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研究課題名（和文）Incorporating Deep Learning and Error Potential Feedback to a BMI System to Enhance User Experience

研究課題名（英文）Incorporating Deep Learning and Error Potential Feedback to a BMI System to Enhance User Experience

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研究成果の概要（和文）：A Brain Machine Interface (BMI) system that integrates an Android robot was successfully developed. Experimental results suggest that android feedback based BCI training improves the modulation of sensorimotor rhythms during motor imagery task to improve the operability of the BMI system.

研究成果の概要（英文）：A Brain Machine Interface (BMI) system that integrates an Android robot was sucessfully developed. The android robot provided realistic visual feedback to the user so that he/she could concentrate better and modulate his/her brain activity. A new training protocol that addresses the deficiencies of the classical approach and takes advantage of body-abled user capabilities was proposed. Experimental results suggest that android feedback based BCI training improves the modulation of sensorimotor rhythms during motor imagery task. Moreover, we discovered that the influence of body ownership transfer illusion towards the android induced thrhough a haptic interface might have an effect in the modulation of event related desynchronization/synchronization (ERD/ERS) activity.

研究分野：Brain Computer Interface

キーワード：BCI

１．研究開始当初の背景

Non-invasive Brain Machine Interface (BMI) systems based on electroencephalography (EEG), have been used to control a robotic wheelchair, home appliances or humanoid robots. The classical approach of a BMI consists in training a classifier to detect changes of brain activity when mental motor imagery (i.e. move left/right hand) is voluntarily generated. Subsequently, detected brain activity is translated into appropriate commands for a computer or robot. This approach highly depends on 1) the system's ability to detect proper motor imagery with accuracy, and 2) the subject's ability to generate the appropriate brain activity that can be recognized by the system.

In past research, a wide variety of methodologies for extracting useful EEG features and detecting motor imagery have been proposed with middle-low acuracy rates. During BMI operation, these medium-low accuracy rates would translate into an unreliable control of the device and may produce user disappointment. Therefore, it is essential to develop new algorithms to improve motor imagery classification accuracy to enhance user experience. Moreover, it is also essential to train the user to module his/her brain activities to operate a BMI. Even if a sophisticated classification algorithm is developed, if the user cannot generate the appropriate EEG brain patterns, the system will not work. For this reason, novel BMI training methodologies that have an enhancing effect on the operator's brain activity are not only important but necessary. As previously mentioned, operating a BMI can be considered as a skill that needs to be acquired through a learning process. However, classical training methodologies might not be suitable for the diversity of learners - since not everybody learns the same way. Therefore, it is necessary to investigate novel training methods that address the deficiencies of the classical training approach and takes advantage of body-abled user capabilities.

２．研究の目的

In this research, we propose a BMI system based on motor imagery that will allow a user to tele-operate a humanoid robot. Although brain activity detection algorithms are important to operate the robot, if the user does not generate efficient brain signal patterns, the system will not work. Therefore, first we investigate BCI training protocols that make the user improve their brain activity based on realistic feedback. The proposed training protocol addresses some of the deficiencies of the classical approach and takes advantage of body-abled user capabilities. The human-like Android robot in this research not only provides a realistic visual feedback, but enables the subjects to have the kinesthetic experience and a demonstration of operation rather than a simple instructed motor imagery. The brain analysis and signal classification is performed using traditional algorithms as well as newly developed algorithms based on deep learning.

３．研究の方法

We conducted a Motor Imagery based BCI experiment with the main goal of finding the difference in performance and changes of brain activity for two groups of users: 1) users who learned to operate a BCI through the classical training protocol (C-BCI), and 2) users who learned through the proposed Android-based training protocol (A-BCI). This experiment was conducted with the approval of the Ethics Review Board of Advanced Telecommunications Research Institute International (ATR), Kyoto, Japan.

Thirty healthy participants were recruited for the experiment most of whom were university students. Data from three participants was not used because it was very noisy and the remaining data from twenty-seven participants (17 males, 10 females) in the age range of 19-25 ($M = 21.5$, $SD = 1.69$) was used. All participants were naive to the research topic and had never used a BCI before. Participants were randomly assigned to one of the two groups giving a total of 13 participants for C-BCI group and 14 for A-BCI group. Subjects received an explanation of the experiment, signed a consent form and were guided to the room where the Android was seated. Participants had the opportunity to experience for the first time the presence of the Android robot and physically touch its hands and face. At the end, participants answered a brief survey and were paid for their participation

Participants sat in a comfortable

chair looking down a screen strategically placed a level above their legs, and were asked to remain motionless. They wore an EEG electrode cap and 27 EEG electrodes were placed over their primary sensory-motor cortex according to the international 10-20 system (FT7, FC5, FC3, FC1, FCz, FC2, FC4, FC6, FT8, T7, C5, C3, C1, Cz, C2, C4, C6, T8, TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8). A reference electrode was mounted on the right ear and a ground electrode on the forehead. Participants were randomly assigned to one of the two groups (C-BCI or A-BCI) and proceeded to conduct the corresponding training while a g.USBamp biosignal amplifier (Guger Technologies) recorded their brain activity. During the experiment, participants were asked to relax and not to move to avoid artifacts.

Classical Training Protocol (C-BCI)

The classical training protocol initially proposed by the Graz group [1] consists of a *calibration* phase for training the system and a *training* phase for training the user before the actual evaluation phase for the intended BCI application. In our experiment, we emulated Graz protocol by using the same three phases: calibration, training and evaluation.

Calibration - Calibration consisted of 40 trials. The timing of events during each trial was performed in the same way proposed by Graz protocol, that is: each trial lasted 7 seconds and started with the display of a fixation cross shown in the center of screen. Participants were asked to rest during the fixation cross. After 2 seconds, a warning was given in form of a "beep" sound. From second 3 to 4.25, an arrow pointing to the left or right was shown and depending on its direction the participant was instructed to imagine a left or right hand movement. This phase was performed without feedback and the recorded data was used to set up a subject specific classifier.

Training - In the same way as calibration phase, for training phase, 40 trials were conducted and the timing of events were kept the same. However, during this phase participants received a unimodal visual feedback indicating the mental task recognized by the classifier together with the confidence in this recognition. The feedback was represented by an extending bar that extended in the required direction if the mental task was correctly recognized and extended in the opposite direction otherwise. The length of the bar

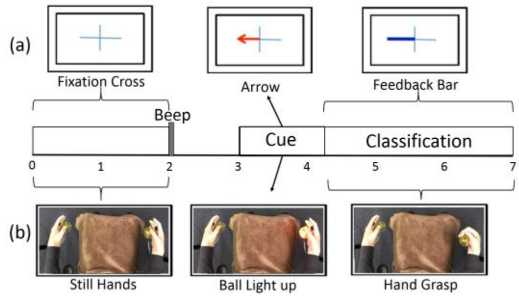

Figure 1. a) Calibration and training phases. b) Evaluation phase

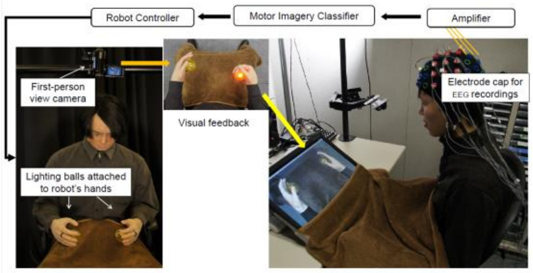

Figure 2. Experimental setup

extension was proportional to the classifier's confidence in its decision (Fig. 1a).

Evaluation - The evaluation phase is when participant's motor imagery skill was tested using the intended BCI application with its corresponding feedback. In our experiment, the intended application consisted in controlling the hands of an android robot, and thus the experimental setup shown in Fig. 2 was prepared and trial timing shown in Fig.1b was implemented for a total of 40 trials.

Android Feedback Training Protocol (A-BCI)}

The proposed Android Feedback based training protocol consisted of four phases: pre-training, training, calibration and evaluation. The order of the phases was proposed this way in order to allow the subject to: 1) rehearse the kinesthetics of hand movements and memorize the physical sensation (Pre-training), 2) practice mental motor imagery by remembering the sensation of the previous phase in order to generate well-defined brain activation patterns (Training), 3) recreate motor imagery practiced in the previous phase and use the data calibrate the classifier (Calibration), and 4) put to practice the learned Motor Imagery skill (Evaluation). Each phase consisted of 40 trials, each lasting 7 seconds. In the same way of the evaluation phase on the classical training protocol, all phases were conducted using the experimental configuration shown in Fig. 2.

Pre-training - This phase was designed to have the user perform motor imagery followed by kinesthetic motor actions for a goal oriented task. After wearing the electrode cap and be seated in front of the display, the user was asked to wear two motion capture markers on the index finger of each hand using finger sacks. A 3D motion-capture system consisting of three Motion Analysis Hawk Digital Cameras and EVaRT motion-capture software was used to track the marker position. Whenever a ball lighted up, participant was asked to imagine grasping the ball for 2 seconds and then slowly physically move his/her own hand with a grasp motion. After tracking the position of the markers, the motion capture system sent the corresponding control command to the robot, providing visual feedback of the robot actions. Participants were told that EEG data collected during this phase was used to train the classification system.

Training - For this phase, motion capture markers were removed and participants were instructed not to move their hands during the experiment. During this phase, participants had to practice motor imagery for the corresponding visual cue observed through the display and received visual feedback of the moving hands of the robot.

Calibration -In the calibration phase, participants had to perform motor imagery after the visual cue, but this time the robot did not move the hands, thus omitting the feedback. EEG data from this phase was used to setup a user-depended classifier to be used in the evaluation phase.

Evaluation - During the evaluation phase, non-biased visual feedback was provided to the participant in accordance to the real output of the classifier.

Classification

The acquired data were processed online under Simulink/MATLAB (Mathworks) for real-time parameter extraction. This process included sampling at 128Hz, cutting off artifacts by a notch filter at 60Hz, bandpass filtering between 0.5 and 30Hz. Although the initial plan was to develop deep learning algorithms to classify the data, after a deep research on the various approaches it was determined that given the small training set (only 40 trials), deep learning algorithms were not the optimal solution for this problem. Therefore, we adopted another algorithm called common spatial pattern (CSP) for a time range of 4s to 7s for every trial, in order discriminate Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) patterns associated with motor imagery task.

CSP method is known to be based on the simultaneous diagonalization of two covariance matrices. During each right or left imagery movement, the decomposition of the associated EEG led to a new time series, which was optimal for the discrimination of two populations. The patterns were designed such that the signal from the EEG filtering with CSP had maximum variance for the left trials and minimum variance for the right trials and vice versa. For classification, the variances of left and right trials were extracted as reliable features in order to build a feature vector and construct a linear classifier. In order to discriminate between left and right imaginations, the output probabilities of the linear classifier were mapped to a range of [-1,1], where -1 denotes the extreme left and 1 denotes the extreme right.

Brain Activity Data Analysis

To quantify the impact of the two types of training protocols, we computed time-frequency maps using the data for each group separately after removing local peak artifacts by artifact subspace reconstruction (ASR). EEG oscillations in the *mu* frequency band (8-13 Hz) recorded over pre-motor cortex are known to be influenced by imagining of motor actions. For all EEG epochs obtained during motor imagery segment in each trial (seconds 4 to 7) and rest segment in each trial (seconds 0 to 2), the integrated power was computed using a fast Fourier transform. Power in the *mu* frequency band at scalp locations corresponding to left and right sensorimotor cortex (C3 and C4) during motor imagery was compared to power during the baseline (rest) condition. This was done by computing the ratio of ERD over ERS.

Negative and positive values of ERD/ERS ratio correspond to ERD and ERS accordingly. *mu* rhythm is defined as oscillations measured over sensorimotor cortex, thus only data from C3 and C4 are

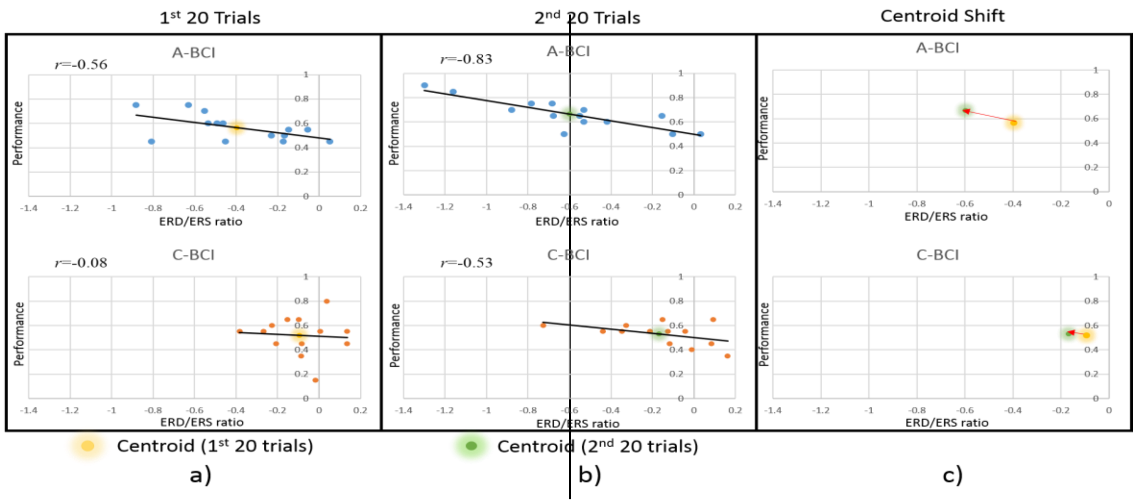

Figure 3. Average ERD/ERS ratio (x axis) from C3 and C4 channels combined for each participant during the evaluation session plotted against their corresponding performance (y axis): (a) First half (1st 20 trials) and (b) Second half (2nd 20 trials)

presented. A ratio was used to control for variability in absolute *mu* power because of individual differences such as scalp thickness and electrode impedance, as opposed to differences in brain activity.

4．研究成果

Figures 3 (a) and (b) show the average ERD/ERS ratio from C3 and C4 channels for each participant during the evaluation session plotted against their corresponding performance. In order to appreciate the changes of ERD/ERS ratio in the *mu* band throughout the session, also known as *mu* suppression, the average ERD/ERS ratio is shown for the first half (1st 20 trials) and second half (2nd 20 trials) of the session along with the corresponding centroids. Pearson product-moment correlation of *mu* suppression and performance computed for the first half indicates a moderate downhill linear correlation in the A-BCI group (r=-0.56) and almost no linear correlation in the C-BCI group (r=0.19). However, in the second half, the A-BCI group shows a stronger downhill correlation (r=-0.83) and the C-BCI group shows a moderate correlation (r=-0.33). Figures 3 (c) shows the centroid shift from the first half to the second half of the session as vector. Compared to C-BCI group, A-BCI group clearly shows a larger centroid shift in direction to a stronger *mu* suppression and higher performance.

We performed t-tests to compare the *mu* suppression of C-BCI and A-BCI groups as indicated by a ratio obtained from the left and right hemisphere electrodes during the corresponding motor imagery (C3 for right MI and C4 for left MI). Fig. 4 shows that the *mu* suppression in both left and right hemispheres of the A-BCI group was significantly larger than the *mu* suppression of the C-BCI group in overall training, calibration and evaluation phases: A-BCI<C-BCI$ (Calibration: C4 t(26) =-0.52, p=0.013; C3 t(26)= -0.29, p=0.033; Training: C4 t(26) =-0.23, p=0.029; C3 t(26)= -0.29, p=0.047; Evaluation: C4 t(26) =-0.60, p=0.005; C3 t(26)= -0.29, p=0.056. These results suggest that subjects of the A-BCI group where able to modulate the sensory-motor rhytms better than subjects of the C-BCI group.

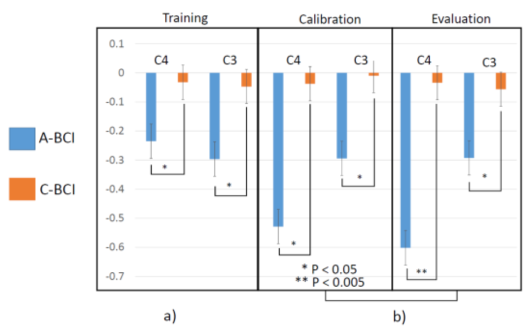

Figure 4. ERD/ERS ratio during each of the experiment

Subject's Online Performance

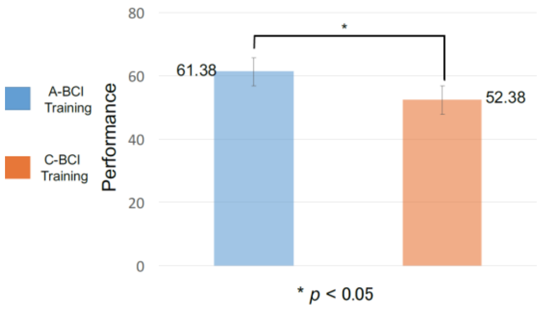

Figure 5. Motor imagery classification performance

The performance metric consisted of the percentage of correct classifications during the evaluation phase only. Results (Fig. 5) showed that participants of A-BCI group had a slightly better performance (Mean=61.38, SD=9.82) as compared to the C-BCI group (Mean=52.38, SD=10.21) with a statistical difference of p=0.025. A permutation test on the data from the two conditions was also conducted (10,000 permutations, alpha=0.05) giving as a result a probability of 2.13 (p=0.021) of how often the observed result would occur if it was random; thus we conclude that the difference in performance between the two groups is statistically significant.

Conclusion

In this research, we proposed a BMI system based on motor imagery that will allow a user to tele-operate a humanoid robot. To operate the BMI, it is important for the user to be able to generate appropriate brain signal patterns that can be recognized by a classification algorithm. Generating these brain patterns are not a trivial matter and thus, most of the research was dedicated to finding effective ways to train the user to generate optimal brain signal patterns for operating a BMI. Therefore, we investigated BCI training protocols that make the user improve their brain activity based on realistic feedback. The proposed training protocol addresses some of the deficiencies of the classical approach and takes advantage of body-abled user capabilities. The human-like Android robot in this research not only provided a realistic visual feedback, but enabled the subjects to have the kinesthetic experience and a demonstration of operation rather than a simple instructed motor imagery. The higher MI classification performance and stronger mu suppression achieved by the experimental group who used the proposed training protocol indicate that in overall there was a positive effect and improvement in the usage of the BMI.

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５．主な発表論文等

〔雑誌論文〕（計　１件）

① Christian I. Penaloza, Maryam Alimardani, and Shuichi Nishio, Android Feedback based Training modulates Sensorimotor Rhythms during Motor Imagery, IEEE Transactions on Neural Systems and Rehabilitation Engineering, （レビュー中）

６．研究組織

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