

Brain Machine Interface Technology Enabling Control of Machine by Human Thought Alone

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ABSTRACT

Recently, brain machine interface (BMI) technology has gathered a lot of attention in regard to controlling a machine without any physical devices. Although this interface is often seen in science fiction, it is becoming realistic due to dramatic progress in brain and computer science. By directly connecting a human's brain with a machine, a machine can be controlled by human thought alone.

Honda has challenged the development of this BMI in collaboration with ATR and Shimadzu. By developing a new brain measurement using electroencephalography (EEG) and near-infrared spectroscopy (NIRS) and applying sparse logistic regression into BMI to detect a human's intention correctly, we successfully developed a highly accurate interface of BMI.

To validate our BMI system, we used 4-motor imagery task often used in BMI research. The performance of our BMI is more than 90% accuracy. This result is competitive against other BMI research groups.

1. Introduction

Because of the dramatic progress in brain science and the rapid development of computer science, the possibility of controlling a robot or a computer by thought alone is becoming more realistic. This technology is called brain machine interface (BMI) or brain computer interface (BCI). By connecting a brain with a machine directly, a machine can be controlled by human thought without any physical devices⁽¹⁾⁻⁽³⁾.

Honda began to research brain machine interface technology in 2005 with collaboration of the Advanced Telecommunication Research Institute International (ATR) in Kyoto. In 2006, Honda and ATR succeeded to control a robot hand by BMI using functional Magnetic Resonance Imaging (fMRI) in real time and showed the potential of BMI^{(4), (5)}. In this experiment, a user lay in fMRI and really performed the game of scissors-paper-rock. The fMRI measured the brain activity in the user's primary motor area that controls the muscle of hand. Then, the data obtained were analyzed to detect a human's task, i.e., scissors, paper

or rock. We achieved more than 85% accuracy of detecting a task to control a robot hand. However, there were several issues to be solved, i.e., the real movement that contradicts the merit of BMI, the huge size of a brain scanner that cannot be used in daily life and the difficulty to show the future possibility with BMI due to the simple machine.

Therefore, we tried to replace a rather big fMRI by electroencephalography (EEG)⁽⁶⁾ and near-infrared spectroscopy (NIRS)⁽⁷⁾ to create a brain-activity scanner which can be used in daily life. In addition, we challenged to realize a BMI system that can control a machine or a robot by a human's thought alone and used a real robot that can more clearly show the future possibility with BMI.

Although both EEG and NIRS can be used in daily life, the noise-signal ratio is worse than fMRI. Therefore, the key-topic of BMI with EEG and NIRS are how to enhance the performance of BMI. Furthermore, the replacement of really performing actions by imagining actions results in weak and unclear signals. To tackle these issues, we developed a new algorithm and simultaneous and real-time brain-activity scanner of EEG and NIRS.

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To validate our BMI system, we performed 4-motor imagery tasks explained later and achieved 91.6% accuracy of BMI. Using this BMI system, we also succeeded to control a robot by human thought alone with high accuracy.

In this paper, we introduce this new BMI which was released to the world on 31st, March, 2009.

2. Future Possibilities with BMI

Figure 1 shows future possibilities if the BMI technology is fully developed. As examples, we show four possibilities. Since BMI has huge possibilities, however, these are only a few examples.

A robot or robots can help perform housework when you are busy like washing dishes (a). A trunk of a car can be opened only by thought when you have a lot of packages (b). The room temperature can be adjusted by controlling the air-conditioner according to a user's own desire (c). One can communicate with other people without any utterance and/or can gather information by imaging an object. If we look around our lives, we can easily find possibilities which BMI can support us and make our lives more fruitful. We strongly believe that the realization of BMI can lead to a more enjoyable life.

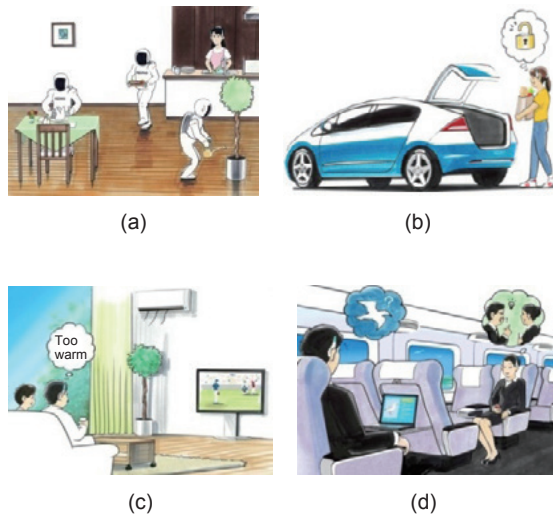


Fig. 1 Images of our future lives using BMI

3. Brain Machine Interface

As the term of BMI explicitly indicates, BMI is a direct interface between a brain and a machine. Following the dramatic progress of brain science and the revelation of brain functionalities, the research for BMI has been encouraged since 1980s and many research outputs have been reported since 2000s⁽²⁾. In the beginning of BMI research, a so-called invasive BMI, which needs surgery to install sensors on/in a cortex, was popular due to clear brain signals. Although invasive BMI has much attention, in particular, in the USA, non-invasive BMI, which needs no

surgery and no damage of a cortex, a skull and a scalp, has started to be researched recently.

We can also classify BMIs reported in the literature into two areas, an input-type BMI and an output-type BMI. An input-type BMI inputs electric signals of a machine into a human's brain. A famous example of this BMI is a cochlear implant which is already used by millions of persons in the world⁽³⁾. Oppositely, an output-type BMI detects brain-activity signals by a brain scanner, understands the meaning of these signals and sends a human's intention to a machine to control it. According to the direction of signals toward a brain or a machine, we can classify BMI as an input-type or output-type BMI.

Our BMI reported here is a non-invasive and output-type BMI since we use scanners which need no damage against human's body. As our BMI is non-invasive, it has the possibility to become an innovative interface for not only disabled people but also healthy people.

The basic flow of a non-invasive and output-type BMI is shown in Fig. 2.

First, scanners measure brain signals generated by the brain activity of the subject, i.e., a user of BMI (a) and obtain the data (b). Although we will explain the details of scanners later, we use both electroencephalography (EEG) whose data is shown in the upper images of (b) and near-infrared spectroscopy (NIRS) whose data is shown in the lower images of (b). Thereafter, a certain signal processing is carried out for the obtained data and the human's intention is determined by a "classifier," which learns the pattern of data and classifies new data to understand the human's intention (c). Finally, this analyzed intention is sent to a machine to do a pre-programmed action (d). From Fig. 2, it is easy to understand the importance of measuring brain signals correctly and detecting a human's intention accurately from the data obtained. These two topics are key issues of BMI.

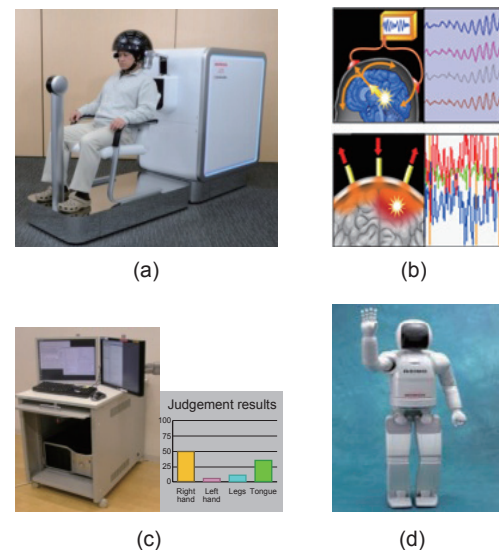


Fig. 2 Basic flow of our BMI

4. Newly Developed Brain-Activity Scanner

We developed a new brain-activity scanner which can simultaneously measure EEG and NIRS and process these data in real time. This scanner is named the “Simultaneous and real-time brain-activity scanner of EEG and NIRS” (hereafter EEG-NIRS scanner). Before our development, the simultaneous EEG-NIRS scanner has been already developed by Shimadzu Corporation⁽⁷⁾. However, this system is an off-line system where the system stores the EEG and NIRS data and the data obtained can be analyzed after an experiment. Therefore, a real-time BMI could not be realized only using this EEG-NIRS scanner. In addition, the EEG and NIRS are controlled independently. This results in the difficulty to synchronize both data and to exploit them to enhance the performance of BMI. Hence, we tried to develop a new EEG-NIRS scanner which can solve the above issues. By developing a new EEG-NIRS scanner, a real-time and highly accurate BMI system can be realized.

In this section, we first explain the basic principles of EEG and NIRS and thereafter we introduce our EEG-NIRS scanner.

4.1. Electroencephalography (EEG)

When a certain region of a cortex works, tiny electric flow exists in the region. Although a skull is nearly an insulator, a small amount of electricity leaks from a skull and flows on a scalp. An EEG measures this flow as electric potential.

Note that cerebrospinal fluid (CSF) which is a conductor, fills up between a cortex and a skull and EEG cannot measure the brain-activity strongly even with the sensor on the working regions. The conductivity of CSF and the insulation of a skull result in the difficulty of determining the working area in a cortex by EEG sensors. Due to this difficulty, the performance of BMI by EEG is dramatically reduced.

4.2. Near-Infrared Spectroscopy (NIRS)

The activated region of a cortex consumes oxygen. To provide new oxygen to this area, blood with oxygenated hemoglobin gathers and brings oxygen. By using near-infrared light, the NIRS watches this blood to determine the activated area. NIRS uses three lights, i.e., 780 nm, 805 nm and 830 nm of wave length, and introduces these lights at the scalp. According to the difference of absorption of these lights passing oxygenated or deoxygenated hemoglobin, NIRS measures brain activity. Since a few seconds are necessary to gather blood in an activated area, NIRS needs a few seconds to measure brain activity. Therefore, as explained later, our experiment is forced to continue a motor imagery for about 10 seconds due to this phenomenon.

4.3. EEG-NIRS Scanner

Figure 3 shows our developed EEG-NIRS scanner. Using a commercial off-line system of simultaneous

measurement by EEG and NIRS (Shimadzu Corporation)⁽⁷⁾, our on-line system of an EEG-NIRS scanner was developed. To realize this system, we developed a synchronization system of EEG and NIRS and a framework of a real time system which can calculate in real time. The former is necessary for measuring brain activity correctly since a gap of a few milliseconds results in the difficulty of understanding brain activity. The latter sends measured signals of EEG and NIRS via local area network (LAN) to another computer that can process signals in real time.

The right-bottom figure in Fig. 3 shows the EEG and NIRS sensors that are installed on a human's scalp. The sensors with black cables are the NIRS and the white cables are the EEG. In the NIRS sensors, the sensors with red labels are transmitters which generate near-infrared light and the ones with blue labels are receivers which receive near-infrared lights passing through the cortex. There are 16 red NIRS transmitters and 16 blue receivers. Since the combination of a transmitter and a receiver consists of one logical channel, our system can measure 48 areas. Each logical channel measures oxygenated hemoglobin and deoxygenated hemoglobin simultaneously. The number of EEG sensors is 66. Since 2 of 66 sensors are used as reference sensors, the EEG can measure 64 areas.

Figure 4 shows the details of the synchronization system and the on-line system. The personal computer with the role of controlling time sends 8-bit TTL signals (0 V or 5 V) to the EEG and NIRS via the BNC cables. Both EEG and NIRS record brain-activity data and the TTL signals. Then, these data are sent to the personal computer with role of synchronization via LAN. Thereafter, the synchronization is carried out using TTL signals in the EEG and NIRS data.

The real-time system mainly consists of sharing files and ring buffers. In a computer where signal processing is performed, several sharing files where ring buffers are installed are made. Using these files, a computer can receive the data of the EEG and NIRS in the real time. Furthermore,

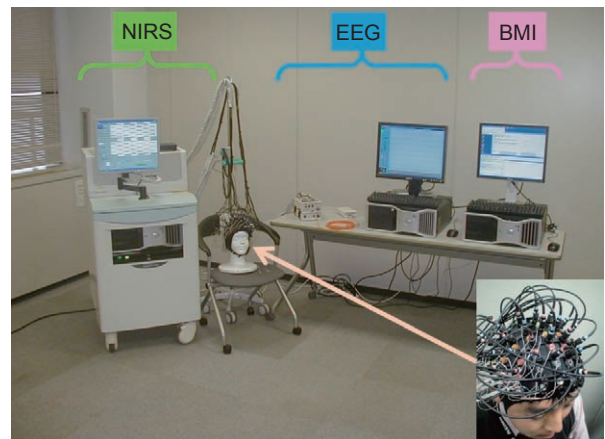


Fig. 3 Brain activity real-time measurement system using EEG and NIRS

the system has the functionality called “broadcasting” to quickly send the data to several computers.

The apparatus shown in Fig. 5 incorporates all the components shown in Fig. 3. Although this collection seems to be easy, an issue appears, e.g., electric-magnetic interference, and results in the worsening of the signal-noise ratio of EEG. Therefore, to minimize the effect of the electric-magnetic interference, we divided the apparatus seen in Fig. 5 so they are independent from others in regard to electric-magnetic interference. Furthermore, the arrangements of each apparatus are optimized to reduce noises. To more easily use this scanner as a BMI system, we added a display that identifies the tasks toward a subject, a chair for the subject, a LED that shows the status of the BMI system and casters that let us easily bring this system. To avoid unnecessary burden for a subject caused by sensors, an arm is located between the big white box and the sensors to help reduce the weight of the sensors.

The approximate size of this apparatus is 2000 (mm) length, 700 (mm) width and 1400 (mm) height and the approximate weight is 300 (kg). Although this apparatus is rather large, it can be used in many places and we believe it is the first step of BMI being used as an innovative interface in daily life.

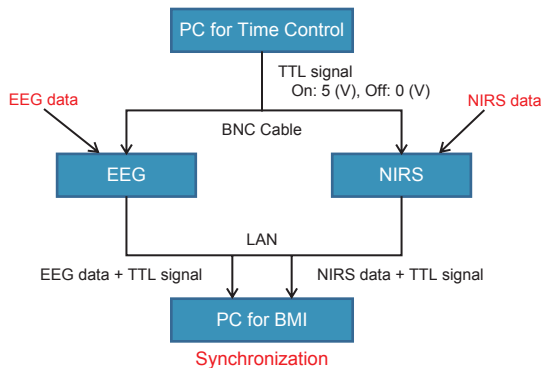


Fig. 4 EEG-NIRS synchronization system



Fig. 5 Brain activity measurement system for BMI

5. Algorithm for the Detection of a Human's Intention

5.1. Extraction of Features

By using our EEG-NIRS scanner, we can obtain 96 data (oxygenated and deoxygenated hemoglobin) from NIRS and 64 data from EEG per one sampling. In this paper, the sampling rate of NIRS is 7.69 Hz and of EEG is 256 Hz. Since a subject images for 10 seconds, about 170 million data can be collected even if we record brain activity during the task of image. Furthermore, as several signal processing can be used, the number of total data becomes too huge.

However, most of the data are not important for detecting a human's intention. Therefore, it is significant to detect the important data correctly. For tackling this issue, we applied Sparse Logistic Regression (SLR) proposed by Yamashita⁽⁸⁾ into our BMI system. By using SLR, we tried to extract the important features from the huge amount of data. The main target of SLR is the calculation of the boundary by automatically eliminating unimportant data from stochastic point of view. In Fig. 6, each point shows the data from a task. Generally, the dimension of the data is very high. To avoid the difficulty of visualization for high dimensional data, we simplify Fig. 6 as 2 dimensional data.

In SLR, the boundary for classifying data is first calculated using the labeled data obtained in the learning session. Thereafter, a test session is started. In the test session, a human's intention will be determined according to whether new data are located in the right side of the boundary or the left side. For example, if new data are the left side of the boundary, these data are considered as ones from the image of A.

5.2. Combination of EEG and NIRS Data

As explained in the latest chapter, we can measure brain activity by EEG and NIRS simultaneously. To exploit this capability, we stochastically combine the results of EEG and NIRS to correctly detect a human's intention. From each data of EEG and NIRS, two results of a human's intention are obtained. At the same time, we can easily calculate the correctness of the resultant class which relates to the distance between considered data and the boundary. In addition, the output of SLR is two of a resultant class

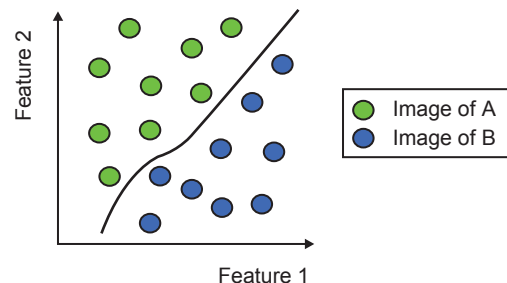


Fig. 6 Image of classification (binary classification shown as example)

and the correctness that can be calculated from the distance between calculated boundary and new data; the correctness is calculated using the distance and the sigmoid function. Since two correctness are calculated from EEG and NIRS, we simply multiply both of them, normalize them and pick up the larger correctness as a final result (Fig. 7).

Let denote P_i^E , P_i^N , I , and T as the probability of the task i by EEG, the one by NIRS, the set of all possible tasks, and the expected task, respectively. The above procedure can be shown in mathematical forms as follows:

$$T = \arg \max_{i \in I} P_i^{Total}$$

Here, P_i^{Total} can be calculated as follows:

$$P_i^{Total} = \frac{P_i^E \cdot P_i^N}{\sum_{i \in I} P_i^E \cdot P_i^N}$$

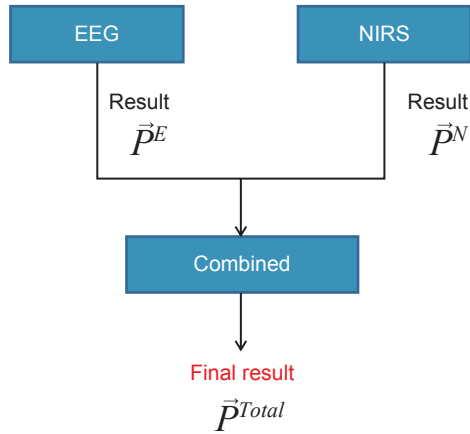


Fig. 7 Combination of EEG / NIRS results

6. Experiments

6.1. Tasks

To validate our BMI system, we use four-motor imagery task which is famous in the community of BMI. In this task, a user's right hand, left hand, tongue or foot is selected and the user imagines the movement of the selected part of body. We did not indicate how to the user should imagine but strictly ordered no body movement while imaging. In this four-motor imagery task, we can easily expect 25% of correctness even if we determine a human's intention randomly. This percentage is called "chance rate" which indicate the expected percentage if you determine randomly. In BMI, the performance of system should be considered comparing this chance rate. It is not necessary to say that we should talk BMI after showing the number of selections and the performance of BMI.

6.2. Experimental Protocol

In this paper, we examine a test consisting of 10 runs (learning sessions) where learning data are obtained and

1 run (test session) where an obtained boundary is tested using test data accordingly. Since the total time of learning sessions is rather long, voluntary intervals are added during sessions.

One run consists of 28 images by combination of each 7 imagery of right hand, left hand, tongue and foot. Here, the order of imagery is random. One image is often called one trial in the BMI community. To indicate which part of the body should be considered, we use a small display in front of a user to order a task. One trial is carried out with a 3-second rest, a beep sound 1 second before task indication, a 1-second task indication, a 10-second imagery and a 6-second rest. To use signal processing easily, we add a 5-second rest and a 10-second rest before an experiment and after an experiment. See Fig. 8 for details.

To learn SLR, we use 280 data (each 70 images of the right hand, left hand, tongue and foot) obtained as learning data in the experimental day and past day (if necessary). After learning SLR, we validate our BMI system using 28 data obtained as test data.

Principally, we do not have to indicate tasks during a test session because the user can freely control a machine or a robot using BMI. However, we indicate the task using the frontal display to evaluate the performance of our BMI since we cannot see a user's intention, that is necessary to check whether the result of BMI is correct or not.

Figure 9 shows examples that identify tasks to a user. To correctly carry out an experiment, we remove EOG signals caused by the movement of eyes and EMG signals generated by the movement of muscles. Furthermore, we

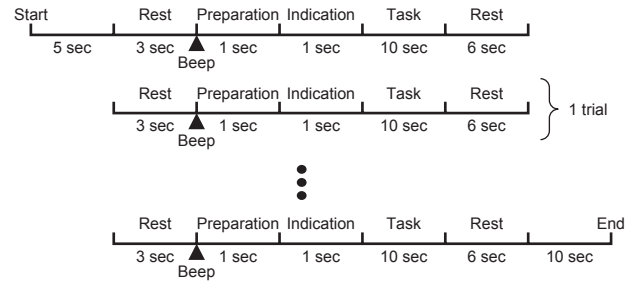


Fig. 8 Experimental protocol. 'One run' includes 28 trials.

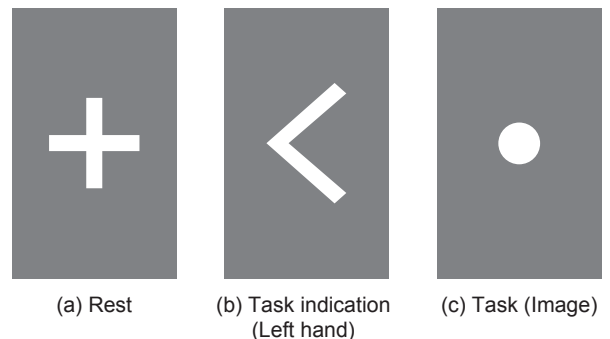


Fig. 9 Indications for subjects

sufficiently avoid big visual stimuli by controlling the brightness of the display.

6.3. Experimental Environment

As explained before, our final target is the usage of BMI in daily life, so we did not use a special environment instead we performed our experiment in a normal meeting room with several windows.

6.4. Sensor Position

The positions of the NIRS sensors on a scalp are shown in Fig. 10. Although EEG can cover a whole head, NIRS cannot because of the restricted number of sensors. Therefore, we install NIRS sensors around the C3 and C4 areas noted in Fig. 10 which are defined by 10-20 method⁽⁶⁾. To cover the C3 area and C4 areas, 4×4 sensors cover one of two. The interval of each sensor is 3 cm.

6.5. Subjects and Informed Consent

Three healthy men (20-40 years old, right handed) participated in this experiment. Based on the ethics provision defined by our company, we explained the details of our experiment and obtained their agreement before carrying out our experiment.

6.6. Performance Evaluation

To evaluate the performance, the correctness in 28 trials in the test session is calculated. Using the latest data in the latest 115 sessions including 10 learning sessions in an experimental day, SLR is learned. Thereafter, 28 trials were tested.

6.7. Data Processing

The data processing used here for EEG and NIRS are as follows. First 9-second data are picked up from original EEG data and adjusted to remove biases. Then, the important sensors are selected and band-pass filtering is done. Finally, we calculate the square of the data and averaged them by moving averaging. These data called as “features” are used for learning SLR. Regarding NIRS, we

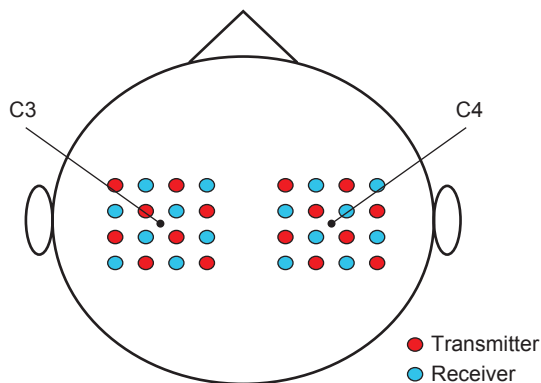


Fig. 10 Positions of NIRS sensors. The red points show transmitters and the blue ones are receivers.

use on-line band-pass filtering, select the important sensors and times. Finally, we carry out moving average to obtain features.

In this flow, several parameters should be fixed, e.g., cut-off frequency, time window, etc. To determine the parameters, we obtained the data for tuning parameters. Using several parameter set, we determined the one of them that shows the best performance of the BMI on the data for tuning parameters. Note that the data for tuning parameters are never used in the validation to avoid overestimation.

7. Results

7.1. Obtained Data

Examples of data obtained are shown in Fig. 11. In Fig. 11, (a) was obtained by EEG and (b) by NIRS. Due to the space limitation, only a part of the data is shown. Each row indicates a task, i.e., left hand, right hand, tongue and foot, respectively, from top to bottom. Using these data and the explained signal processing, we can obtain features which are used as features for the classifier.

7.2. Effects of Newly Developed Methods

The resultant performance of our BMI is shown in Fig. 12. In Fig. 12, 18-day results are shown.

Although a certain variance can be observed, the averaged performance is 91.6% which is world-wide level of 4 motor-imagery tasks in BMI. Note that the performance of 91.6% is little bit different from the one which was introduced on 31st, March, 2009. The main reason of this difference is a change in signal processing.

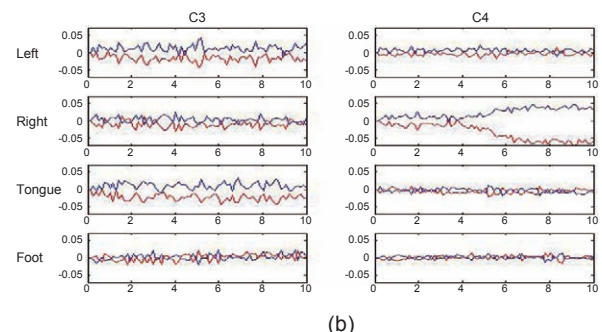
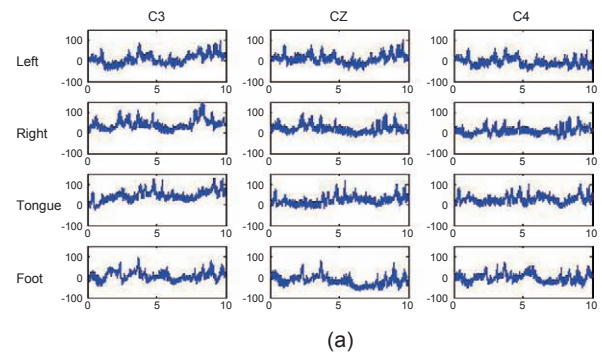


Fig. 11 Raw data of EEG (a) and NIRS (b)

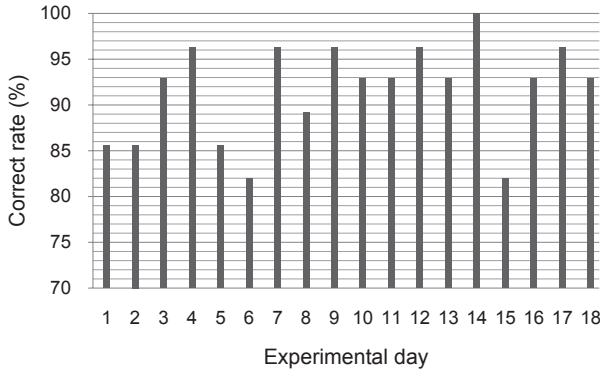


Fig. 12 Performance of our BMI system under 4 motor imagery tasks

8. Demonstration using a Robot

In a test session, we really move a machine. For this experiment, we used a humanoid robot, ASIMO. The intention (right hand / left hand / tongue / foot) determined by our BMI is sent to ASIMO as a command by a wireless LAN, and then ASIMO acts the predefined action shown in Table 1 and Table 2. By this, we can control a robot using a human's intention alone. Note that the tables are one of examples of motions.

When ASIMO receives a result as a command from the BMI system, ASIMO first speaks the sentences defined in Table 1 according to $P_{T^{Total}}$. As explained before, $P_{T^{Total}}$ is the probability of the task T . Then, ASIMO acts and speaks according to T (the expected task) shown in Table 2.

9. Summary and Future Works

This paper introduces a new technology called brain machine interface (BMI) that enables the control of a robot / a machine by a human's thoughts. By developing an information extraction scheme and an EEG-NIRS scanner, we achieved 91.6% accuracy in the 4-motor imagery task. Furthermore, we succeeded in the combination of our BMI and a humanoid robot ASIMO to be controlled by a human's thought alone. In the future, we would like to develop a smaller scanner which can easily be used in our daily life and to improve the performance of our BMI system.

Acknowledgment

This research was done with strong collaboration of the Honda Research Institute Japan, Honda R&D, Advanced Telecommunications Research Institute International and Shimadzu. We appreciate the many staffs for their devoted support. In particular, we would like to express our gratitude to Mr. Takao Sako, Mr. Takahito Tamagawa and Mr. Ryosuke Hayashi. Without their contribution, we could not have finished this work.

Table 1 First actions of ASIMO in BMI experiment

Range of $P_{T^{Total}}$	Action and speech of ASIMO
$P_{T^{Total}} \geq 0.90$	Speaks "Hai, kekka wo uketorimashita. Machigai nai to omoimasu". (Yes, I received the result. I strongly believe that the result is correct.)
$0.90 > P_{T^{Total}} \geq 0.70$	Speaks "Hai, kekka wo uketorimashita. Tabun, atteiru to omoimasu". (Yes, I received the results. Maybe, the result is correct.)
$0.70 > P_{T^{Total}}$	Speaks "Hai, kekka wo uketorimashita. Chotto jishinga arimasenga". (Yes, I received the results. I am not sure that the result is correct.)

Table 2 Second actions of ASIMO in BMI experiments

Image by subject	Action and speech of ASIMO
Right hand	Raises a right hand. Speaks "Migi-desu" (right hand)
Left hand	Raises a left hand. Speaks "Hidari-desu" (left hand)
Tongue	Imitates eating. Speaks "Shita-desu" (tongue)
Foot	Steps. Speaks "Ashi-desu" (foot)

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