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Vision Combined with MI-Based BCI in Soft Robotic Glove Control

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***Abstract*—This work focuses on reducing false execution of brain-computer interface(BCI) based Soft Robotic Glove by considering visual information received by the first-person-view camera equipped by the user. The proposed method intends to seek to lower the false positive rate while providing an intuitive interface by allowing the glove to execute depending on motor imagery(MI) only when the hand is in sight. When the hand is out of sight, no electroencephalogram(EEG) information is given to operate the glove. Two sessions of online soft robotic glove control were conducted on six participants, one session each for BCI-based and BCI/Vision-based glove control. The result showed that using visual information with BCI helped the participants remain rested than they did with BCI-based soft robotic glove. However, additional experiments from different participants are necessary to ensure the effect that using visual information could have on grasping and releasing action of BCI-based soft robotic glove as well.**

***Keywords*—BCI, EEG, motor imagery, soft glove, vision based**

I. Introduction

People with a disease such as a stroke often end up with either partially or fully impaired hand function, which requires them to receive help in a daily task such as object grasping. The help of assistive tools for gripping objects is crucial in the sense that it can ease the burden of patients with impaired hand function in such tasks by enabling them to perform fine movement of hands. For this reason, glove based wearable soft robots were implemented in various works [1]–[5].

When using wearable soft robots, being able to hold objects at the right timing based on the user's desire is important for a good user experience. In other words, applying the grasping forces of the soft robot by accurately recognizing the moment the user intends to hold an object leads to a satisfying experience. For instance, precisely recognizing the moment the user plans to perform an action could prevent unnecessary grasping actions by the soft robot even when the user didn't mean to. By preventing such possibly uncomfortable experiences, the user's satisfaction may improve. Thus, it is essential that the robot accurately interpret the user's purpose.

The brain-computer interface (BCI) is widely used to interpret a user's intention by converting brain signals into a computer command. Numerous BCI paradigms have been applied to control devices such as robots or wheelchairs in other works [6]–[8]. Among all the paradigms, studies that involved motor-imagery(MI) based BCI, a BCI paradigm that requires the imagination of a body movement such as hand, feet, or tongue movement, provides meaningful performances in various device control [9] [10]. Therefore, employing MI-based BCI is one way of manipulating the soft robot based on the user's intention using electroencephalogram (EEG). On top of that, MI-based BCI could provide intuitive control for the user especially when the user has to move a soft robotic glove. Nevertheless, device control methods purely based on MI-based BCI possess a critical drawback that limits its usage. High false positive rate (FPR) [11], where FPR refers to the rate of incorrect classification when the user has no intention of controlling a device, is a problem that comes with using BCI and MI-based BCI is no exception. Poor FPR is often exhibited especially when BCI is performed in an asynchronous (self-paced) manner [12]–[14]. For this reason, FPR is used as an evaluation metric to assess the performance of MI-based BCI which is an example of asynchronous BCI [15]–[17].

We propose a BCI/Vision-based soft robotic glove that can resolve a previously mentioned limitation of BCI by taking visual information into account while recognizing the user's intention. The visual information is received by a first-person-view camera that is attached to the glasses. The camera constantly receives an image which is later processed by ResNet18 to recognize whether the soft robotic glove is within the received image frame or not. The MI EEG signal will not be in use unless the glove is spotted in the input image. For instance, if the user imagines the MI of a 'Right hand' while the glove is within sight, the glove either performs a grasp or a release action. However, if the glove is not fully in sight, MI EEG signal is not decoded, hence no command is not given to control the glove.

This approach shows a significantly lower FPR than a pure BCI approach. Our approach can achieve this while providing an intuitive interface when the user attempts to grab an object as the camera captures the surroundings from the first-person point of view.

II. Methods

A. Wearable Soft Robot Control Strategies

The soft robotic glove control strategy consists of decoding visual information and EEG. Brain signals are obtained by

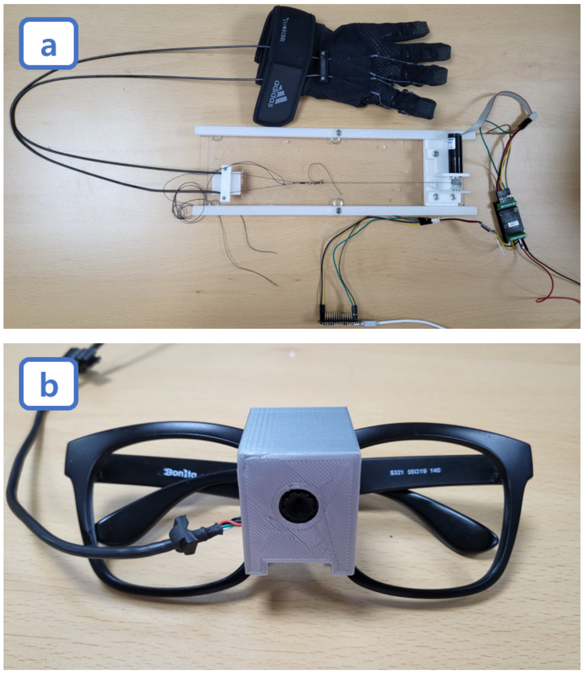

Fig. 1: (a) The tendon-driven soft robotic glove for grasping. (b) The vision glasses with a camera attached.

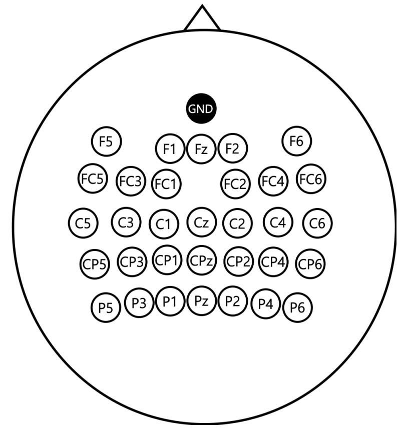

Fig. 2: The electrodes positions for the 32-channel EEG acquisition. EEG signals are referenced and grounded to channel Fz and AFz, respectively.

a brainvision recorder and visual information is received by the first-person-view camera attached to the glasses. Visual information decides whether the soft robotic glove should ignore the EEG information or not while the EEG information decides whether the soft robotic glove should be executed or not. Due to the higher priority of visual information over EEG information, no EEG information will go through under certain visual conditions. When EEG information goes through, a soft robotic glove will either rest or operate. All in all, the glove is executed based on given information about visual and EEG.

B. Hardware

1) Wearable soft robotic glove: In this study, we use tendon-driven soft robotic gloves to assist in grasping objects. As shown in Fig. 1a, the tendons are wired from the actuator to the glove along the palmar side of the index finger and the middle finger through cables.

The glove has FSR402 sensor attached to the fingertip of the index finger. The sensor value received by the sensor reflects the pressure applied to the index finger. When the pressure value exceeds the threshold, the glove detects an object and stops the grasping motion. The glove uses the sensor value to suitably grasp objects that differ in size and shape.

2) Vision glasses: As shown in the Fig. 1b, the vision glasses have a camera attached to the center of the glasses placed at an angle similar to the person's gaze. The glasses are based on the work of Kim et al. [2].

C. EEG Acquisition

To obtain the EEG data from participants, Brainvision antiCHamp was used. A total of 33 electrodes were used, mainly placed around the sensorimotor cortex to record the EEG of the participants, having AFz as the ground and Fz as the reference electrode. The brain signal was acquired with a sampling rate of 500Hz.

D. Classification Model

Our method involves two different classification tasks, hand detection, and MI classification. Thus, it requires two models that are dedicated to each task.

ResNet18 is used to detect whether the hand wearing a soft robotic glove is completely included in the image received by the first-person-view camera or not. The model we used was trained using manually labeled images, each labeled as either 'hand' or 'background'.

Images were acquired from each frame of a video that includes the surroundings and the hand wearing a soft robotic glove. Each frame is resized into an image of size 224 x 224 before it is given as an input to the model. ResNet18 classification result is displayed on the screen with the word 'Hand' if a hand wearing a robotic glove is detected. Otherwise, 'Background' will be displayed on the screen indicating that no hand is detected in the most recently received image. The model labels an image as 'hand' only when the glove is completely included in the image. Partial inclusion of the glove in the image will be regarded as 'background' by the model.

We used *Shallow ConvNet* in order to perform MI classification [18]. For each subject, training data obtained during the training session was preprocessed using data augmentation, where the data was split into 2 second time windows with a stride of 0.1 seconds. The data were band-pass filtered between 4 and 38Hz. The model was trained using the training set produced by the aforementioned process. During the online sessions, the model receives the most recent 2 second time window of EEG every 0.5 seconds and classifies the signal into either 'Right hand' or 'Rest'.

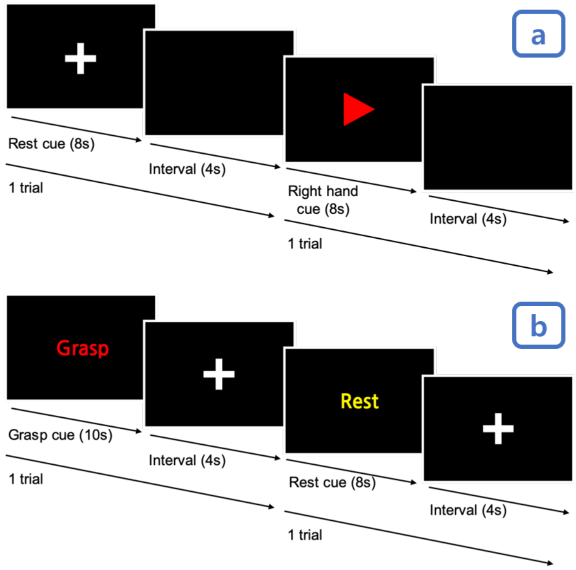

Fig. 3: (a) The figure is the protocol of the train session and it is the example of the screen which we showed to participants. The figure shows two trials, each 'Rest' cue, and the 'Right hand' cue. (b) The figure is the protocol of the online session and it is the example of the screen which we showed to participants. The figure shows two trials, each 'Grasp' cue, and the 'Rest' cue.

E. Participants

We recruited six male participants for this study. Participants were 22-27 years of age, all of them healthy without any disability. All the participants have prior experience of BCI and half of them have experienced MI-based BCI device control.

F. Experimental Procedure

There are three sessions in the experiment: one MI training session followed by two online soft robot control sessions, each session being BCI-based control and BCI/Vision-based control session. We divided the participants into two groups. Each group participated in the online session in a different order, one group starting the session with BCI-based control first and the other group starting with BCI/Vision-based control first.

1) Data Collection: The MI training session for collecting the data is comprised of 20 trials of two MI tasks: 'Right hand', 'Rest'. Each trial involves 8 seconds visual cue display and 4 seconds interval. While the visual cue is displayed on the screen, the participant either imagines the movement of the right hand or rest. Fig. 3a shows the protocol of the training session. Participants are asked to imagine nothing while the 'Rest' cue is displayed and right hand movement when the 'Right hand' cue is displayed. The order of tasks in the section is a repetition of 'Rest' and 'Right hand' throughout the session. A red triangle pointing right and fixation cross is given as visual cues for the 'Right hand' and for the 'Rest' command, respectively.

2) Online Evaluation: The online control of BCI-based glove consists of 20 trials that involve three commands 'Rest', 'Grasp', and 'Release'. When the user is asked to imagine the right hand movement, 'Grasp' is displayed on the screen when the glove is already in a released state and 'Release' is displayed when the glove is in a grasping state. 'Rest' is displayed on the screen when the user is expected not to move the glove. Thus, 10 trials ask the user to perform 'Rest', and the other 10 trials display either 'Grasp' or 'Release' which asks the user to imagine the right hand movement to execute the soft robotic glove. The order of commands is given in a random order, but the order for BCI and BCI/Vision-based control sessions are identical. Each trial of the session lasts 14 seconds, where 10 seconds is given to carry the command and 4 seconds is given as the interval for the participant to rest. Visual cues are given to the participants by displaying a word on the screen during the command part and fixation cross during the interval. Fig. 3b simply shows the experimental protocol of the online session. The same procedure follows for online control of BCI/Vision-based glove. The only difference is the presence of vision glasses

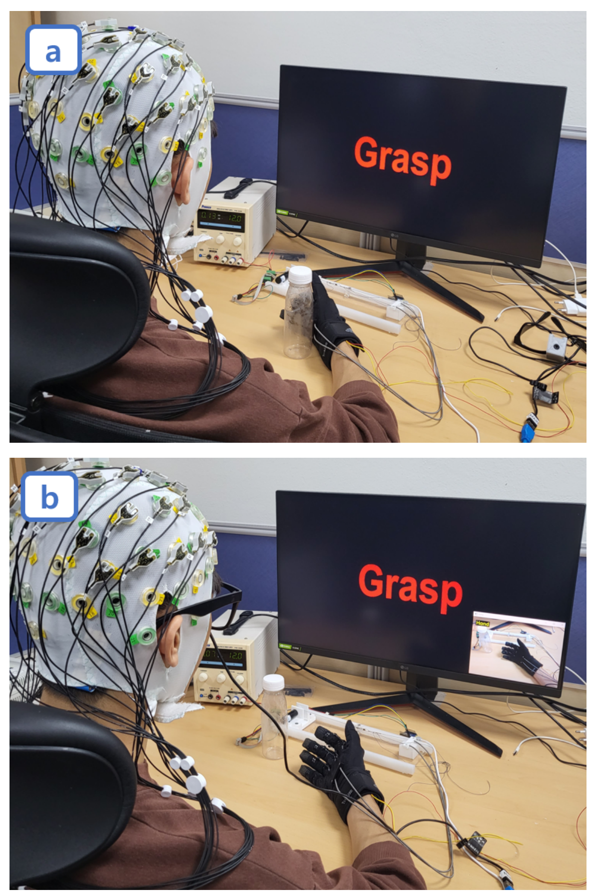

Fig. 4: (a) The figure is the BCI-based online session. It shows the command by GUI cue. (b) The figure is the BCI/Vision-based online session. It shows the GUI cue and the camera frame with the classification result in real-time.

TABLE I: Online session result of soft robotic glove control after 5 minutes of training. Value of 'Rest' and 'Right' denotes the number of correct trials out of 10 trials each. 'Total' refers to the number of total correct trials out of 20 trials. Subject 1,2, and 3 started the online session with BCI session followed by BCI/Vision session (group 1) while subject 4,5, and 6 started the session with BCI/Vision session first and ended with BCI session (group 2).

	BCI			**BCI/Vision**		
Subject	Rest	Right Hand	Total	Rest	Right Hand	Total
1	8	6	14	10	6	16
2	3	10	13	9	10	19
3	0	10	10	10	10	20
4	0	10	10	7	10	17
5	6	10	16	9	5	14
6	1	10	11	10	8	18
Average	**3/10**	**9.33/10**	**12.33/20**	**9.17/10**	**8.17/10**	**17.33/20**

TABLE II: The average response time of the 'Rest' cue and FPR of each online session by subject. The response time refers to the average time spent until the participant executed the glove during the 'Rest' cue. If the user successfully rested, the response time is recorded as 10 seconds. The FPR is an inaccurate classification rate during the 'Rest' cue.

	Response Time		**False Positive Rate**	
Subject	BCI	BCI/Vision	BCI	BCI/Vision
1	8.65	10.00	0.2	0.0
2	4.15	9.09	0.7	0.1
3	2.41	10.00	1.0	0.0
4	2.52	8.17	1.0	0.3
5	6.88	9.10	0.4	0.1
6	1.91	10.00	0.9	0.0
Average	**4.42**	**9.39**	**0.7**	**0.08**

showing the visual information that the camera is receiving, which is displayed on the bottom right side of the screen. Fig. 4a shows the command screen of BCI-based glove control and Fig. 4b shows the command screen of BCI/Vision-based glove control which includes the camera screen that the BCI-based control session screen did not have.

During the online evaluation, we obtain the number of successful trials from each participant. A trial is considered a success in 'Grasp' and 'Release' when the user succeeds to execute the soft robotic glove within 10 seconds. With 'Rest' on the screen, it is considered a success if the user manages to keep the glove still without moving it for 10 seconds, but is regarded as a failure if the glove moves before the 10 seconds mark passes.

Furthermore, the average response time and FPR of 'Rest' are computed from the result of BCI and BCI/Vision, and the respective values are compared. The response time represents the elapsed time until the user executed the glove when the 'Rest' cue was given. If the user successfully kept the glove from operating, the response time was recorded as 10 seconds. FPR is the rate of false execution that happened during the 'Rest' cue of the online session.

The voting method is applied in operating a soft robotic glove in the online session. A trained *Shallow ConvNet* receives a 2-second time window every 0.5 seconds and the result is pushed into a voting list. A voting list is a queue that contains the five most recent classification results from the model. A result that receives the most votes in a voting list is adopted in executing the robotic glove.

III. Results and Discussion

The numerical result of BCI-based and BCI/Vision-based soft robot control session from every participant is given in table I. Subject 1,2,3 started the session with the BCI session while the other three started with BCI/Vision session. The value in the table refers to the number of trials correctly executed by the participants. For instance, subject 1 performed 8 successful trials out of 10 'Rest' trials and 6 successful 'Right Hand' trials out of 10, going through 14 trials correctly out of 20 trials in the BCI session. Participants correctly executed 12.33 trials in the BCI session while the number improved to 17.33 in BCI/Vision session to record 61.67% and 86.67% accuracy in each session, respectively. The result indicates that the classification average improved significantly in the BCI/Vision session. This is due to a huge difference in the average accuracy of rest commands, where the mean number of correct trials was 3 in the BCI session while it was 9.17 in the BCI/Vision session. A difference in the number of correct execution of 'Right Hand' wasn't as significant as in 'Rest' trials.

The average response time taken when the 'Rest' cue was given and the FPR of each session from every subject are illustrated in table II. There was a noticeable difference in average response time of 'Rest' between BCI/Vision-based and BCI methods, where each method recorded 4.42 and 9.39 seconds, respectively. The average FPR of each method was 0.7 and 0.08. Given the fact that such a result was carried out without a huge difference in 'Right Hand' performance, this implies that using BCI along with vision glasses helps subjects in vastly improving the overall performance.

Failure to perform several 'Rest' commands in BCI/Vision session is likely from the fact that a group of participants who started the session with BCI/Vision wasn't familiar enough in utilizing BCI and vision information simultaneously compared to the other group. Our inference regarding this issue is that participants may have needed more time to get used to controlling robots and vision glasses proficiently simultaneously.

A further change could be made in the first-person view camera to enhance the performance. The gaze of the camera attached to the glasses and the gaze of the participants may not be perfectly aligned as each participant stares at the object at a different angle, in contrast to the camera angle which is fixed. For this reason, a camera may fail to recognize the hand with a glove on even when the user is in fact staring at the hand. A slight modification of hardware such as using a rotatable camera that rotates in a way that suits the individual user could achieve a better result.

Another possible change can be made to the vision classification model for this method to work better. The model we used in vision classification was sensitive when there were a lot of distractions around the glove and often misclassified other objects as a glove. With more robust performance of the vision classification model, we expect the method to be more applicable under various circumstances.

IV. Conclusion

In this study, experiments were conducted to inspect whether the use of vision glasses can improve the performance of controlling the soft robotic glove when combined with MI-based BCI. We compared the performance of BCI-based and BCI/vision-based soft robotic glove control and had each participant control the glove. The results of the experiments show that vision glasses can play a role in reducing FPR and enhancing the control of soft robot glove in MI-based BCI. In addition to that, the result indicates that this change was made while maintaining the level of performance of glove movement which is carried out by the imagination of right hand movement. However, further improvement of vision glasses hardware and vision classification algorithm could lead to better performance in controlling the soft robotic glove, and additional participants could statistically confirm the result.

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