F. 健康危険情報

該当なし

G．研究発表

（これまでの関連研究の成果を含む）

1．関連する論文発表

1) Atsushi Tsukahara, Ryota Kawanishi, Yasuhisa Hasegawa and Yoshiyuki Sankai: ″Sit-To-Stand and Stand-To-Sit Transfer Support for Complete Paraplegic Patients with Robot Suit HAL,″ Advanced Robotics, Vol. 24, No. 13, 2010.

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（これまでの関連研究の成果を含む）

1) 山海嘉之，Cybernics：その現状と未来，第 23 回 人工知能学会 全国大会，2009. 6. 18

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H. 知的財産権の出願・登録状況
（これまでの関連研究の成果を含む）

1. 関連する特許取得（平成２１年度 出願）

１）発明の名称：装着式動作補助装置

出願人：筑波大学

出願番号：PCT/JP2008/072081

２）発明の名称：重心位置検出装置及び重心位置検出装置を備えた装着式動作補助装置

出願人：筑波大学

出願番号：PCT/JP2008/072344

３）発明の名称：生体信号計測装着具及び装着式動作補助装置

出願人：筑波大学

出願番号：PCT/JP2009/65825

４）発明の名称：装着式動作補助装置のフレーム構造

出願人：筑波大学

出願番号：PCT/JP2009/66364

５）発明の名称：装着式動作補助装置

出願人：筑波大学

出願番号：2009-094695

６）発明の名称：動作補助装置、及び該動作補助装置を管理する情報管理装置

出願人：筑波大学

出願番号：特願 2009-115295

７）発明の名称：装着補助具

出願人：筑波大学

出願番号：特願 2009-123733

2 実用新案登録

該当なし。

3. その他

該当なし。

III.　研究成果の刊行に関する一覧表

研究成果の刊行に関する一覧表

書籍

著者氏名	論文タイトル名	書籍全体の編集者名	書　籍　名	出版社名	出版地	出版年	ページ
Kansaku, K	The Intelligent Environment: Brain-Machine Interfaces for Environmental Control	Ferguson-Pell, M., Stefanov, D	Smart Houses: Advanced Technology for Living Independently	Springer Verlag	Berlin		in press
神作憲司	脳のセンシング技術を用いた新しい福祉機器.	ヒューマンサイエンスとセンシング調査研究委員会編	心とからだのセンシング：健康・医療・福祉のためのテクノロジー	海文堂	東京	2009	146-154

雑誌

発表者氏名	論文タイトル名	発表誌名	巻号	ページ	出版年
Kansaku, K., Hata, N., Takano, K	My thoughts through a robot's eyes: an augmented reality-brain-machine interface	Neuroscience Research	66(2)	219-222	2010
Takano, K., Komatsu, T., Hata, N., Nakajima, Y., Kansaku, K	Visual stimuli for the P300 brain-computer interface: a comparison of white/gray and green/blue flicker matrices	Clinical Neurophysiology	120(8)	1562-1566	2009
Kato, J., Ide, H., Kabashima, I., Kadota, H., Takano, K., Kansaku, K	Neural correlates of attitude change following positive and negative advertisements	Frontiers in Behavioral Neuroscience	3(6)	1-13	2009
神作憲司	ブレイン・リーディング	Clinical Neuroscience			印刷中
池上史郎、神作憲司	ブレイン-マシン・インターフェイス（BMI）の今後の展開	作業療法ジャーナル			印刷中
Atsushi Tsukahara, Ryota Kawanishi, Yasuhisa Hasegawa and Yoshiyuki Sankai	Sit-To-Stand and Stand-To-Sit Transfer Support for Complete Paraplegic Patients with Robot Suit HAL	Advanced Robotics			in press

佐藤帆紡, 川畑共良, 田中文英, 山海嘉之	ロボットスーツHALによる移乗介助動作の支援	日本機械学会誌(C編)	76(762)	227-236	2010

IV.　研究成果の刊行物・別刷

Clinical Neurophysiology 120 (2009) 1562–1566

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Visual stimuli for the P300 brain–computer interface: A comparison of white/gray and green/blue flicker matrices

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ABSTRACT

Objective: The white/gray flicker matrix has been used as a visual stimulus for the so-called P300 brain–computer interface (BCI), but the white/gray flash stimuli might induce discomfort. In this study, we investigated the effectiveness of green/blue flicker matrices as visual stimuli.
Methods: Ten able-bodied, non-trained subjects performed Alphabet Spelling (Japanese Alphabet: Hiragana) using an 8×10 matrix with three types of intensification/rest flicker combinations (L, luminance; C, chromatic; LC, luminance and chromatic); both online and offline performances were evaluated.
Results: The accuracy rate under the online LC condition was 80.6%. Offline analysis showed that the LC condition was associated with significantly higher accuracy than was the L or C condition (Tukey–Kramer, $p < 0.05$). No significant difference was observed between L and C conditions.
Conclusions: The LC condition, which used the green/blue flicker matrix was associated with better performances in the P300 BCI.
Significance: The green/blue chromatic flicker matrix can be an efficient tool for practical BCI application.

1. Introduction

Brain–computer interface (BCI) or brain–machine interface (BMI) is a new interface technology that utilizes neurophysiological signals from the brain to control external computers or machines (Birbaumer, 2006; Birbaumer and Cohen, 2007). One research approach to BCI utilizes neurophysiological signals such as the neuronal firing that is emitted directly from a single cell; this approach can be categorized as invasive BCI. The other approach utilizes neurophysiological signals from the brain accessed in the absence of surgery; this is called non-invasive BCI. Electroencephalography (EEG), a technique for recording neurophysiological signals using electrodes placed on the scalp, represents the primary non-invasive methodology for studying BCI.

EEG-based non-invasive BCI can be easily used but has been regarded as providing only limited information. However, Wolpaw and McFarland recently succeeded in achieving two-dimensional cursor control (Wolpaw and McFarland, 2004) using EEG signals. These researchers applied the EEG power spectrum, using the beta-band power for vertical and the mu-band power for horizontal cursor control. Motor imagery tasks have been used in BCI research; for example, Pfurtscheller et al. used a motor imagery task and reported event-related beta-band synchronization and mu-waves de-synchronization (Bai et al., 2005; Guger et al., 2003; Pfurtscheller et al., 2006). Our research group has reported that a wrist motor imagery task elicited desynchronization in the alpha-band deriving from the sensorimotor area and synchronization in the alpha-band deriving from the occipital area in both able-bodied participants and those with spinal cord injuries (Komatsu et al., 2007).

Sensory evoked signals have also been utilized in EEG-based non-invasive BCI. One popular system, the P300 speller, uses elicited P300 responses to target stimuli placed among row and column flashes (Farwell and Donchin, 1988). Recent studies have evaluated the use of systems relying on sensory evoked signals among patients with amyotrophic lateral sclerosis and other diseases (Piccione et al., 2006; Sellers and Donchin, 2006). Our research group recently modified the Donchin P300 speller and applied it through an Environmental Control System (ECS) (Takano et al., 2008); we found that a C3/C4-level quadriplegic patient was able to use the system successfully (28 correct signals/28 trials) without significant training (Komatsu et al., 2008).

Practical use of EEG-based non-invasive BCI requires a stable system characterized by high levels of accuracy. In order to increase accuracy rates, feature extraction or classification procedures have been investigated, including step-wise discriminant analysis (Donchin et al., 2000; Sellers et al., 2006), wavelets

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(Bostanov, 2004), and support vector machines (Kaper et al., 2004). Moreover, it is important that sensory stimulation involved in using the BCI system based on the P300 speller not induce discomfort. In this study, we attempted to identify better sensory stimuli than those in the P300 speller.

The P300 speller has mainly used white/gray flicker matrices as visual stimuli (Kaper et al., 2004; Krusienski et al., 2008; Sellers et al., 2006). It is possible that such flickering visual stimuli could induce discomfort. Parra and colleagues evaluated the safety of chromatic combinations for those with photosensitive epilepsy (Parra et al., 2007). In their study, 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) of four frequencies (10, 15, 20, and 30 Hz) were used as the visual stimuli. Under the white stimulation condition, flickering stimuli with higher frequencies, especially those greater than 20 Hz, have been found to be potentially provocative. Under the alternating-color stimulation condition, as suggested by the Pokemon incidence, the 15-Hz blue/red flicker was most provocative. It is noteworthy that the green/blue chromatic flicker emerged as the safest and evoked the lowest rates of EEG spikes. In the current study, we used a green/blue chromatic combination for the visual stimuli used to elicit visually evoked responses. We showed that green/blue flicker matrices, representing milder visual stimuli, were also able to facilitate adequate performances in the P300 BCI.

2. Materials and methods

2.1. Subjects

Ten healthy, non-trained naive subjects (aged 25–47 years; nine females and one male) who had never participated in this study were recruited as participants. All subjects were neurologically normal and strongly right-handed (min/mean/max = 0.7/0.91/1), according to the Edinburgh Inventory. The studies received approval from the Institutional Review Board. All subjects provided written informed consent according to institutional guidelines.

2.2. Experimental design

We modified the so-called 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 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.

In this study, we prepared an 8 × 10 hiragana matrix for the P300 speller (Fig. 1), modified from a 6 × 6 matrix using the English alphabet, for this experiment. Three types of intensification/rest flicker combinations were prepared. We 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) for the luminance and chromatic flicker. Luminance was measured using a chromatic meter (CS-200, Konica Minolta Sensing Inc., Osaka, Japan). The order of the experimental conditions (the type of flicker matrix) was randomized among subjects.

The subjects entered hiragana characters from the Japanese alphabet using a row and column flicker panel with an 8 × 10 matrix. Fifteen letters were required for the spelling task involved in each experimental condition: L, C, and LC. The duration of the intensification/rest flicker involved 100 ms of intensification and 75 ms of rest. This intensification/rest timing was derived from the BCI competition III (Blankertz et al., 2006). One complete cycle of eight row and ten column intensifications constituted a sequence. Online performance was evaluated, and each letter was selected in a series of 10 sequences (180 intensifications for hiragana characters). The differences in the accuracy rates among the matrices were evaluated by two-way repeated ANOVAs and the Tukey-Kramer test as a post hoc test. Additionally, the difference in the accuracy rate for each sequence between each matrix was evaluated by a paired *t*-test.

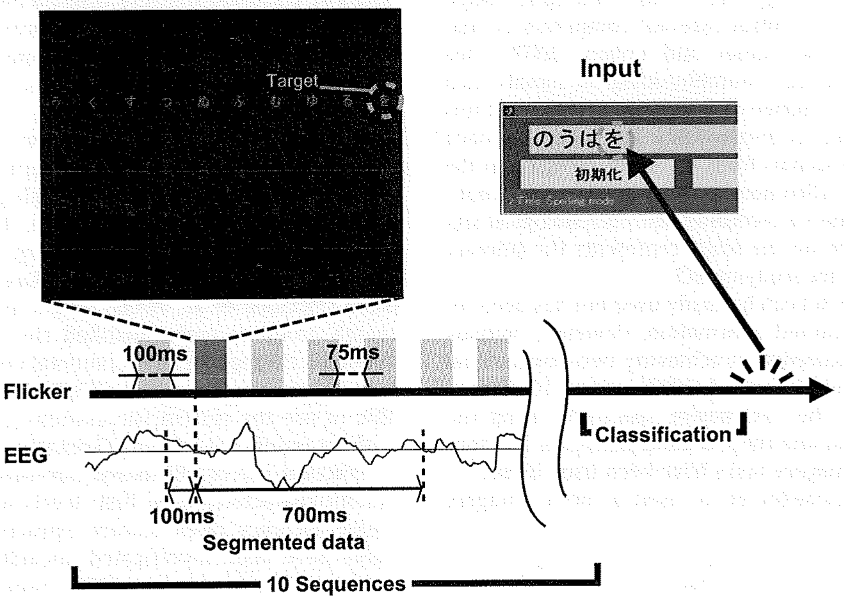

Fig 1. Hiragana matrix and experimental procedure. The row or column intensifications were presented, and ERP data were recorded. The red solid line of the EEG data indicates the segmented portion used for the classification. The target was predicted by Fisher's linear discriminant analysis after 10 sequences (180 intensifications).

The subject sat in an unshielded room 90 cm from a LCD display and was required to pay attention to a target, which was displayed in the 8 × 10 (hiragana spelling) matrix. The 8 × 10 matrix subtended 12.7°H × 15.8°W (20 × 25 cm). The distance between characters was 0.95° (1.5 cm) and the size of each character was 0.63° (1.0 cm) square.

2.3. EEG recording and analysis

Eight-channel (Fz, Cz, Pz, P3, P4, Oz, PO7, PO8, see Fig. 2) EEG data were recorded using a cap (Guger Technologies OEG, Graz, Austria) (Krusienski et al., 2007; Lu et al., 2008). 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 OEG, Graz, Austria), digitized at a rate of 256 Hz, and stored.

In the analyses, recorded EEG data were down-sampled to 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 subjects to input six letters for training and for gathering data to derive the feature vectors for the subsequent test session. The EEG data were sorted using the information about flash timing, and Fisher's linear discriminant analysis was then performed to generate the feature vector to discriminate between target and nontarget. The 700 ms of baseline-corrected EEG using a sampling rate of 21 Hz correspond to 15 data points, and data were collected by 8 EEG channels. Thus, the feature vector had 120 dimensions. The feature vectors were derived for each condition. In the test session, visual evoked responses from EEG features were evaluated by the feature vectors. The result of classification was construed as the maximum of the summed scores for the respective rows and columns, and the target was located in the matrix at the intersection of the predicted row and column.

3. Results

3.1. Offline evaluation

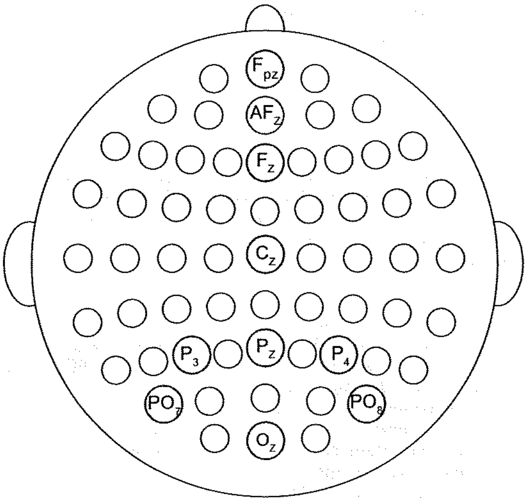

Fig. 2. Electrode montage and channel set. Eight channels used for analyses (red; Fz, Cz, Pz, P3, P4, Oz, PO7, PO8), a reference (blue; Fpz), and a ground (green; Apz).

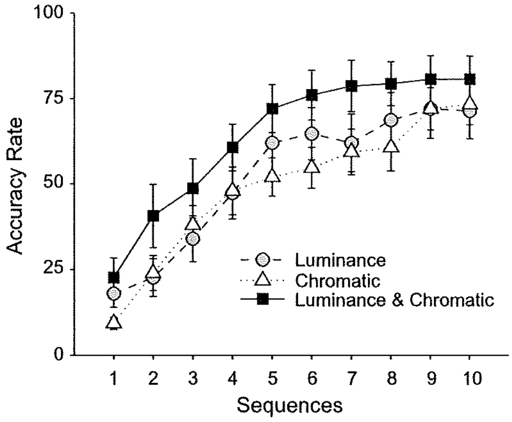

Fig. 3. Mean performance curves at each condition for all 10 sequences. Mean performances in L, C, and LC conditions are plotted by the broken line with gray circles, the dotted line with white triangles, and the solid line with black squares, respectively. Error bars indicate SE.

We asked the subjects to focus on one of the characters displayed on an 8 × 10 matrix panel, and 15 letters were required for the spelling task involved in each experimental condition: L, C, and LC. Fig. 3 shows the results of the offline analysis for each condition. It is noteworthy that accuracy was higher in the LC condition than in the two other conditions; a significant difference emerged between the LC and the two other conditions ($F(2,270) = 12.9$, $p < 0.01$), and no significant interaction was observed ($F(18,270) = 0.25$, $p = 0.99$). Post hoc testing revealed significant differences between the LC and the other conditions (Tukey–Kramer test, $p < 0.05$). A paired t-test was also applied for each sequence (Table 1). The LC and L conditions showed significant differences in regard to the sequences: [7, 9, 10]; the LC and C conditions showed significant differences on the sequences: [5, 6, 7, 8] (Paired t-test, $p < 0.05$, uncorrected). In contrast, there was no significant difference between the L and C conditions. These results indicate that a combination of luminance and chromatic characteristics of the visual stimuli proved most effective for increasing accuracy rates, and that chromatic and luminance flickers can be associated with similar levels of accuracy.

3.2. Online performance

Online performance was evaluated and each letter was selected in a series of 10 sequences. The accuracy rates were as follows: LC: 80.6% > C: 73.3% ⩾ L: 71.3%, and transfer bit rates (bit/min) (Wolpaw et al., 2002) were: LC: 8.14 > C: 7.03 ⩾ L: 6.75. A significant difference in the accuracy rate was observed between the LC and L conditions ($t(9) = 2.41$, $p < 0.05$, uncorrected).

Fig. 4 shows the online performance for each subject. One of 10 subjects performed most accurately in the L condition, four of 10 subjects did so in the C condition, and five of 10 subjects did so

Table 1
Significant differences between all sequences and conditions.

Sequences	L vs. C	L vs. LC	C vs. LC
1	0.070	0.487	0.058
2	0.726	0.065	0.835
3	0.329	0.068	0.175
4	0.928	0.130	0.208
5	0.165	0.130	0.018*
6	0.181	0.052	0.024*
7	0.705	0.021*	0.033*
8	0.288	0.074	0.036*
9	1.000	0.039*	0.258
10	0.758	0.020*	0.253

* $P < 0.05$.

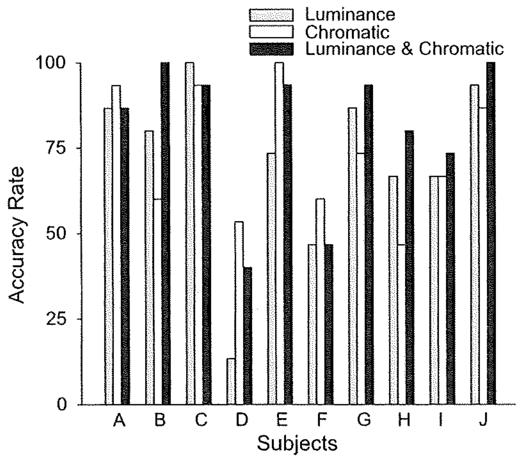

Fig. 4. Accuracy rates for each subject. The accuracy rates in L, C, and LC conditions for each subject (A–J) are indicated by gray bars, white bars, and black bars, respectively.

in the LC condition. Please note that the participants were not trained and had not previously participated in this experiment.

4. Discussion

In this study, we used a green/blue chromatic combination as visual stimuli to elicit visual evoked responses because it is possible that flickering visual stimuli induce discomfort. Following a previous study on photosensitivity in epilepsy (Parra et al., 2007), we used a green/blue chromatic combination.

We prepared a white/gray flicker (L condition) matrix for the luminance flicker, a green/blue isoluminance flicker (C condition) matrix for the chromatic flicker, and a green/blue luminance flicker (LC condition) for the luminance and chromatic flicker. We showed that accuracy rates were significantly higher in response to the luminance chromatic flicker condition (LC) than in response to the luminance (L) or chromatic (C) flicker condition.

In pursuit of increasing accuracy in operating the BCI system, as well as of developing better classification methods (Bostanov, 2004; Donchin et al., 2000; Kaper et al., 2004; Sellers and Donchin, 2006), some studies have attempted to identify better and more efficient experimental settings by manipulating such factors as the matrix size and the duration of intensification (Sellers et al., 2006), the channel set of the EEG (Krusienski et al., 2008), and random flashes (Sellers et al., 2008). This study proposed a method for combining luminance and chromatic information to increase the accuracy rate of performances in the P300 BCI, and this method can be applied with the proposed methods listed above.

Elucidation of the neuronal processes underlying the perception/cognition/attention with regard to visual stimuli might be helpful in clarifying why accuracy rates increased under the LC condition compared to the L or C condition. Unit recording studies exploring chromatic change among macaque monkeys found specialized color modules that showed specific color sensitivities in the parietal, occipital, and temporal areas (Conway et al., 2007); such studies also found color-selective neurons in the inferior temporal cortex (Koida and Komatsu, 2007). Previous unit recording studies of luminance change have reported activation at V1, V2 (Peng and Van Essen, 2005), and the pretectal olivary nucleus (Gamlin et al., 1995) in monkeys; and in the occipital and parietal areas in humans using MEG (Portin et al., 1998) and ERP (Johannes et al., 1995). It is conceivable that a wide range of neurons in the parietal, occipital, and temporal areas specialized for processing color information, and in the occipital and parietal areas specialized for processing luminance information may be activated under the LC condition, thereby contributing information that enriches the recorded EEG signals. However, additional investigations are necessary to enhance understanding of the neuronal processing underpinning the perception/cognition/attention with regard to visual stimuli.

Our results indicate that chromatic and luminance flickers are associated with similar levels of accuracy. Each condition (L or C) was correlated with mean accuracy rates of over 70%. This online performance and the results of offline analysis suggest that the chromatic flicker can be of similar usefulness as the luminance flicker. The choice of luminance and chromatic values was arbitrary in this experiment; therefore, future research might identify the optimal combination of luminance values. Furthermore, identification of the optimal visual stimuli for each individual subject might be beneficial.

We conducted the experiments in an unshielded room in order to present better visual stimuli in a situation closely resembling the actual environments in which the BCI system will be used daily by potential users such as quadriplegic patients. The LC condition was associated with better performance. In addition, even by applying the isoluminance C condition, it provided similar results to the L condition. The relatively better performance under conditions including chromatic changes might derive from the greater constancy in the chromatic condition (Barbur and Spang, 2008), which may enable greater stability vis-a-vis environmental changes. Further investigation is necessary to evaluate how environmental light affects performances, and studies in this regard might contribute to determining the best visual stimuli for the situations in which the BCI system is actually used.

In this study, we investigated the effect of chromatic change in visual stimuli in a modified P300 BCI, which had primarily used luminance change in visual stimuli in previous research. We applied a green/blue chromatic flicker and showed that the green/blue flicker matrices, which might represent milder visual stimuli, were useful in improving performances in the operation of the P300 BCI. Additional studies applying interdisciplinary approaches from engineering and neuroscience might provide better and more practical ways to enhance the ability of the P300 BCI to help individuals with disabilities.

Acknowledgments

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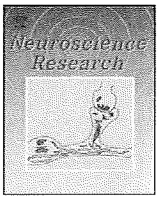

Rapid communication

My thoughts through a robot's eyes: An augmented reality-brain–machine interface

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ABSTRACT

A brain–machine interface (BMI) uses neurophysiological signals from the brain to control external devices, such as robot arms or computer cursors. Combining augmented reality with a BMI, we show that the user's brain signals successfully controlled an agent robot and operated devices in the robot's environment. The user's thoughts became reality through the robot's eyes, enabling the augmentation of real environments outside the anatomy of the human body.

Technologies for direct functional interfaces between brains and artificial devices, the so-called brain–machine (BMI) or brain–computer (BCI) interfaces, have grown impressively in the last decade (Lebedev and Nicolelis, 2006; Birbaumer and Cohen, 2007). One research approach to BMI utilises neurophysiological signals, such as neuronal firing by a single cell. Electrophysiology studies using monkeys or rats have succeeded in multidimensional control of robot arms (Chapin et al., 1999; Moritz et al., 2008), aiming to control revolutionary prostheses that feel and act like the extremities. Another approach utilises neurophysiological signals from the brain, accessed non-invasively, primarily using electroencephalography (EEG), a technique for recording neurophysiological signals using electrodes placed on the scalp. An EEG-based BMI succeeded in achieving two-dimensional cursor control (Wolpaw and McFarland, 2004).

Extensive BMI research has enabled users to control external devices within their own environment; however, the use of brain signals to control devices outside the user's environment remains a new concept for BMI. In situations where humans acquire new visual perspectives, recent neuroscience studies have reported that our body scheme may change (Botvinick and Cohen, 1998; Ehrsson et al., 2004; Lenggenhager et al., 2007), *e.g.*, manipulation of the visual perspective can affect the usual ongoing experience of being located inside our body, and the perceptual illusion of swapping bodies with another person or an artificial body can occur (Petkova and Ehrsson, 2008). Therefore, one challenge for developing a new BMI is to place the user's visual perspective in another environment directly. This may also raise various points that have to be evaluated further. Another possible direction for new BMI is that of preparing a controllable agent robot that has a visual perspective, and then letting the user see what the robot "sees". Here, we describe a new BMI system that permits the control of devices outside the user's own body environment; we combined augmented reality (AR) with BMI techniques, and showed that brain signals not only controlled movements of an agent robot but also operated a light in the robot's environment, acting through its eyes. The user's thoughts became reality through the robot's eyes, enabling the augmentation of real environments outside the anatomy of the human body.

Ten healthy, non-trained naive subjects (aged 19–39 years; two females and eight males) who had not previously participated in this study were recruited as participants. All of the subjects were neurologically normal and strongly right-handed according to the Edinburgh Inventory. The study was approved by the Institutional Review Board. All subjects provided written informed consent according to institutional guidelines.

The AR-BMI system consists of a personal computer (PC), monitor, lab-made agent robot, USB camera (QCAM-200V, Logicool, Tokyo, Japan), EEG amplifier (gUSBamp, Guger Technologies OEG, Graz, Austria), and EEG cap (g.EEGcap, Guger Technologies OEG, Graz, Austria) (Fig. 1). When the robot's eyes detect an AR marker (*e.g.*, Fig. 2a), the pre-assigned infrared appliance becomes

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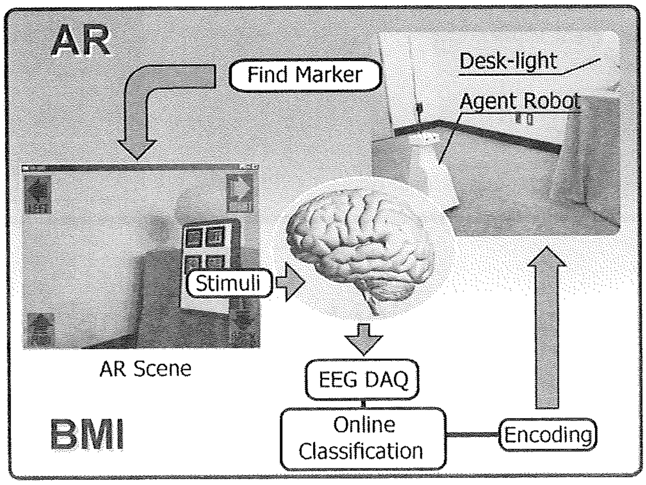

Fig. 1. The augmented reality-brain–machine interface. Subjects were required to watch a computer monitor that displays the scene detected by the USB camera on the agent robot. Four icons to control the robot's movements (forward, backward, right, and left) are shown in the corners of the monitor. When the robot's eyes detect an AR marker, the pre-assigned infrared appliance becomes controllable. A panel with four icons to control the light (turn on, turn off, make brighter, and make dimmer) is also shown on the monitor. Consequently, the subjects can operate the light in the agent robot's environment.

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. In order to control our system by using brain signals, we modified a Donchin P300 speller. This uses the P300 paradigm, which presents a selection of icons arranged in a matrix. The subject focuses attention on one of the icons in the matrix as a target, and each row/column or single icon in the matrix is intensified in a random sequence. The target stimuli are presented as rare stimuli (Oddball Paradigm). A P300-related response to the target stimuli is elicited, and then this response can be extracted and classified to determine the target (Farwell and Donchin, 1988). Note that the direction of attention is needed to elicit the P300-related response, and not necessarily the direction of eye-gaze. Recently, our research group modified the Donchin P300 speller (Takano et al., 2009), and applied it through an environmental control system (ECS), enabling a C3/C4-level quadriplegic patient to use the system successfully (28 correct signals/28 trials) without significant training (Komatsu et al., 2008).

The AR-BMI system uses ARToolKit (Kato and Billinghurst, 1999) and OpenGL. The ARToolKit C-language library was used to detect and determine the location of the AR markers, and the OpenGL C-language library was used to draw the 3D control panels. Fig. 2b shows a 3D model of the control panel used to

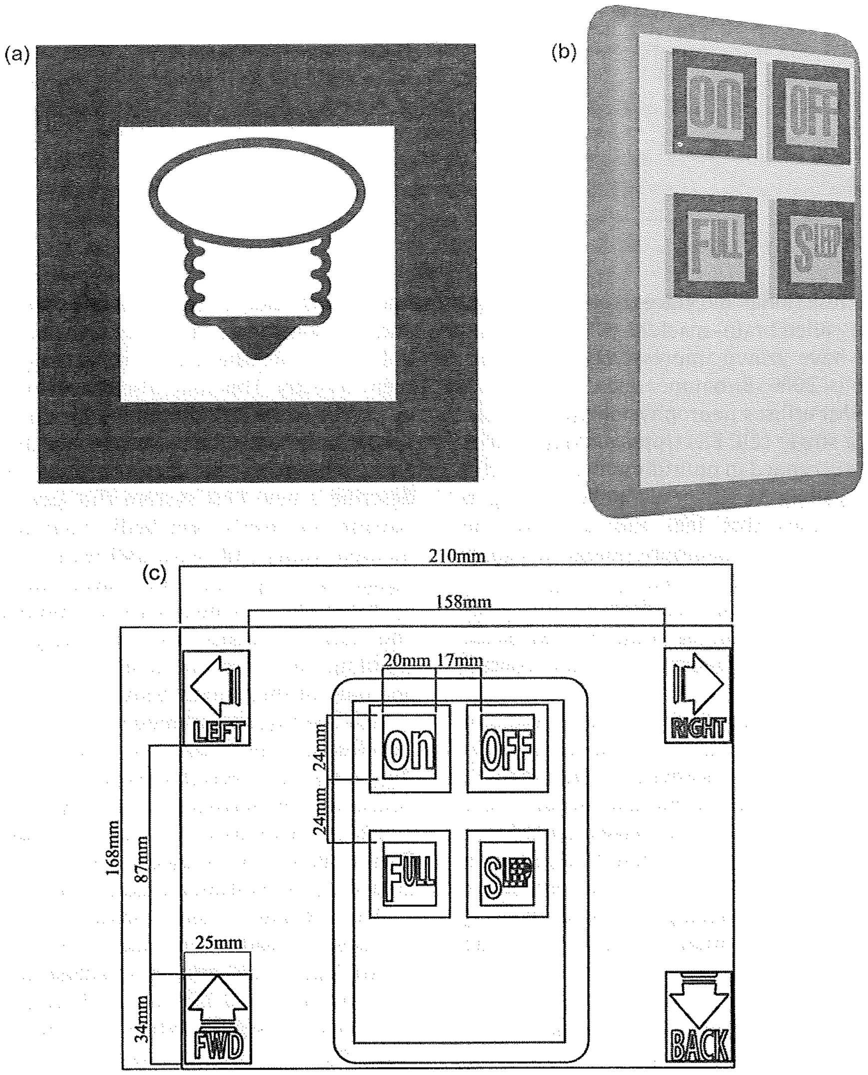

Fig. 2. An AR marker and panels for the AR-BMI. (a) An AR marker for the desk-light control. When the robot's eyes detect the AR marker, it becomes controllable. (b) A 3D model of the control panel used to control the desk light. (c) A drawing of the scene displayed on the PC monitor.

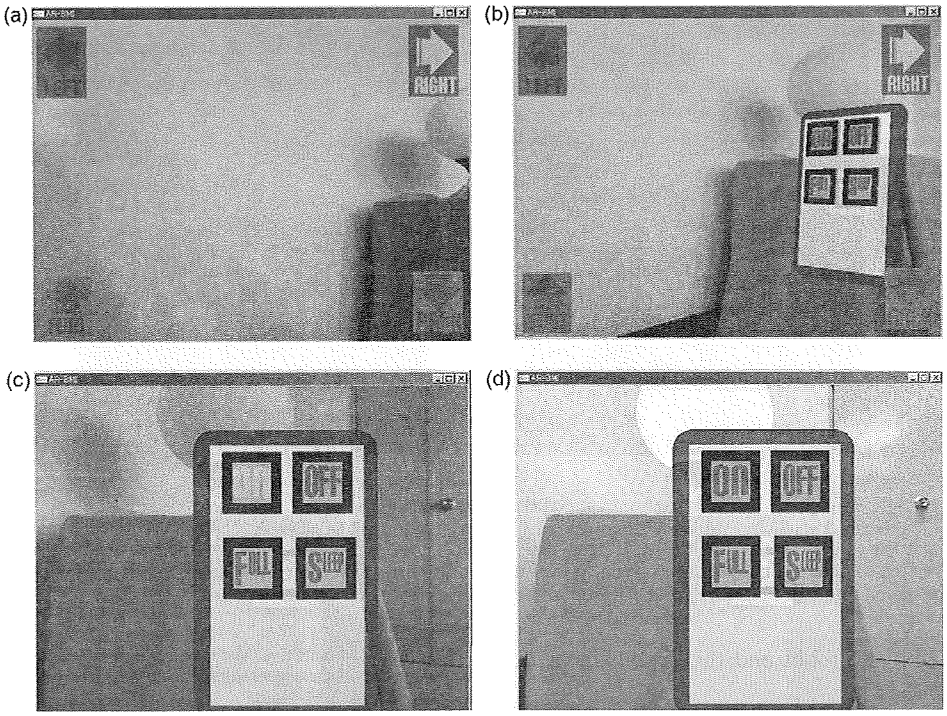

Fig. 3. Experimental scenes. Examples of scenes that the subjects saw during the experiments. (a) The robot approaching the light. (b) The AR marker is detected by the robot's eyes, and the light control panel is displayed. (c) The light control panel flickered. (d) A command to turn on the light was successfully sent.

control the desk light. Fig. 2c shows a drawing of the scene displayed on the PC monitor. Note that 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 (Takano et al., 2009), 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 carried out every 15 sequences. Subjects were 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.

Eight-channel (Fz, Cz, Pz, P3, P4, Oz, PO7, and PO8 of the extended International 10-20 System) EEG data (Krusienski et al., 2007; Lu et al., 2008) were recorded using the EEG cap. All channels were referenced to Fpz and grounded to AFz. The stored EEG data were passed through an eighth-order high-pass filter at 0.1 Hz and a fourth-order 48–52-Hz notch filter, and amplified/digitised at a rate of 128 Hz. A first-order band-pass filter (8.0–18.0 rad/s) was applied to the recorded EEG data. Then, 120 samples of event-related potential (ERP) data were recorded according to the timing of the intensification. Data from the first 20 samples (before intensification) were used for baseline correction. The last 100 samples (after intensification) were down-sampled to 25.6 Hz, and Fisher's linear discriminant analysis was used for classification. In the Fisher's linear discriminant analysis, we first collected data to derive the feature vectors for the subsequent test session. Four targets were assigned to make the feature vectors. The EEG data were sorted using the flash-timing information, and then Fisher's linear discriminant analysis was used to generate the feature vector (160 dimensions, 20 dimensions per EEG channel), to discriminate between target and non-target. Feature vectors were derived for each condition. In the test session, visual evoked responses from EEG features were evaluated using the feature vectors. The result of the classification was construed as the maximum of the summed scores.

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 (Fig. 3a and b). 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' eyes detected the AR marker of the desk light, a flicker panel for controlling the appliance was displayed on the screen (Fig. 3c and d). 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%.

Fig. 4 shows the offline evaluation of the performance of the participants under the robot-control (a) and light-control (b) conditions. The performance for controlling the robot and desk light differed significantly, and an interaction effect was observed by 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, $p < 0.05$). The difference might be related to the differences in the relative locations of the flicker icons on the screen (Cheng et al., 2002) (see also Fig. 2c).

By applying the AR technique with the BMI, we successfully showed that brain signals not only controlled an agent robot but also operated home electronics in the robot's environment. BMI research has developed revolutionary prostheses that feel and act like the user's extremities (Chapin et al., 1999; Moritz et al., 2008) or computer devices (Wolpaw and McFarland, 2004), but these have not yet controlled devices outside the user's environment. In this study, we applied the AR technique and succeeded in augmenting a real environment. We also applied the P300 speller algorithms, and succeeded in translating the subjects' thoughts as a command pre-assigned to each icon; the subjects' thoughts

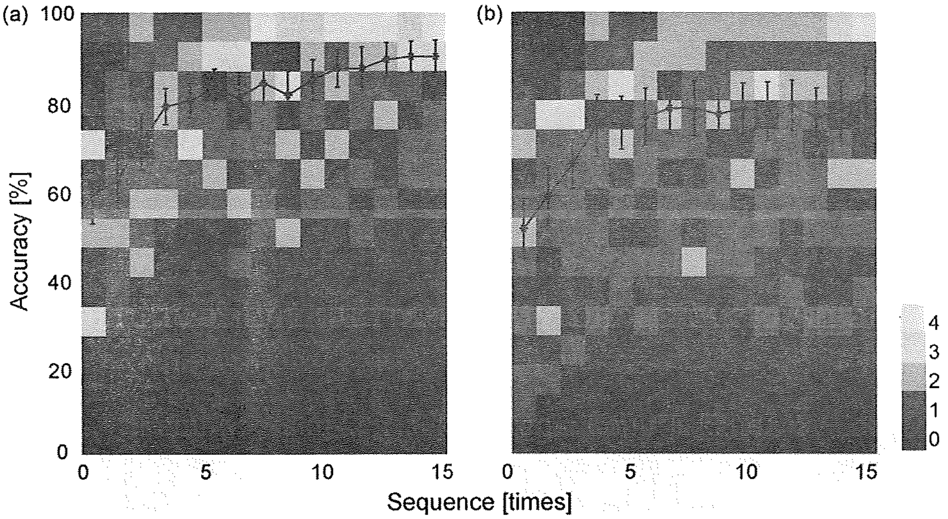

Fig. 4. Subjects' control accuracy. The accuracy for controlling the: (a) robot and (b) light are shown. The horizontal axes indicate the number of sequences, and the vertical axes indicate the accuracy. The red solid lines show the mean accuracy with the standard error (SE). The blue squares behind the red solid lines are two-dimensional histograms, and each blue square indicates the frequency of the subjects in each sequence and their accuracy.

successfully operated both the robot and the desk-light in the robot's environment.

In this study, humans succeeded in using an agent that has another perspective, external to the human body. Other possible approaches could include providing a new visual perspective to the user directly; careful application is needed in this respect, because this may easily alter the user's body scheme (Botvinick and Cohen, 1998; Ehrsson et al., 2004; Lenggenhager et al., 2007; Petkova and Ehrsson, 2008). The extension of the environment for human activities along these lines, using either non-invasive neurophysiological signals or neuronal firing data in the future could enable new daily activities for persons with physical disabilities and 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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