A SLAM Integrated Hybrid Brain-Computer Interface for Accurate and Concise Control

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***Abstract*—In this paper we present a hybrid brain-computer interface (BCI) system that manipulates simultaneous localization and mapping (SLAM) for convenient control of a robot. Due to the low accuracy of classifying multi-class neural signals, using brain signals alone has been considered inadequate for precise control of a robotic systems. To overcome the negative aspects of BCI systems, we introduce a hybrid system where the BCI control of a robot is aided by SLAM. Subjects used electroencephalography (EEG) and electrooculography (EOG) to remotely control a turtle robot that is running SLAM in a maze environment. With the supplementary information on the surroundings provided by SLAM, the robot could calculate potential paths and rotate at precise angles while subjects give only high-level commands. Subjects could successfully navigate the robot to the destination showing the potential of utilizing SLAM along with BCIs.**

***Index Terms*—brain computer interfaces, simultaneous localization and mapping, electroencephalography, robot control**

I. Introduction

Brain-computer interfaces (BCIs) are systems where humans can use their brain signals to communicate with a computer or a device. While the use of BCIs have been researched widely over the past few years, the application of BCIs in controlling robots and vehicles has been of great interest. Non-invasive BCIs that use electroencephalography (EEG) and electrooculography (EOG) to control not only wheelchairs but also drones or robots have been widely researched .

Precision is crucial when controlling robots or vehicles. Unlike the traditional techniques of controlling, such as keyboards or joysticks, BCIs often lack the precision in their control mechanics. This is because accurately classifying the subjects commands from neural signals is highly difficult. Because classification accuracy greatly decreases as the number of classes to categorize into increases, emerging BCIs tend to support only the minimum number of commands. This means that subjects can only make high-level commands such as move forward or turn left, making accurate control and navigation of the robotic system much more difficult.

While forward movements are fairly simple, turning left or right, or rotating at a certain angle require more precision than just turn left and turn right commands. If a system could predict users' intended direction of rotation, users may use simpler commands instead of having to continuously interact with the system. To cover up for the lack of precise user commands, the precision of machines and their ability to recognize the environment are utilized. For example, new wheelchair interfaces are proposed where the human and the wheelchair have shared control, and the use of sensors such as LiDARs and Kinects have been proved to make the navigation of such machines easier [1] [2] [3].

In this paper, Simultaneous Localization and Mapping (SLAM) is manipulated with BCI for easier control of a turtle robot [4]. Using a mixed model of EEG and EOG, subjects navigate the robot across a maze using only the commands move forward, turn left, or turn right [5]. The robot, equipped with a LiDAR and an IMU, runs SLAM within the maze environment. Using the information about its location and surrounding, the robot finds potential paths that the subject could direct to and rotates exactly to the direction of that path at the subjects commands. This way, even though subjects can use only a limited set of commands, the robot can maintain precise movements by determining the subjects intended path and adjusting to its environment. The results show that with the hybrid BCI system, subjects are able to navigate through the maze easily with their limited commands.

The remainder of this paper is organized as follows. We first explain the details of the hybrid BCI. Then we describe the procedure of our experiments and share our results. Finally we conclude with a general discussion on limitations and future works.

II. Methods

A. Overview

In the proposed hybrid brain-computer interface (BCI), the control of the robot was shared between the subject and the robot controller. The subject, through the BCI, had control over the high-level movements of the robot such as to move forward or to turn left, while the robot controlled the precise movements such as how much to turn. Fig. 1 shows the control flow between the BCI, robot controller and the robot hardware. Communication between the BCI and the robot controller was done through TCP sockets while communication between the

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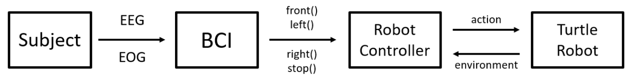

Fig. 1. Control flow of the hybrid BCI system.

robot controller and the hardware was done through Robot Operating System (ROS) Topics [6].

B. BCI

The BCI was responsible for sending high-level commands to the robot. To send these commands, subjects used a combination of electroencephalography (EEG) and electrooculography (EOG). To measure the EEG and EOG signals from the subjects, BrainProducts actiCHamp actiCAP was used. Both the EEG and EOG signals were obtained from four dry electrodes from the frontal cortex of the subject (F7, FP1, FP2, F8). The ground electrode and the reference electrode were placed on the forehead and on the TP10 electrode respectively. Fig. 2 shows the configuration of the electrodes used. A band-pass filter was applied to our signals to filter the data within the 1 to 15Hz frequency range.

The EEG model was used for classifying neural signals of forward movements and resting states: subjects concentrated start or stop the forward movement of the robot and remained still to take no action. The EOG model was used for classifying neural signals of left and right rotations: subjects blinked their left or right eye to make the robot turn left or right respectively.

In order to classify both the EOG and EEG signals, classification models for the two signals were constructed separately. For the classification of eye blinking signals, xDAWN algorithm was used to lessen the noise from the signal. The support vector machine (SVM) was utilized for building the classification model. For the EEG signals, a common spatial pattern (CSP) was used in order to extract features during concentration. The signals were then applied to the SVM for the classification model.

C. Robot Controller

The robot system was built on top of the iClebo Kobuki Turtlebot 2. The ROS integration of the 2D SLAM algorithm of Google Cartographer was used with Microstrain's 3DM-GX5-25 as the IMU and Velodyne LiDAR's PUCK VLP-16 as the point scanner, both of which were built on top of the Kobuki Turtlebot.

The robot controller was responsible for forwarding the commands from the BCI to the robot, while also considering the current environment. Furthermore, the robot was responsible for keeping track of the position of the robot relative to the current map, which was managed using the information provided by SLAM. With the information from SLAM, the robot controller performed two main functions: path dependent rotation and obstacle aware movement.

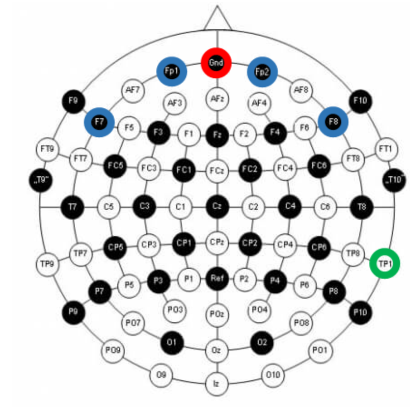

Fig. 2. The four dry electrodes for EEG and EOG signals are indicated in blue. The ground electrode is indicated in red and the reference electrode is indicated in green.

When subjects commanded the robot to turn either left or right, the robot controller used its position and map information to immediately find all the potential paths that the robot could head into. By setting a minimum length and width for potential paths, and searching its surrounding map for such paths, the robot controller formed a list of all the paths the robot could take from the current point. This can be represented as the following equation:

$$paths = \{a | -\pi \leq a < \pi, free(a, p, l, w)\} \quad (1)$$

where a is the angle of the path, p the current position of the robot, l the minimum length of a path, and w the minimum width of a path, such that *free(a,p,l,w)* returns whether a l meter long and w meter wide path starting from p at an angle of a is free. Fig. 3 shows how (1) chose potential paths in respect to the robot's surroundings.

Using its current position on the map, the robot decided the closest path on the left or right side. Once the goal path was

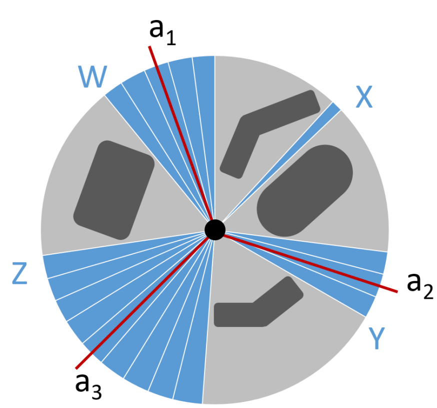

Fig. 3. The robot is represented as the black circle in the middle and obstacles are indicated in dark gray. The blue sections (W, X, Y, Z) indicate paths with no obstacles along the way and the red lines (a_1, a_2, a_3) indicate the final chosen paths. No paths are chosen from section X because it does not meet the minimum width.

chosen, the robot rotated towards that direction until its global orientation matched the orientation of the goal path. With this algorithm subjects didn't have to continuously send commands to the robot in order to control the length of rotation. Instead subjects only had to send a single command every time they wanted to rotate to the next path.

When subjects commanded the robot to move forward, the robot controller used the information from SLAM to make sure that there were no obstacles directly in front of the robot. If any obstacle or wall appeared within the minimum safe distance, the robot instantly halted. This function was added because the inaccuracy of EEG signal classifications could lead to the subject not being able to successfully send a stop command to the robot in urgent situations. Because the robot could only move forward, the minimum safe distance was checked only at the front of the robot.

III. Experiments

Five male subjects aged between 22 to 27 volunteered to carry out the experiments. 2 subjects had previous experience with BCIs while the rest had no experience. Each subject performed one trial of the experiment, consisting of a model training session followed by a robot navigation session. Subjects were required to keep the actiCAP on for the whole duration of the experiment, from the beginning of the model training session until the end of the robot navigation session. Before the start of the experiment, subjects were briefly informed by the instructor about the steps of the experiment and were also allowed to take a look around the map.

A. Environment

The experiments were performed in a maze-shaped map in a closed room of roughly 7 meters by 7 meters in size. The shape of the maze changed randomly for each subject but it always contained at least three branches. At the beginning of the experiment, the robot was positioned at the leftmost branch of the maze, facing the center of the map. Different positions on the map were numbered randomly, acting as destinations for the robot. After the subjects took a look around the map in the first room, they were sent to a second room, so that the only way to observe the position of the robot was through the map visualizer on the laptop provided.

B. Model Training

Before controlling the robot in the navigation session, subjects had to complete a model training session. Subjects were seated in the second room, in front of a laptop through which the EOG/EEG signals were to be classified. The training session took roughly five minutes for each model and consisted of 10 trials of EOG training and 10 trials of EEG training.

At each trial of the EOG training, subjects were visually cued with the words "blink left eye", "blink right eye", and "rest". Right after each cue, subjects were required to perform the action by blinking their left eye, blinking their right eye, and resting (gazing at the monitor) respectively. The changes in EOG signals when subjects blinked their left and right eye are shown on Fig. 4. For the left eye blink, signals on the F7 and FP1 channels changed significantly while for the right eye blink, signal changes mainly occurred on the F8 and FP2 channels.

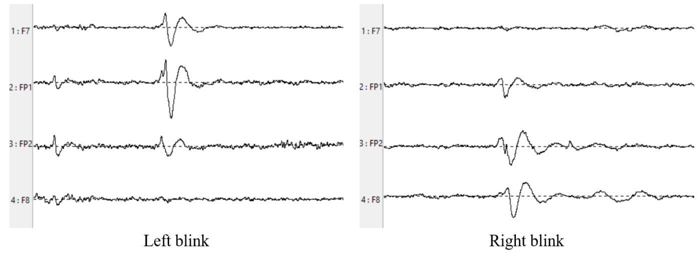

Fig. 4. Visualization of the EOG signal changes on the four electrodes from the frontal cortex: (from the top) F7, FP1, FP2, and F8.

After the EOG training was finished, at each trial of the EEG training, subjects were visually cued with the words "concentrate" and "rest" where subjects were required to either concentrate on the screen or just rest after each cue. For the concentration phase the subjects were asked to lightly close their eyes and focus on their breathing until the screen in front of them flashed to indicate the end of the phase. While subjects kept their eyes closed, 5 two second EEG samples were collected sequentially. During this period an increase in the power spectral density of EEG signals in the alpha frequency range could be detected [7].

C. Robot Navigation

Once the model training session finished, subjects were instructed to control the robots. Subjects could observe the position of the robot only through the laptop which displayed a birds-eye view visualization of the map produced by SLAM running on the robot.

At the beginning of the robot navigation session, subjects were given a random sequence of numbers by the instructor. Each number indicated a specific area in the maze-shaped map and the subjects were required to navigate the robot to visit each of these points in the given order. To control the robot, subjects were expected to perform the actions that correspond to the intended command: left blink to turn left, right blink to turn right, concentrate to start/stop moving forward, and rest to do nothing.

IV. Results

To examine the positive impacts that SLAM can have on the proposed hybrid BCI system of this paper, the accuracies of the detection of EOG and EEG signals were calculated separately. The accuracies shown on Table I were calculated using 10-fold cross validation, where the signals from a single trial were tested with a classification model built from the rest of the signal data.

The cross-validation results for EOG signals contained three classifications: right eye blinking, left eye blinking, and resting state. The average accuracy of the evaluation of EOG classification for the five subjects was 84.6%, with subject 2

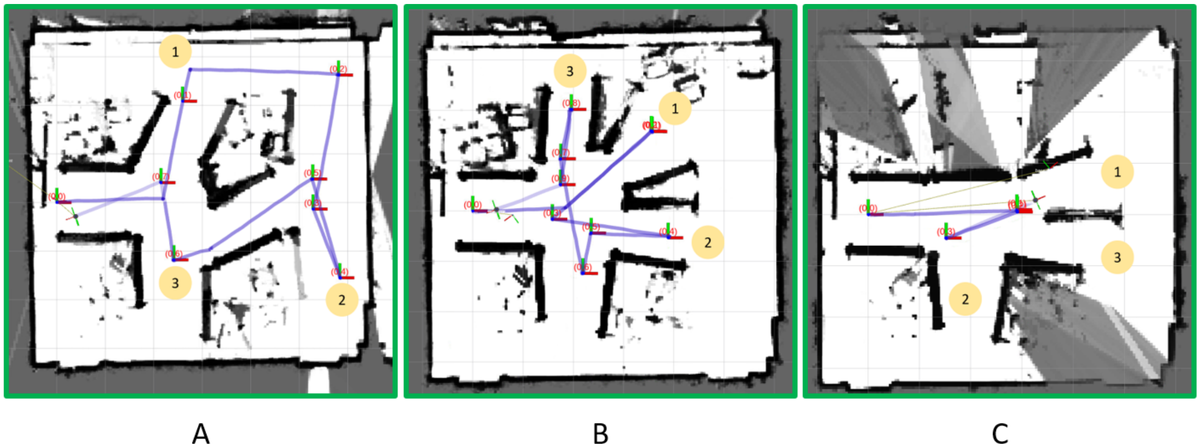

Fig. 5. Figures A and B show the trajectories of successful trials. The circular numbers represent the destination points on the map. The robots were required to visit each destination point in increasing number order. Figure C shows the trajectory for an unsuccessful trial where the robot got stuck at an obstacle not shown on the map.

having the highest accuracy of 97% and subject 1 having the lowest.

The evaluation for EEG signals contained two classifications: resting state and concentration state. Signals from a single trial, which consisted of 10 two second resting and concentration EEG samples, were evaluated while the EEG data from the remaining trials were used to build the classification model. The accuracies for the five subjects in the EEG cross validation were averaged at 78.4%, with the highest and lowest accuracies of the individuals being 88% and 66%, respectively.

In addition to the cross validation of the EOG and EEG signals, the navigation of the robot using the hybrid BCI was examined. Ultimately, 4 out of 5 subjects were able to finish the task provided by the instructor. One subject failed to finish the given task due to a small obstacle that was outside the scanning range of the LiDAR. The command through the BCI took a certain delay and the robot crashed with the obstacle, which led to the stop of the experiment for that subject. Although one subject failed to complete the given task, 4 other subjects successfully navigated the vehicle through the desired positions.

Fig. 5 shows the trajectories of the robot's movements for successful and unsuccessful trials, plotted using RViZ. Fig. 5-A and 5-B show that in most cases, only a single command was needed to rotate to the correct direction from a junction.

TABLE I
CROSS VALIDATION ACCURACY

Subject	EOG	EEG
1	0.73	0.86
2	0.97	0.82
3	0.80	0.66
4	0.80	0.88
5	0.93	0.70
Av.	0.85	0.78

Furthermore, Fig. 5-A shows the case where the robot stopped autonomously when it confronted an obstacle (at area 1), thereby preventing itself from crashing. The trajectory for the failed trial shown on Fig. 5-C shows that the robot did not return to its original position, implying that the experiment was aborted. Although the obstacle was positioned right in front of the robot, the LiDAR was not able to recognize it, as shown on the map.

V. DISCUSSION

We have proposed a new hybrid BCI system that manipulates SLAM to make the control and navigation of a robot through a given maze easier. By using the information from SLAM, precise autonomous control of the robot such as path dependent rotation and obstacle aware movement was possible.

However these designs of our system are quite inflexible and have many limitations. The path dependent rotation can only work in fork-shaped environments such as the maze-shaped map in our experiment. Although this could be useful in environments with many branches such as corridors, out in the open this mechanism would not work. Furthermore, because we use the map information from SLAM to detect obstacles, while stationary obstacles such as walls can be easily detected, moving obstacles such as people or cars would not be detected as obstacles. Like this, real life environments will be much more complex than the simple maze environment we experimented in. With effective manipulation of information from SLAM, we aim to create more flexible hybrid BCIs that support automatic path finding and dynamic obstacle detection.

Through this study we have shown the potential of combining SLAM with hybrid BCIs. Although BCIs are researched widely these days, current technology does not support applications of BCI that are suitable for daily use. Due to the low classification accuracy of neural signals and the large amount of training needed beforehand, using BCIs alone to control mobile robots is not feasible. In this paper we aimed to solve this problem with a system that manipulates external sources of information and as a result requires less work from BCIs.

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