 76% (SD = 2.06) with the HMD; however, the results were not significantly different. The results were also not significantly different in an offline evaluation. Thus, our AR–BMI system could be operated not only by using a PC display, but also by using an HMD.

CHANNEL SELECTION

We further investigated the effects of channel selection on the operation of the AR–BMI using an HMD and LCD monitor. We divided the EEG channels into different sets and evaluated their accuracy.

When we analyzed the data in two horizontal channel sets [A (P3, Pz, and P4) and B (Po7, Oz, and Po8; Figure 4A)], set B (posterior set) showed significantly higher accuracy than set A (anterior set) in all sessions and under all conditions ($p < 0.05$, two-way repeated ANOVA, no interaction).

When we analyzed the data in three vertical channel sets [C (P3 and Po7), D (Pz and Oz), and E (P4 and Po8; Figure 4B)], set D (middle set) showed significantly lower accuracy than the others (left and right sets) in all sessions and under all conditions ($p < 0.05$, two-way repeated ANOVA, no interaction, and Tukey–Kramer as a post hoc test).

These results show that the posterior and lateral (right or left) channel sets provided better performance in the operation of the AR–BMI with both the HMD and LCD monitor.

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**FIGURE 3 | Subjects’ control accuracy.** Accuracy in controlling the TV and desk light are shown. The horizontal axes indicate the number of sequences, while the vertical axes indicate the accuracy. White solid lines show the mean accuracy with the SE. The blue squares behind the white solid lines are two-dimensional histograms; each blue square indicates the frequency of the subjects in each sequence and their accuracy [(A): LCD, (B): HMD].
contributed favorably to the operation of the AR–BMI with both the HMD and LCD monitor. Important roles for pos-
tero-lateral channels in driving a P300-based BMI have been
reported (Krusienski et al., 2008; Rakotomamonjy and Guigue,
2008). Rakotomamonjy and Guigue (2008) scored the effective-
ness of channels in a P300-based BMI using a support vector
machine and found an advantage with Po7 and Po8. Krusienski
et al. (2008) showed that the occipito-parietal (Po7, Oz, and
Po8) and midline (Fz, Cz, and Pz) electrodes provided better
accuracy.

The neuronal mechanisms of the P300 have been investigated,
and it has been noted that the P300 reflects stimulus-driven
and top-down attentional processes with other cognitive process,
including categorization (Bledowski et al., 2004; Polich, 2007).
Our tasks used green/blue color stimuli so that the processing
of chromatic information, which occurs primarily in the V4
area, was also required (Lueck et al., 1989; Plendl et al., 1993;
Murphey et al., 2008). Additional studies are necessary to fully
understand the neuronal processes underlying the P300 para-
digm with green/blue color flickering stimuli; however, this
study suggests the importance of posterior and lateral (right
or left) channel sets in the operation of an AR–BMI with both
an HMD and LCD display.

**DISCUSSION**

In this study, we found that by applying an AR–BMI system operated
with a see-through HMD, which can provide suitable control panels
to users when they come into an area close to a controllable device,
participants successfully operated system-compatible devices with-
out significant training.

**HMD VS. LCD MONITOR**

When visual-evoked potentials are applied to a BMI system, the
effects of visual stimuli can be better evaluated. Townsend et al.
(2010) reported that a checkerboard paradigm for visual stimuli
increased accuracy. Our group found that green/blue flicker stimuli
improved performance during operation of a P300-based BMI
(Takano et al., 2009b). A BMI study that used an immersive HMD
and LCD monitor to provide visual stimuli showed no significant
difference between the two technologies (Bayliss, 2003).

In this study, we applied both a see-through HMD and an LCD
monitor to an AR–BMI system to further evaluate the effect of
different types of visual stimuli, and in the online evaluation,
the performance with the HMD was not different from that with the
LCD monitor. The percent accuracy in this study ranged from 76
to 88%; because the incidence of correct responses exceeded 70%,
the system is considered to have reached the level of actual usage
(Kubler and Birbaumer, 2008; Nijboer et al., 2008).

In offline analyses, the see-through HMD provided significantly
lower accuracy for TV control than the LCD monitor. Because icon size
and the distance between icons can affect the accuracy of classification
(Sellers et al., 2006), this may have been caused by the different types of
visual stimuli between the HMD and LCD monitor. Thus, the effects
of visual stimuli on BMI operation should be investigated further.

**CHANNEL SET**

We also investigated the effects of channel selection on opera-
tion of the AR–BMI using an HMD and LCD monitor, and
found that posterior and lateral (right or left) channel selections

**FIGURE 4 | Control accuracy in the channel sets.** Accuracy in controlling the TV
and desk light are shown in different channel sets (A–E). The horizontal axes indicate
the number of sequences, while the vertical axes indicate the accuracy. (A): channel
sets A (P3, Pz, and P4) and B (Po7, Oz, and Po8); (B): channel sets C (P3 and Po7), D
(Pz and Oz), and E (P4 and Po8). Solid lines indicate performance with the LCD,
while broken lines indicate performance with the HMD for each channel set.

Toward Advanced Intelligent Environments

Several combinations between BMI and other technologies have been
attempted, such as BMI with eye tracking (Popescu et al.,
2006), and BMI with robotics (Valbuena et al., 2007). AR was com-
bined with SSVEP BMI to provide a rich virtual environment (Faller
et al., 2010), and we used AR with an LCD monitor and an agent
robot in P300 BMI so that the users could operate home electronics
in the robot’s environment (Kansaku et al., 2010). In this study, we
developed an AR–BMI system operated with a see-through HMD,
which may be useful in building advanced intelligent environments
(Kansaku, in press).
The systems developed by our group use a modified P300 speller (Farwell and Donchin, 1988). Although the P300 speller has primarily been used for communication using spelling alphabets, the system has recently been used to control more complex system-compatible devices, including robots (Bell et al., 2008; Komatsu et al., 2008). Thus, each icon expresses the user’s thoughts by assigning more complex meanings.

Our AR–BMI with a see-through HMD can be used to control more types of devices; thus, the system may be helpful in expanding the range of activities for persons with disabilities. The future extension of the environment for human activities along these lines, using either non-invasive neurophysiological signals or neuronal firing data, may enable new daily activities not only for persons with physical disabilities, but also for able-bodied persons.

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