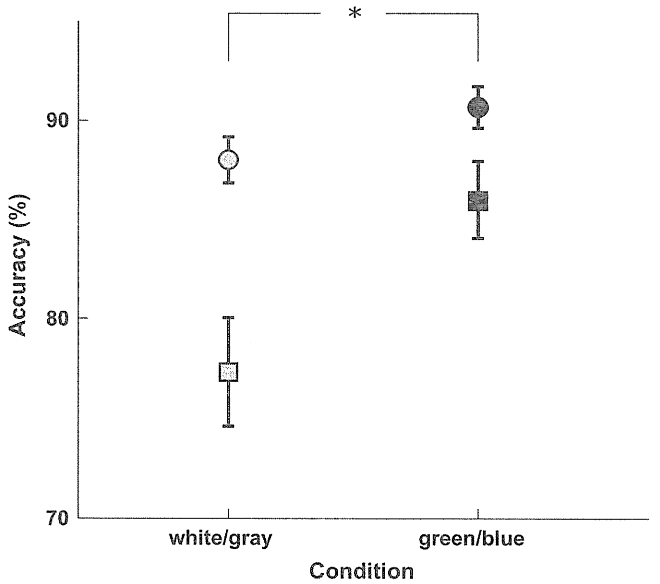

Fig. 2. Online accuracy of subject groups (SCI and controls) for each condition (white/gray and green/blue). Squares, control group; circles, SCI group. Error bars indicate S.E.M.

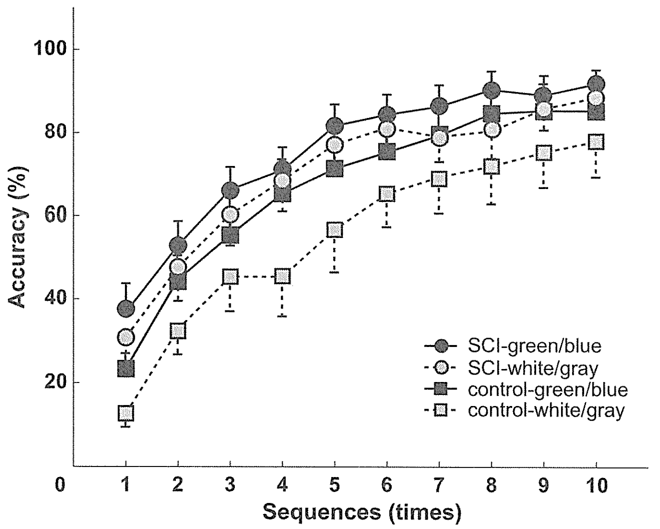

Fig. 3. Offline evaluation for each sequence. Mean accuracy of the control group and SCI group are plotted using squares and circles; the dotted line indicates white/gray, and the solid line indicate green/blue conditions. Accuracy in the first through seventh sequences was significantly lower than that in the tenth sequence, as revealed by post hoc testing ($p < 0.05$, Bonferroni correction). Error bars indicate S.E.M.

Table 2
Offline accuracy, bit rate and letter/min during the tenth, eighth, and fifth sequences in SCI subjects.

Sequence (times)	White/gray		Green/blue	
	Accuracy (%)	bit/min	Accuracy (%)	bit/min
10	88.0	9.8	90.7	10.2
8	80.4	10.9	90.4	12.8
5	77.2	16.2	81.7	17.5

mean accuracy was 77.3% for the control group and 88.0% for the SCI group. Under the green/blue condition, the mean accuracy was 86.0% and 90.7% for control and SCI groups, respectively (Fig. 2). For the SCI group, the mean bit rates (Wolpaw et al., 2002) were 9.8 bit/min and 10.2 bit/min under the white/gray and green/blue conditions, respectively (Table 2). Note that the time interval between character selections was not included for the bit rate calculation. The mean bit rates for controls were 8.4 bit/min and 9.6 bit/min for the white/gray and green/blue conditions, respectively. No significant correlations were observed between the accuracy or bit rate of SCI subjects and demographic characteristics (age, time since injury, ASIA impairment scale score; Spearman's rank correlation coefficient, $p > 0.05$).

We used a two-way repeated-measure ANOVA to examine the effects of group (SCI vs. control) and of condition (white/gray vs. green/blue) on online accuracy. ANOVA revealed a main effect of flicker matrix condition ($F(1,9) = 5.2$, $p < 0.05$). A trend toward greater accuracy in the SCI group compared to controls was observed; however, no main effect of group ($F(1,9) = 1.2$, $p = 0.30$) and no significant interaction ($F(1,9) = 0.61$, $p = 0.45$) was found. These results did not basically change if bit rate was substituted for accuracy.

4.2. Offline evaluation

Fig. 3 shows the results of the offline analysis of subject groups for each condition. We conducted a three-way repeated-measure ANOVA with group (SCI vs. controls), condition (white/gray vs. green/blue), and sequence number (1–10) as factors. Main effects of condition ($F(1,9) = 9.4$, $p < 0.05$) and sequence ($F(9,81) = 93.2$, $p < 0.001$) were significant, but no main effect of group ($F(1,9) = 1.9$, $p = 0.20$) and no significant interaction ($F(9,81) = 0.89$, $p = 0.54$) was found. Thus, the P300 BCI with the green/blue flicker matrix is effective not only in able-bodied subjects but also in individuals with cervical SCI. Accuracy in the first through seventh sequences was significantly lower than that in the tenth sequence, as revealed by post hoc testing ($p < 0.05$, Bonferroni correction).

In the SCI group, the mean online bit rate was 9.8 bit/min and 10.2 bit/min for the white/gray and green/blue conditions, respectively, as calculated from the tenth sequence accuracy (Table 2). In the fifth sequence, the mean accuracy of the SCI group exceeded 70% under both conditions (77.2% for white/gray, 81.7% for green/blue), and the mean bit rate was 16.2 bit/min and 17.5 bit/min for the white/gray and green/blue conditions, respectively (Table 2). In the fifth sequence, the bit rate was significantly higher than in the tenth sequence, but accuracy was significantly lower under both conditions (paired t-test, $p < 0.05$). By contrast, in the eighth sequence, accuracy was not significantly different from that in the tenth sequence (80.4% for white/gray, 90.4% for green/blue), and the bit rate was 10.9 bit/min and 12.8 bit/min for white/gray and green/blue, respectively. This bit rate was significantly greater than that in the tenth sequence for green/blue (paired t-test, $p < 0.001$), but not for white/gray (paired t-test, $p > 0.05$). Thus, the green/blue flicker matrix was more effective than the white/gray flicker matrix by the eighth sequence.

5. Discussion

We investigated the accuracy of P300-based BCI performance in individuals with chronic cervical SCI using white/gray and green/blue flicker matrices. SCI patients successfully controlled our BCI system without significant training, and the green/blue flicker matrix provided higher accuracy than the white/gray matrix.

5.1. Effect of the color combination in P300 BCI

A number of studies have attempted to increase P300 BCI performance accuracy, primarily by examining classification methods

(Donchin et al., 2000; Kaper et al., 2004; Krusienski et al., 2006; Bashashati et al., 2007; Hoffmann et al., 2008). Other studies have examined modifying matrix size and inter-stimulus intervals (Sellers et al., 2006), type of flash (Guger et al., 2009; Townsend et al., 2010) and background colors (Salvaris and Sepulveda, 2009). We recently reported that a green/blue luminance and chromatic flicker matrix provided higher accuracy than a white/gray luminance flicker matrix and a green/blue isoluminance flicker matrix (Takano et al., 2009b). In the present study, the mean accuracy among both able-bodied and cervical SCI subjects was significantly higher under the green/blue condition than under the white/gray condition. No accuracy difference between SCI and able-bodied groups was found.

Online performance of the SCI group reached 90% accuracy and a bit rate of 10.2 bit/min (1.9 letter/min) under the green/blue condition, comparable to previous reports studying disabled subjects (Piccione et al., 2006; Sellers and Donchin, 2006; Hoffmann et al., 2008; Nijboer et al., 2008). This performance is thought to be sufficient for satisfactory use of a BCI, which requires greater than 70% accuracy (Sellers et al., 2006; Kübler and Birbaumer, 2008; Nijboer et al., 2008). Offline analysis showed that number of sequences can be reduced from 10 to 8 while preserving accuracy and significantly increasing the bit rate. This effect was not apparent under the white/gray condition. Thus, the green/blue flicker matrix was more effective for fast communication.

5.2. BCI performance in SCI subjects

P300-based BCI has been examined in SCI subjects in two previous reports of one cervical SCI patient each (Piccione et al., 2006; Hoffmann et al., 2008). One patient controlled a four-choice P300 BCI with an online accuracy of 75.7% (Piccione et al., 2006), and the other controlled a six-choice P300 BCI with an offline accuracy of 100% (Hoffmann et al., 2008). The main BCI method used with SCI subjects is sensorimotor rhythm (SMR) for binary choice (Pfurtscheller et al., 2000; Krausz et al., 2003; McFarland et al., 2005; Kauhanen et al., 2007; Kübler and Birbaumer, 2008). Kauhanen et al. (2007) reported that the mean online accuracy for binary-choice SMR BCI with five cervical SCI subjects was 48%.

Although the brain remains intact in SCI subjects, the deafferentation of sensory input that occurs after SCI can result in brain reorganization and altered scalp EEG activity compared with able-bodied controls (Green et al., 1998; Tran et al., 2004; Herbert et al., 2007). Accordingly, SMR BCI, which uses beta or mu waves from sensory motor areas, would be more affected by this reorganization. Indeed, Kauhanen et al. (2007) reported that the binary-choice SMR BCI performance of five cervical SCI subjects was worse than that of able-bodied subjects (not matched for age and sex). In the present study, individuals with cervical SCI controlled the P300 BCI with similar accuracy to able-bodied individuals. Although the data are limited, the P300 BCI may be easier for SCI subjects to use.

5.3. Toward clinical applications

For practical use of the P300 BCI, the system has to be accurate, fast, and reliable. We used 10 sequences for EEG data acquisition for online analyses, but offline analyses showed that the green/blue flicker matrix was more effective than the white/gray flicker matrix by the eighth sequence. Further reducing the number of sequences to five still provided greater than 70% accuracy with a higher bit rate. The mean accuracy at the fifth sequence became lower than that at the tenth sequence, so if the users needed to complete their sentences by correcting misspelled characters, it would take a longer time (Townsend et al., 2010). The sequence times may be determined by individual user preference, as some prefer to control devices quickly with lower fidelity, whereas others prefer to communicate precisely and more slowly (Sellers and Donchin, 2006).

The severity of the patient impairment may also have implications for practical BMI use. Kübler and Birbaumer (2008) reviewed a number of BCI studies using P300, SMR, and slow cortical potential (SCP) and reported a relationship between physical impairment [subdivided into minor, moderate, major, locked-in state and complete locked-in state (CLIS)] and BCI performance. When they included CLIS patients, they found a strong correlation between impairment and BCI performance; however, after removing the CLIS patients, the correlation disappeared. Nijboer investigated the efficacy of a P300 BCI in eight advanced ALS patients (Nijboer et al., 2008) and showed that online BCI performance was not correlated with the degree of disability according to the ALS Functional Rating Scale (Cedarbaum and Stambler, 1997). Thus, for patients with ALS, it is suggested that BCI be applied before the onset of CLIS (Birbaumer, 2006; Kübler and Birbaumer, 2008). In the present study, we found no correlation between performance and ASIA impairment scale score (complete or incomplete) in SCI patients, nor did we observe a correlation between performance and time since injury. We previously reported that the BMI performance of subacute SCI subjects, whose time since injury was less than a year, was worse than that of chronic SCI subjects (Ikegami et al., 2009). Further investigation is required to determine the optimal time for applying BCI to individuals with SCI.

In conclusion, the P300 BCI system for environmental control and communication with a green/blue flicker matrix provided better accuracy than that with a white/gray flicker in individuals with cervical SCI, and future studies may aid the development of practical BCI for these individuals to expand their range of activity and communication.

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

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The brain–machine interface (BMI) or brain–computer interface 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

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 computers or machines (Birbaumer et al., 1999; Wolpaw and Mcfarland, 2004; Birbaumer and Cohen, 2007). Electroencephalography (EEG), in which neurophysiological signals are recorded using electrodes placed on the scalp, represents the primary non-invasive methodology for studying BMI. Our group applied EEG and developed a BMI-based system for environmental control and communication. In this system, we modified a P300 speller (Farwell and Donchin, 1988). The P300 speller uses the P300 paradigm and involves the presentation of a selection of icons arranged in a matrix. According to this protocol, the participant focuses on one icon in the matrix as the target, and each row/column or a single icon of the matrix is then intensified in a random sequence. The target stimuli are presented as rare stimuli (i.e., the oddball paradigm). We elicited P300 responses to the target stimuli and then extracted and classified these responses with respect to the target. In our former study, we prepared a green/blue flicker matrix because this color combination is considered safest (Parra et al., 2007). We showed that the green/blue flicker matrix was associated with a better subjective feeling of comfort than was the white/gray flicker matrix, and we also found that the green/blue flicker matrix was associated with better performance (Takano et al., 2009a,b). The BMI system was satisfactorily used by individuals with cervical spinal cord injury (Komatsu et al., 2008; Ikegami et al., 2011).

Such a system could be used by persons with disabilities to support their daily activities. In this type of system, users rely on control panels that are pre-equipped; thus, each system is specialized for the user's specific environment (e.g., his or her home). To expand the range of possible activities, it is desirable to develop a new system that can be readily used in new environments, such as hospitals. To make this possible, here, we added an augmented reality (AR) feature to a P300-based BMI. In the system, we used a see-through head-mount display (HMD) to create control panels with flicker visual stimuli, thereby giving users suitable panels when they come close to a controllable device. 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 scene via the HMD (**Figures 1 and 2**).

We used a see-through HMD in this study. To evaluate the effects of different types of visual stimuli on the new AR–BMI, we compared a see-through HMD with an LCD monitor. The participants were asked to control devices using the AR–BMI system with both a see-through HMD and an LCD monitor. In doing so, we found that the AR–BMI system with the see-through HMD worked well.

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 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**).

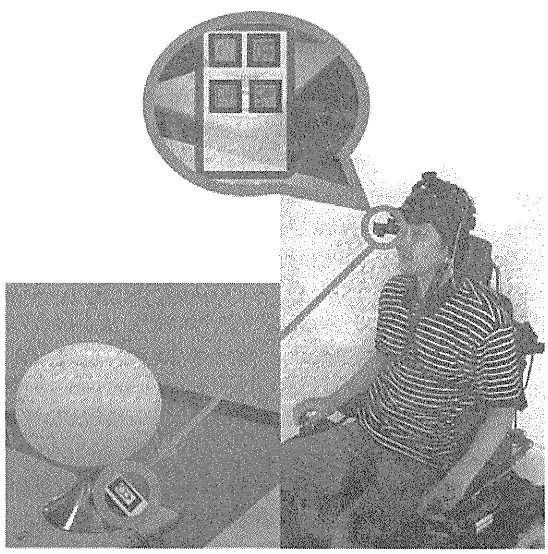

FIGURE 1 | Diagram of the AR–BMI system. When the USB camera detects an AR marker, the control panels for a pre-assigned appliance (e.g., desk light) are added to the user's sight and the device becomes controllable. The subjects are able to operate the appliance by focusing on an icon on the augmented control panel.

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)

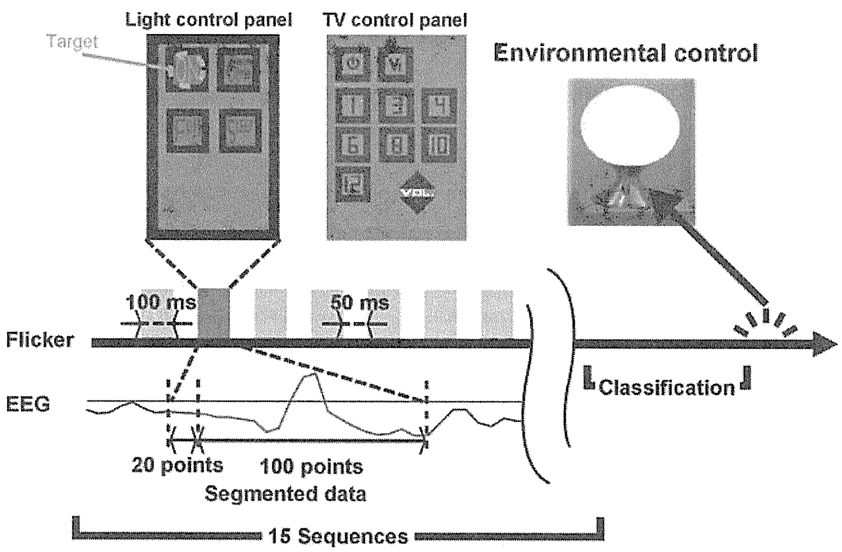

FIGURE 2 | Experimental procedure. The icons change color from blue to green at the time of intensification, and the elicited ERPs are recorded. The red solid line in the EEG data indicates the segmented portion used for classification. The target was classified by Fisher's linear discriminant analysis after 15 sequences. The light control panel had four icons (turn on, turn off, light up, and dim), whereas the TV control panel had 11 icons (turn on, change channel, change video mode, volume up, and volume down).

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.

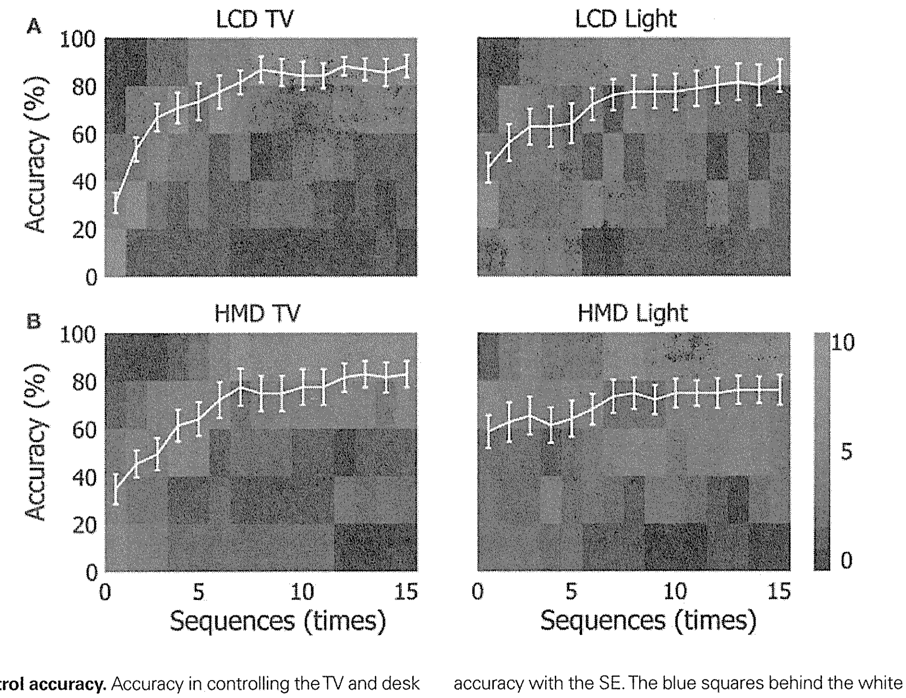

FIGURE 3 | Subjects' control accuracy. Accuracy in controlling the TV and desk light are shown. The horizontal axes indicate the number of sequences, while the vertical axes indicate the accuracy. White solid lines show the mean accuracy with the SE. The blue squares behind the white solid lines are two-dimensional histograms; each blue square indicates the frequency of the subjects in each sequence and their accuracy [**(A)**: LCD, **(B)**: HMD].

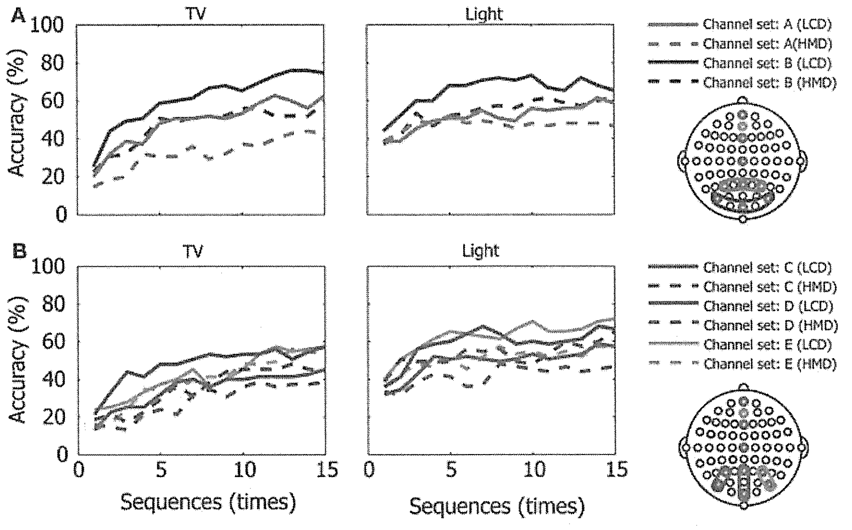

FIGURE 4 | Control accuracy in the channel sets. Accuracy in controlling the TV and desk light are shown in different channel sets (A–E). The horizontal axes indicate the number of sequences, while the vertical axes indicate the accuracy. **(A)**: channel sets A (P3, Pz, and P4) and B (Po7, Oz, and Po8); **(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.

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 without 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 operation of the AR–BMI using an HMD and LCD monitor, and found that posterior and lateral (right or left) channel selections contributed favorably to the operation of the AR–BMI with both the HMD and LCD monitor. Important roles for postero-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 effectiveness 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 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 paradigm 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.

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 combined 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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「ブレインーマシン・インターフェイス（BMI）による障害者自立支援機器の開発」

総括・分担研究報告書

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