

Brain–Machine Interfaces for Persons with Disabilities

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Abstract The brain–machine interface (BMI) or brain–computer interface (BCI) is a new interface technology that utilizes neurophysiological signals from the brain to control external machines or computers. We used electroencephalography signals in a BMI system that enables environmental control and communication using the P300 paradigm, which presents a selection of icons arranged in a matrix. The subject focuses attention on one of the flickering icons in the matrix as a target. We also prepared a green/blue flicker matrix because this color combination is considered the safest chromatic combination for patients with photosensitive epilepsy. 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. We further added augmented reality (AR) to make an AR-BMI system, in which the user’s brain signals controlled an agent robot and operated devices in the robot’s environment. Thus, the user’s thoughts became reality through the robot’s eyes, enabling the augmentation of real environments outside of the human body. Studies along these lines may provide useful information to expand the range of activities in persons with disabilities.

Introduction

The brain–machine interface (BMI) or brain–computer interface (BCI) is a new interface technology that utilizes neurophysiological signals from the brain to control external machines or computers [1, 2]. One research approach to BMI utilizes neurophysiological signals directly from neurons or the cortical surface.

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These approaches are categorized as invasive BMI, as they require neurosurgery [3–5]. Another approach utilizes neurophysiological signals from the brain accessed without surgery, which is called non-invasive BMI. Electroencephalography (EEG), a technique for recording neurophysiological signals using electrodes placed on the scalp, constitutes the primary non-invasive methodology for studying BMI.

Electroencephalography-based non-invasive BMI does not require neurosurgery, but is thought to provide only limited information. However, Wolpaw and McFarland succeeded in achieving two-dimensional cursor control [6] using EEG signals. They applied the EEG power spectrum, using the beta-band power for vertical cursor control and the μ -band power for horizontal cursor control. Motor imagery tasks have been used in BMI research, for example, Pfurtscheller et al. used motor imagery tasks and reported event-related beta-band synchronization and μ -wave desynchronization [7–9].

Sensory evoked signals have also been utilized in EEG-based non-invasive BMI. One popular system, the P300 speller, uses elicited P300 responses to target stimuli placed among row and column flashes [10]. Recent studies have evaluated the use of systems relying on sensory evoked signals in patients with amyotrophic lateral sclerosis and other diseases [11–13].

Our research group has applied the P300 paradigm to a BMI system that enables environmental control and communication. We tested the system on both quadriplegic and able-bodied participants and showed that participants could operate the system with little training [14, 15]. We also looked for better visual stimuli to use in the system and found that the green/blue color combination is a better visual stimulus for controlling the system [16, 17]. We then added augmented reality (AR) to make an AR-BMI system [18, 19]. This chapter introduces a series of our recent studies on BMI and discusses how these new technologies can contribute to expand the range of activities of those with disabilities.

A BMI System for Environmental Control and Communication

Our research group used EEG signals to develop a BMI system that enables environmental control and communication (Fig. 1). We modified the so-called P300 speller [10], which uses the P300 paradigm and presents a selection of icons arranged in a white/gray flicker matrix. With this protocol, the participant focuses on one icon in the matrix as the target, and each row/column or 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 regard to the target.

For the visual stimuli of the BMI-based environmental control system (BMI-ECS), we first prepared four panels with white/gray flicker matrices; one each for the desk light, primitive agent-robot, television control, and hiragana spelling. These consisted of 3×3 , 3×3 , 6×4 , and 8×10 flicker matrices, respectively. We tested the system on both quadriplegic and able-bodied participants and reported that the system could be operated effortlessly [14]. Based on the experience of this

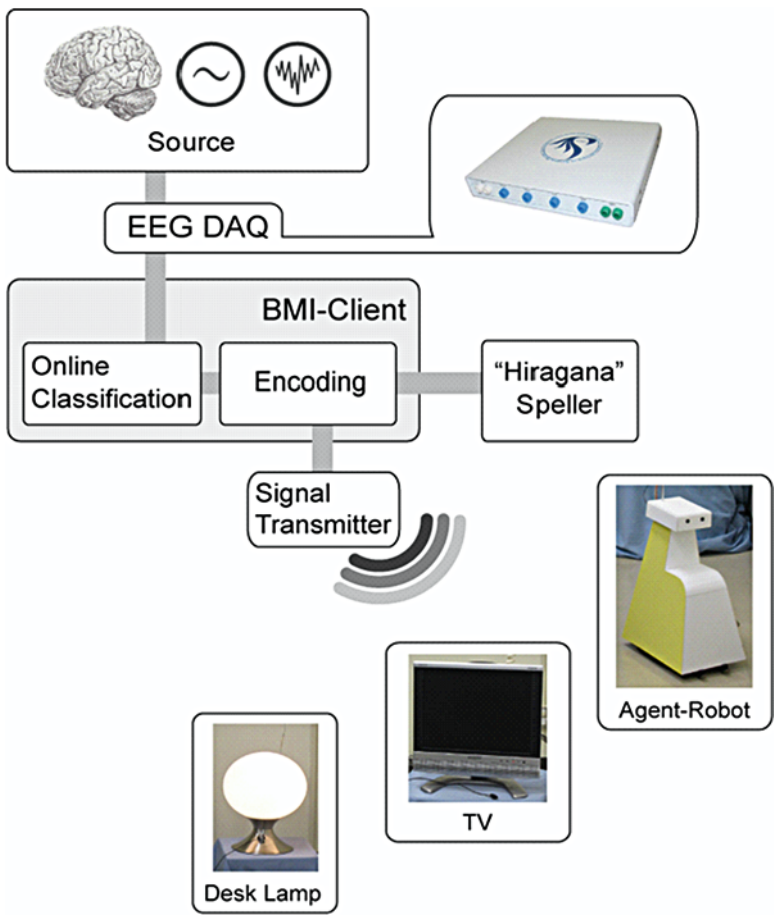


Fig. 1 A BMI system for environmental control and communication (color online)

successful preliminary experiment, we began a series of studies to build a practical BMI system for environmental control and communication, which could be useful for individuals with disabilities.

Effects of Color Combinations

Subjective Feeling of Comfort

The P300 speller has used mainly white/gray flicker matrices as visual stimuli [20–22]. It is possible that such flickering visual stimuli could induce discomfort. Parra et al. evaluated the safety of chromatic combinations in patients with photosensitive epilepsy [23]. They used five single-color stimuli (white, blue, red, yellow, and green) and four alternating-color stimuli (blue/red, red/green, green/blue,

and blue/yellow with equal luminance) at four frequencies (10, 15, 20, and 30 Hz) as the visual stimuli. Under the white stimulation condition, flickering stimuli at higher frequencies, especially those greater than 20 Hz, were found to be potentially provocative. Under the alternating-color stimulation condition, as suggested by the Pokémon incidence, the 15-Hz blue/red flicker was most provocative. The green/blue chromatic flicker emerged as the safest and evoked the lowest rates of EEG spikes. Following the study of Parra et al., we conducted studies that applied a green/blue chromatic combination to elicit visually evoked responses.

In the first study, we prepared panels with 3×3 and 8×10 matrices, which were intensified using two color combinations (green/blue or white/gray), and these were used for the desk-light control and hiragana spelling. We compared the green/blue and white/gray flicker conditions, and the order of the experimental conditions (type of flicker matrix) was randomized among subjects. The flicker consisted of 100 ms of intensification and 75 ms of rest in both conditions (Fig. 2). After the experiments, the subjects were required to evaluate the conditions by their subjective feeling of comfort using a visual analogue scale. Eight non-trained able-bodied subjects (age 25–47 years; four females; all right-handed) were recruited.

This series of studies was approved by the institutional review board, and all subjects provided informed consent according to institutional guidelines. The data recordings and analyses that we applied were rather conventional. We recorded eight-channels (Fz, Cz, Pz, P3, P4, Oz, PO7, and PO8 of the extended international 10–20 system) of EEG data using a cap (Guger Technologies OEG, Graz, Austria) [24, 25]. All channels were referenced to the Fpz, and grounded to the AFz. The EEG was band-pass filtered at 0.1–50 Hz, amplified with a g.Usbamp (Guger Technologies), digitized at a rate of 256 Hz, and stored. For the analyses, recorded and filtered EEG data were down-sampled to about 21 Hz. Data from 800 ms of the EEG were segmented according to the timing of the intensification. Data from the initial 100 ms were used for baseline correction. Data from the final 700 ms were used for classification purposes, using Fisher's linear discriminant analysis. First, we asked the subjects to input six letters to gather data to derive the feature vectors for the subsequent test session. The EEG data were sorted using the information on flash timing, and Fisher's linear discriminant analysis was then performed to generate the feature vector to discriminate between target and non-target. Feature vectors were derived for each condition. In the test session, visually evoked responses from EEG features were evaluated by the feature vectors. The result of the classification was construed as the maximum of the summed scores.

In the first study, the measured subjective feelings of comfort for the white/gray and green/blue flicker matrices were 55.0 and 89.0%, respectively, for the desk-light control and 38.7 and 65.1% for the hiragana spelling. The differences under each condition were significant ($p < 0.05$). We also evaluated online performance. In this experiment, each command was selected in a series of ten sequences. In addition to the observation that the green/blue flicker matrix was associated with a better subjective feeling of comfort than was the white/gray flicker matrix, the accuracy rates for the white/gray and green/blue flicker matrices were 55.8 and 80.8%, respectively, for the desk-light control and 50.8 and 75.0% for the hiragana spelling ($n = 8$, Fig. 3) [16]. The differences under each condition were significant ($p < 0.05$).

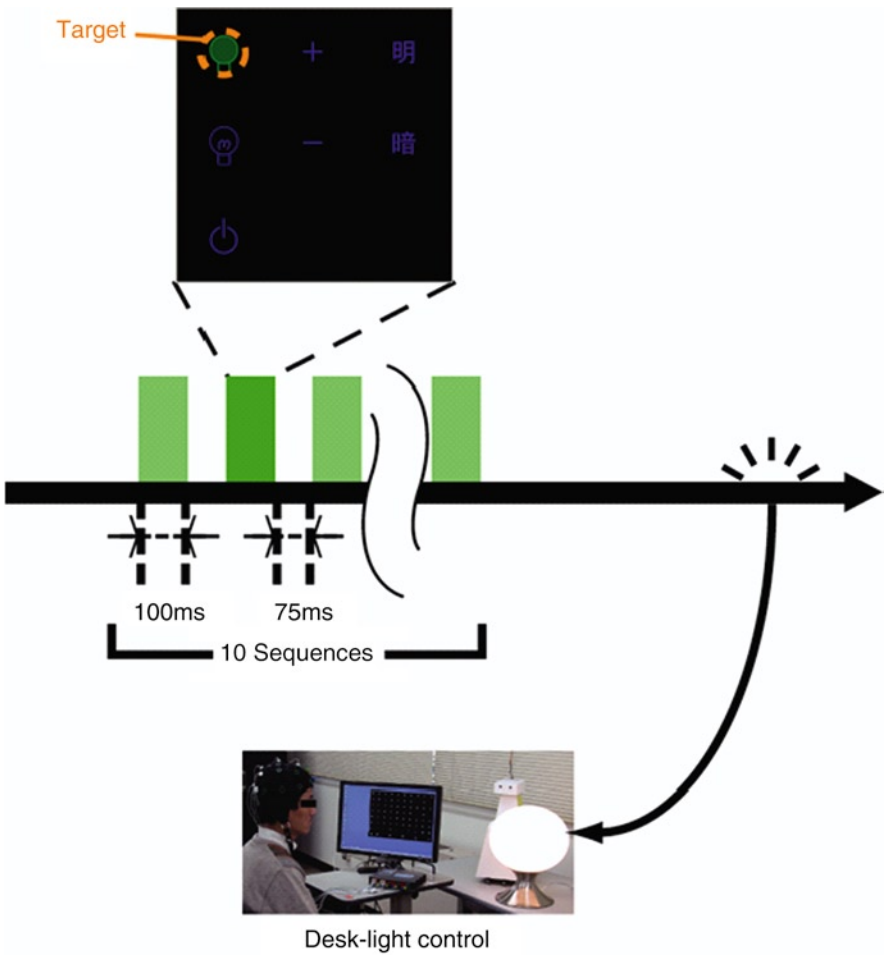


Fig. 2 Task timing

Effects of Luminance and Chromatics

Because the green/blue flicker matrix was associated with not only better subjective feelings of comfort but also better performance, we further evaluated the effects of luminance and chromatics on the visual stimulus combinations. In the second study, we prepared an 8×10 hiragana matrix for the P300 speller. Three intensification/rest flicker combinations were prepared: a white (20 cd/cm)/gray (6.5 cd/cm) flicker (L condition) matrix for the luminance flicker, a green (9.5 cd/cm)/blue (9.5 cd/cm) isoluminance flicker (C condition) matrix for the chromatic flicker, and a green (20 cd/cm)/blue (6.5 cd/cm) luminance flicker (LC condition) matrix for the luminance and chromatic flicker. The flicker consisted of 100 ms of intensification and 75 ms of rest. Luminance was measured using a chromatic meter (CS-200, Konica Minolta

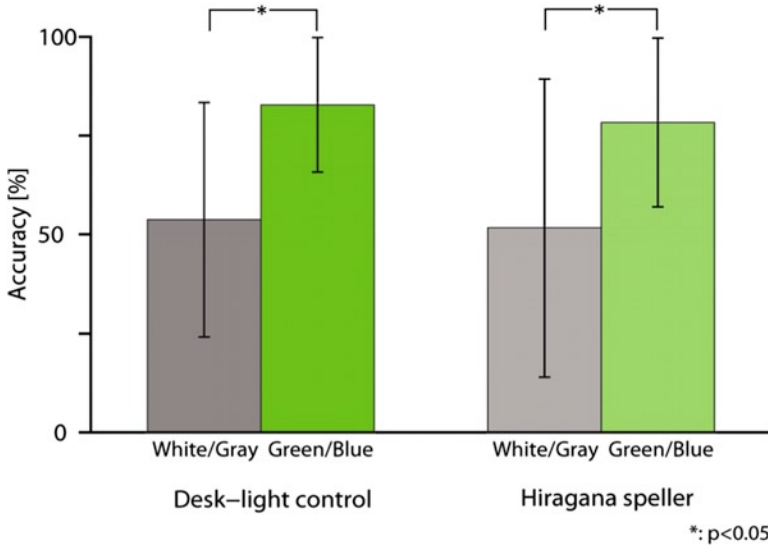


Fig. 3 Operation accuracy for the desk-light control and the hiragana speller (color online)

Sensing, Osaka, Japan). The order of the experimental conditions (type of flicker matrix) was randomized among subjects. Ten healthy, non-trained naive subjects (aged 25–47 years; nine females and one male; all right-handed) who had never participated in this study were recruited as participants.

Online performance was evaluated. In this experiment, each letter was selected in a series of ten sequences. The accuracy rate was in the order LC: 80.6% > C: 73.3% ≥ L: 71.3%. The transfer bit rates (bit/min) [26] were in the order LC: 8.14 > C: 7.03 ≥ L: 6.75. The difference in the accuracy rate between the LC and L conditions was significant ($t(9) = 2.41$, $p < 0.05$, uncorrected) ($n = 10$, Fig. 4) [17].

The LC condition was associated with better performance, whereas the isoluminance C condition gave similar results to the L condition. An examination of the online performance of each subject showed that one, four, and five of the ten subjects performed most accurately in the L, C, and LC conditions, respectively. This information may be used to select the best visual stimuli for situations in which the BMI system is actually used.

AR-BMI

A System Operated with a See-Through Head Mount Display

As an extension of the BMI-ECS, we combined AR with BMI. AR is a technique for live viewing of a physical real-world environment whose elements are augmented by virtual computer-generated imagery. We developed the AR-BMI because the new system can provide suitable panels to the users when they come to the area close to

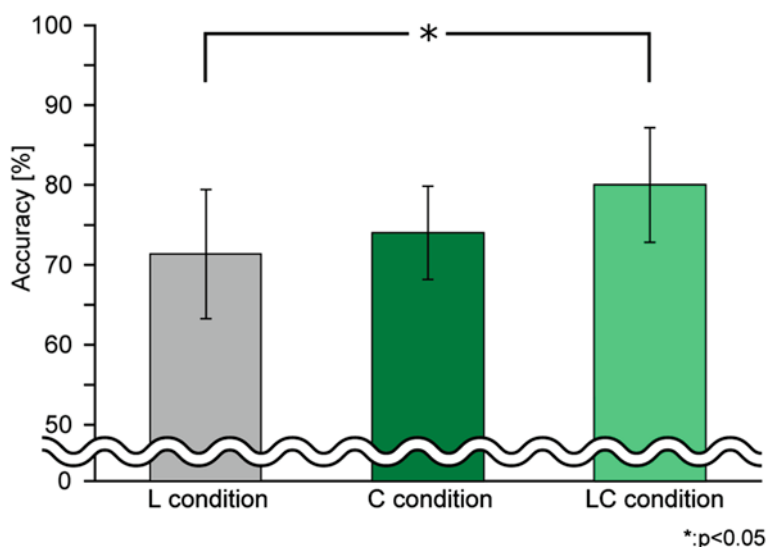


Fig. 4 The LC condition, which used the green/blue flicker matrix, was associated with better performance (color online)

the controllable devices. In this study, a USB camera was mounted on a camera platform or see-through HMD, and 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 appliances was created by the AR system and superimposed on the sight of the subject's environment. When the camera detects the AR marker of the TV or desk light, a flicker panel to control it is displayed on the screen devices (Fig. 5). The AR-BMI system uses ARToolKit [27]. The subjects were required to use their brain signals to operate targets on an LCD monitor or a see-through HMD.

Two control panels of the TV and desk light were used. The TV control panel had 11 icons (power on, seven TV programs, video input, volume up and down), and the light control panel had four icons (turn on, turn off, light up, dim). We prepared the green/blue flicker matrices [17], and the duration of the intensification/rest was 100/50 ms. All icons flickered in a random order and it made a sequence. One classification was conducted per 15 sequences. Participants were required to send five commands to control both the TV and the light. Fifteen able-bodied subjects who had not previously participated in this study were recruited (aged 19–46 years; 3 females and 12 males; all right-handed).

Online performance was evaluated, and the mean accuracy rate for the TV control was 88% in the LCD monitor condition and 82.7% in the HMD condition, and these were not significantly different. In offline evaluation, these were significantly different (two-way repeated ANOVA $F_{(1,420)} = 13.6$, $p < 0.05$, Tukey–Kramer test $p < 0.05$).

The mean accuracy rate for the light control was 84% in the LCD monitor condition and 76% in the HMD condition, and these were not significantly different. These were also not significantly different in the offline evaluation (Fig. 6) [19].



Fig. 5 An AR-BMI system operated with a see-through head mount display

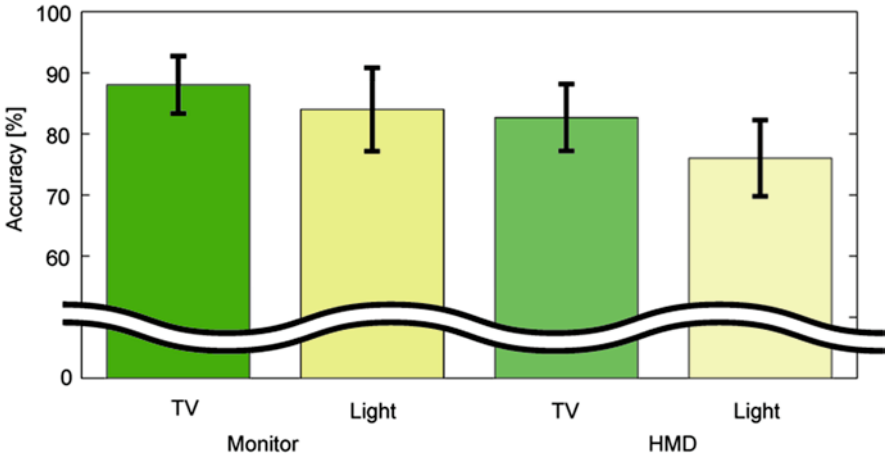


Fig. 6 Operation accuracy for the AR-BMI system with a monitor and a see-through HMD (color online)

The AR-BMI system can be operated not only by using the LCD monitor but also by using the HMD.

A System Operated Through an Agent Robot’s Eye

We further prepared an agent robot for the AR-BMI system, because the new system can provide suitable panels to the users when the agent robot comes to the area close to the controllable devices, even without the appearance of the real users. In the system, when the robot’s eyes detect an AR marker, the pre-assigned infrared appliance becomes controllable. The position and orientation of the AR marker were calculated from the images detected by the camera, and a control panel for the appliance was created by the AR system and superimposed on the scene detected by the robot’s eyes (Fig. 7). To control our system using brain signals, we modified a Donchin P300 speller. The AR-BMI system can control both the agent robot and the desk light. The robot control panel has four icons (forward, backward, right, and left), as does the light control panel (turn on, turn off, make brighter, and make dimmer). We prepared green/blue flicker icons [17], and the duration of the intensification/rest of the flicker was 100/50 ms. All of the icons flickered in random order, which formed a sequence (600 ms). One classification was conducted every 15 sequences. Subjects were

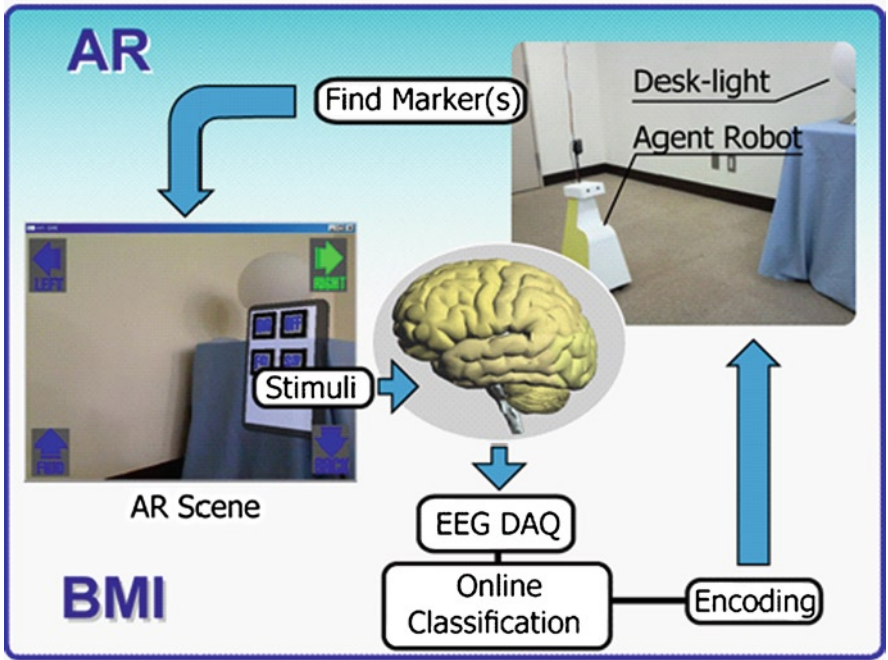


Fig. 7 An AR-BMI system operated through an agent robot’s eye

required to send 15 command infrared signals to control both the robot and light. Before the trials, we checked the commands that the subjects were going to send, and then the information was used to evaluate the subjects' online performance. We also performed an offline evaluation using the recorded data.

Ten healthy, non-trained naive subjects (aged 19–39 years; two females and eight males) were recruited as participants. Using the EEG-based BMI system, the participants were first required to make the robot move to a desk light in the robot's environment. To control the robot, each command was selected in a series of 15 sequences, and the participants were required to send 15 commands. Online performance was evaluated, and the mean accuracy for controlling the robot was 90.0%.

When the robot's eyes detected the AR marker of the desk light, a flicker panel for controlling the appliance was displayed on the screen. Then, the participants had to use their brain signals to operate the light in the robot's environment through the robot's eyes. To operate the light, each command was selected in a series of 15 sequences, and the participants were required to send 15 commands. Online performance was evaluated, and the mean accuracy for light control was 80.7%.

Figure 8 shows the offline evaluation of the participant's performance under the robot-control and light-control conditions. The performance for controlling the robot and desk light differed significantly, and an interaction effect was observed by a two-way repeated ANOVA ($F_{(1,280)}=6.53, p<0.05$). *Post-hoc* testing revealed significant differences between the robot-control condition and the light-control condition (Tukey–Kramer test, $p<0.05$) [18]. The difference might be related to the differences in the relative locations of the flicker icons on the screen [28].

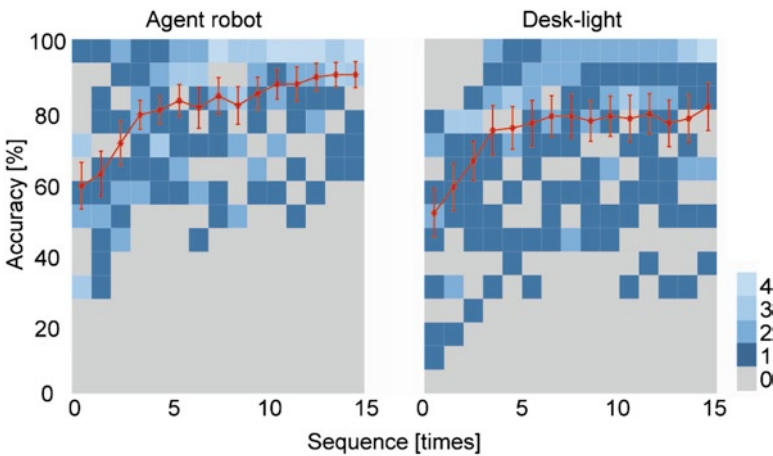


Fig. 8 Operation accuracy for the AR-BMI system (color online)

Discussion

In our series of studies, we used EEG signals for a BMI system that enables environmental control and communication using a modified P300 speller [10]. In a preliminary experiment, we prepared four panels with white/gray flicker matrices, one each for the desk light, primitive agent-robot, television control, and hiragana spelling. We tested them on both quadriplegic and able-bodied participants and found that both groups succeeded in operating the system without much training [14]. We then prepared a green/blue flicker matrix for the visual stimuli, because this color combination is considered to be the safest [23]. As expected, we found that the green/blue flicker matrix was associated with a better subjective feeling of comfort than was the white/gray flicker matrix. Further, we found that the green/blue flicker matrix was associated with better performance than was the white/gray flicker matrix [16, 17].

To increase accuracy when operating the BMI system and to develop better classification methods [12, 20, 29, 30], some studies have attempted to identify better, more-efficient experimental settings by manipulating factors such as matrix size and duration of intensification [21], channel set of the EEG [22], and flash pattern of the flicker matrix [31]. We proposed a method that combines luminance and chromatic information to increase the accuracy of performance using the P300 BMI, and this method can be applied with the methods proposed in the aforementioned reports.

Our BMI system equipped with the P300 paradigm was tested on both patients with quadriplegia and able-bodied persons, and it worked well for environmental control and communication [14, 15]. Note that the participants could use the system with little training. The participants only had to input six letters to gather data to derive the feature vectors for the subsequent test session, and this took only a few minutes. Using adequate visual stimuli, such as the green/blue flicker matrix, also helped to improve the system. Note that directed attention is needed to elicit P300-related responses, and this is not necessarily the direction of eye-gaze; therefore, this system may potentially benefit persons who cannot move their eyes freely.

One specific merit of the P300 speller algorithms is that we can easily translate the subject's thoughts as a command pre-assigned to each icon. Therefore, our system can be used for various applications in environmental control and communication. This should also help to expand the range of options for applications. For example, it was possible to combine AR techniques with BMI to make an AR-BMI system [18, 19]. The new AR-BMI system provided suitable panels to the users when they or their agent came to an area close to the controllable devices. Further, in our recent study, in which we used a hybrid BMI platform (a combined platform with a P300-based BMI and a sensorimotor rhythm-based BMI) [32], we prepared life-sized robot arms that could supply driving forces to a wearer's upper-limb motions, such as reaching and grasping, and developed an assist suit for persons with physical disabilities and those undergoing occupational therapy (Fig. 9) [33].

To deliver the new technologies to persons with disabilities, we made an in-house BMI system for environmental control and communication [32]. The hardware system includes an EEG amp, electrodes, cap, PC, programmable IR remote

and does not require constructing new circuits in the brain with extensive training. Our experience developing BMI technology has suggested that it is useful for supporting those with disabilities, and one future direction of study would be to build BMI-based intelligent houses (Fig. 10).

Conclusion

We used electroencephalography signals in a BMI system that enables environmental control and communication using the P300 paradigm, which presents a selection of icons arranged in a matrix. 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. We further added AR to make an AR-BMI system, in which the user's brain signals controlled an agent robot and operated devices in the robot's environment. BMI technology could be used to build BMI-based intelligent houses to support those with disabilities.

Acknowledgements These studies were conducted with the NRC post-doctoral fellows Drs. Kouji Takano, Tomoaki Komatsu, Shiro Ikegami, and Naoki Hata. I thank Dr. Günter Edlinger for his help, and Drs. Yasoichi Nakajima and Motoi Suwa for their continuous encouragement.

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<http://www.springer.com/978-4-431-53998-8>

Systems Neuroscience and Rehabilitation

Kansaku, K.; Cohen, L. (Eds.)

2011, XIV, 140 p., Hardcover

ISBN: 978-4-431-53998-8