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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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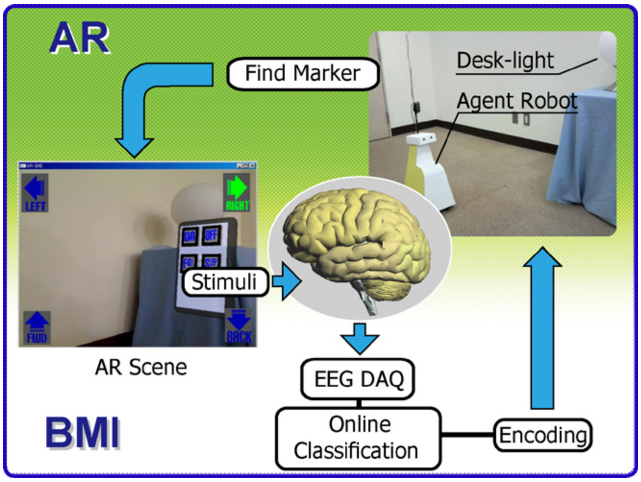

Fig. 1. The augmented reality-brain–machine interface. Subjects were required to watch a computer monitor that displays the scene detected by the USB camera on the agent robot. Four icons to control the robot's movements (forward, backward, right, and left) are shown in the corners of the monitor. When 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

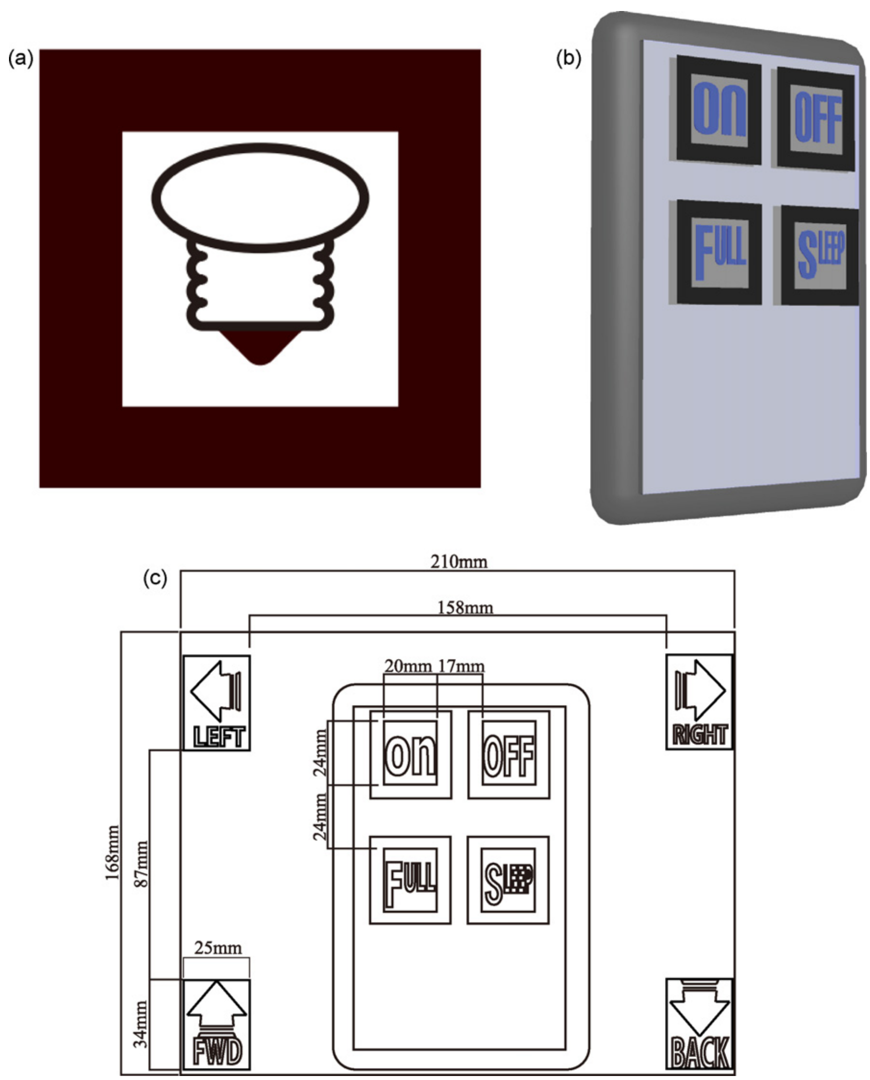

Fig. 2. An AR marker and panels for the AR-BMI. (a) An AR marker for the desk-light control. When the robot's eyes detect the AR marker, it becomes controllable. (b) A 3D model of the control panel used to control the desk light. (c) A drawing of the scene displayed on the PC monitor.

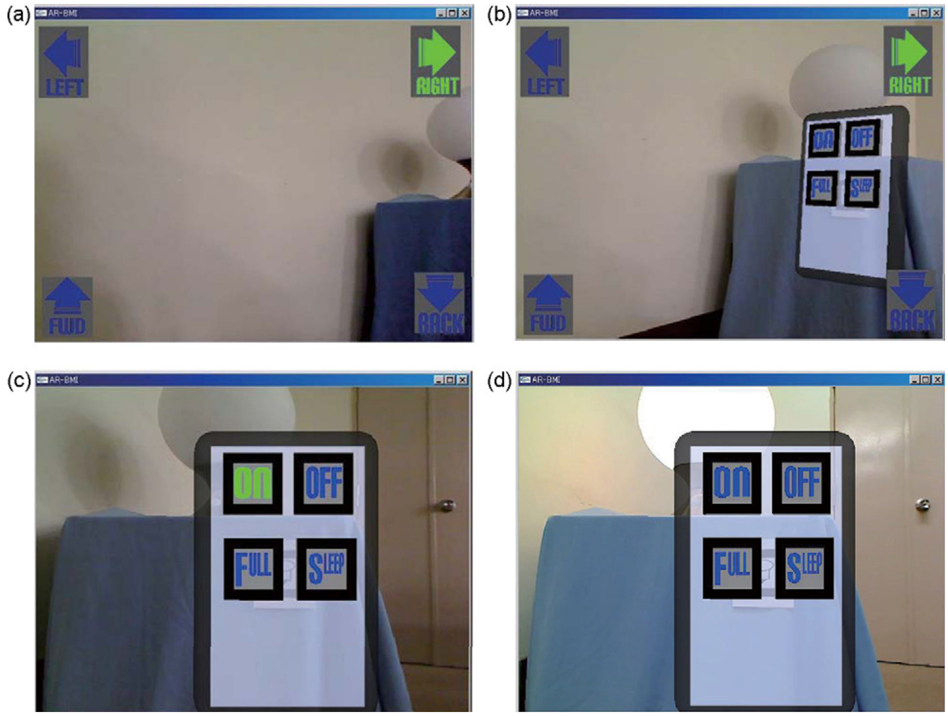

Fig. 3. Experimental scenes. Examples of scenes that the subjects saw during the experiments. (a) The robot approaching the light. (b) The AR marker is detected by the robot's eyes, and the light control panel is displayed. (c) The light control panel flickered. (d) A command to turn on the light was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

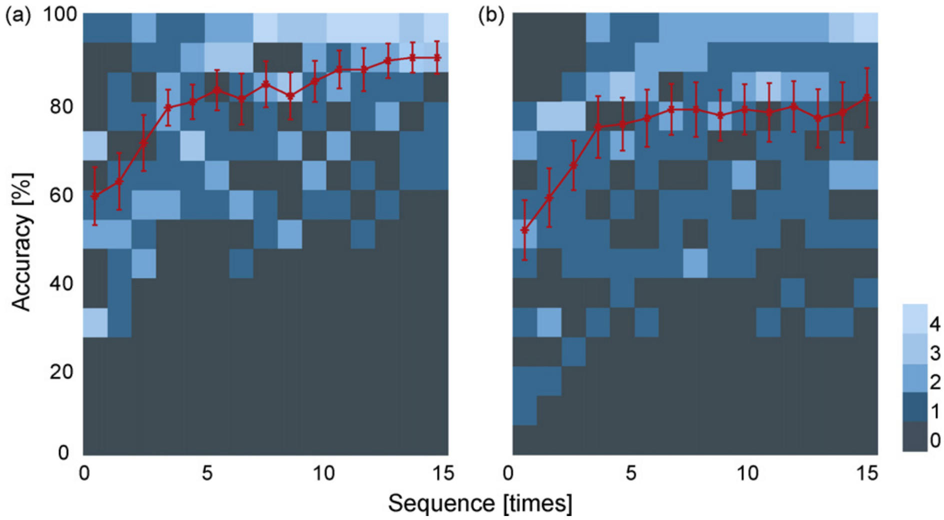

Fig. 4. Subjects' control accuracy. The accuracy for controlling the: (a) robot and (b) light are shown. The horizontal axes indicate the number of sequences, and the vertical axes indicate the accuracy. The red solid lines show the mean accuracy with the standard error (SE). The blue squares behind 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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References

Birbaumer, N., Cohen, L.G., 2007. Brain–computer interfaces: communication and restoration of movement in paralysis. J. Physiol. 579, 621–636.
Botvinick, M., Cohen, J., 1998. Rubber hands 'feel' touch that eyes see. Nature 391, 756.
Chapin, J.K., Moxon, K.A., Markowitz, R.S., Nicolelis, M.A., 1999. Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. Nat. Neurosci. 2, 664–670.
Cheng, M., Gao, X., Gao, S., Xu, D., 2002. Design and implementation of a brain–computer interface with high transfer rates. IEEE Trans. Biomed. Eng. 49, 1181–1186.
Ehrsson, H.H., Spence, C., Passingham, R.E., 2004. That's my hand! Activity in premotor cortex reflects feeling of ownership of a limb Science 305, 875–877.
Farwell, L.A., Donchin, E., 1988. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr. Clin. Neurophysiol. 70, 510–523.
Kato, H., Billinghurst, M., 1999. Marker tracking and HMD calibration for a video-based augmented reality conferencing system. In: Proceedings of the International Workshop on Augmented Reality, San Francisco, CA, USA.
Komatsu, T., Hata, N., Nakajima, Y., Kansaku, K., 2008. A non-training EEG-based BMI system for environmental control. Neurosci. Res. Suppl. 61, S251.
Krusienski, D.J., Sellers, E.W., Vaughan, T.M., 2007. Common spatio-temporal patterns for the P300 speller. In: Proceedings of the 3rd International IEEE EMBS Conference on Neural Engineering. Kohala Coast, HI, USA pp. 421–424.
Lebedev, M.A., Nicolelis, M.A., 2006. Brain–machine interfaces: past, present and future. Trends Neurosci. 29, 536–546.
Lenggenhager, B., Tadi, T., Metzinger, T., Blanke, O., 2007. Video ergo sum: manipulating bodily self-consciousness. Science 317, 1096–1099.
Lu, S., Guan, C., Zhang, H., 2008. Unsupervised brain computer interface based on inter-subject information. In: Proceedings of the 30th Annual International IEEE EMBS Conference. Vancouver, BC, Canada, pp. 638–641.
Moritz, C.T., Perlmutter, S.I., Fetz, E.E., 2008. Direct control of paralysed muscles by cortical neurons. Nature 456, 639–642.
Petkova, V.I., Ehrsson, H.H., 2008. If I were you: perceptual illusion of body swapping. PLoS ONE 3, e3832.
Takano, K., Komatsu, T., Hata, N., Nakajima, Y., Kansaku, K., 2009. Visual stimuli for the P300 brain–computer interface: a comparison of white/gray and green/blue flicker matrices. Clin. Neurophysiol. 120, 1562–1566.
Wolpaw, J.R., McFarland, D.J., 2004. Control of a two-dimensional movement signal by a noninvasive brain–computer interface in humans. Proc. Natl. Acad. Sci. U.S.A. 101, 17849–17854.