Research Article

Telebot: Evaluating the Efficacy of Thought Patterns in an Electroencephalographically-Controlled Mobile Robotic Manipulator

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ABSTRACT

Telebot aims to create a mentally operated mobile robotic manipulator that bolsters human productivity by changing the way humans interact with the world. Human brainwaves recorded noninvasively through electroencephalography can be used to mentally operate a mobile robotic manipulator through machine learning. This study determines the most compatible and effective type of brain activity to use as mental commands by comparing users' visualization of images versus actions, as well as generic visualizations versus personalized ones. There were 6 participants in this study to evaluate the efficacy. Each trial was conducted while each participant wore an EMOTIV EPOC X–14 Channel Wireless EEG Headset running the EMOTIV Brain-Computer Interface (BCI). The participants were asked to think of generic images, individualized images, generic actions, and individualized actions. Each participant established a neutral baseline and references for each mental command through five, eight-second calibrations and then performed four live tests, one for each mental command. The data recorded the thoughts that were sustained above the detectable threshold, the number of false starts, and other metrics. The result uses the main metric to analyze the general efficacy, which measures the uptime of the mental command being above the detectable threshold. The data showed that, on average, generic images are effective 58.8% of the time, individualized images 74.3%, generic actions 59.7%, and individualized actions 77.7%. These findings contribute to the development of mobile robotic manipulators, potentially transforming the way humans interact with the world.

Keywords: EEG (Electroencephalogram); Brain-Computer Interface (BCI); Mental Commands; Mental Input; Robotics

INTRODUCTION

Electroencephalograms (EEGs) are used in various industries to better understand the human brain by measuring the electrical impulses emitted by brain activity. They are typically used for medical research, understanding mental states, and diagnosing certain medical conditions, such as epilepsy and seizures (1). The brain activity measured by EEGs when repeating certain thought patterns is very similar –– enough that a machine learning algorithm can reliably distinguish when the thought pattern is occurring (2). In this way, mental commands can be established as a form of input (3).

The use of EEGs as a form of mental input is a

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developing technology that is beginning to be used in assistive devices such as prosthetics and wheelchairs (4, 5, 6, 7). Electroencephalography is a powerful tool as it allows for the brain-actuated control of Internet of Things devices without any mechanical human input (8). Brain-actuated devices have enormous implications for quadriplegic individuals. Such a device has, on average, a 74% performance ratio compared to manual mechanical input (9). Simple mental imagery of human hand movement can be used to control a robot with significant success (10). This study determines the most compatible and effective type of brain activity to use as mental commands by comparing users' visualization of images versus actions, as well as generic visualizations versus personalized ones. There were 6 participants in this study to evaluate the efficacy. Each trial was conducted while each participant wore an EMOTIV EPOC X–14 Channel Wireless EEG Headset running the EMOTIV Brain-Computer Interface (BCI).

METHODS AND MATERIALS

In the pursuit of bringing Telebot to fruition, we started by creating an initial prototype.

This basic robot used a Raspberry Pi 4 as the processing unit. There is a series of hardware, software, and system settings involved in receiving input from mental commands on the Raspberry Pi. The primary hardware used was the EMOTIV EPOC X – 14 Channel Wireless EEG Headset, which directly measures the electrical impulses of the user/participant. The EEG connects via Bluetooth to the EMOTIV Brain-Computer Interface, a software installed on a Raspberry Pi used to process the raw EEG signals and convert them to usable output. In order to convert these mental commands to mechanical output, Node-Red — a flow-based programming language useful in creating Internet of Things devices — was installed on the Raspberry Pi. The custom EMOTIV Brain-Computer Interface (BCI) toolbox was imported onto Node-Red. This allows for mental commands to be used to trigger certain responses, such as activating an output pin on the Raspberry Pi with Pulse-Width Modulation (PWM). For each unique action by the robot, four blocks are needed: "EMOTIV," "Profile Name," "Mental Commands: (followed by the name of a pre-trained command)," and the action (Figure 1).

A series of basic, replicable mental commands are set on the BCI for Telebot to detect and translate into motion. It takes eight seconds to train the EEG with a new mental command. When mental commands are replicated, EMOTIV-BCI's machine learning algorithm recognizes the unique electrical signals from unique areas of the brain. Each specific mental command is essentially "keybinded" to a corresponding kinematic output. It should also be noted that none of these mental commands are set in stone, as they are easily swappable (11). This study will evaluate the efficacy of different types of mental commands.

Each potential participant and their parents signed an informed consent form that fully outlined the study prior to experimentation. Participants were verbally instructed during the experiment based on a script and had no pre-experimental training or experiences with EEGs.

During post-experimentation, two-tailed t-tests were the statistical analysis method used in addition to averages to compare all participants' trial data.

RESULTS

To test the efficacy of mental commands, we utilized the performance metrics measured by the EEG headset and provided by the EMOTIV-BCI. In each of the initial tests for each subject (generic image, generic action, individualized image, individualized action), the subject visualized the given or personal thought for five, eight-second trials. The first two trials of each test served as the calibration for the designated thought. This means that the EEG evaluated the subject's attention, energy, excitement, interest, relaxation, and stress levels on a scale from 0-100, and associated that brain-wave pattern with the labeled action. For example, in one subject's individualized action test, the EEG captured the brain pattern of their first two trials, as shown in Figure 2. In this test, the subject was visualizing their flute repertoire, which created a distinct brain wave pattern.

In order to better recognize and categorize each different thought pattern, the software compares each trial

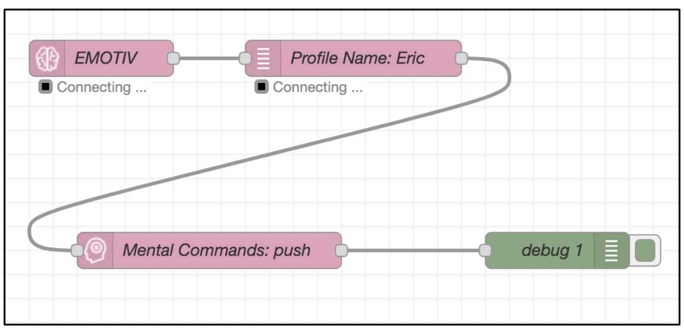

Figure 1. EMOTIV, Profile Name, Commands, and the Action.

to the subject's previously recorded baseline statistics. As seen in Figure 3, the same subject's thought pattern differed significantly during their baseline test and their individualized action test (Figure 2), so the EEG could distinctly recognize when the user was intentionally thinking of the coded action. As mentioned above, the first two trials were used to calibrate the output action to be associated with a specific thought. The last three out of the five trials were then used to evaluate how well the subject could match their thought pattern. After each of the last three, eight-second tests, the user was given a score based on how well that trial matched the brain wave pattern created in the first two tests. Users were scored on a scale of 1-100. A score of 100 for the subject in Figure 2, for example, means that the user's thought pattern for that trial completely matched the one shown. This means that each of the six categories (attention, energy, etc.) was detected at the same level. Higher scores (80 or above) were also used to further calibrate the thought (similar to what occurred in trials 1 and 2) to ensure that the subject's brain pattern was as accurate and replicable as possible, and could be easily distinguished from the baseline test, or other images/actions.

From the six participants tested in our study, 18 scores were gathered from each of the four tests. First, were the generic image visualizations, then the generic action visualizations, and finally the personal images then actions. In Figure 4, each of the 72 total scores is plotted by category, and the average lines display the increasing scores for each category.

Figure 5 more clearly displays how the averages of generic and personal images were lower than those of

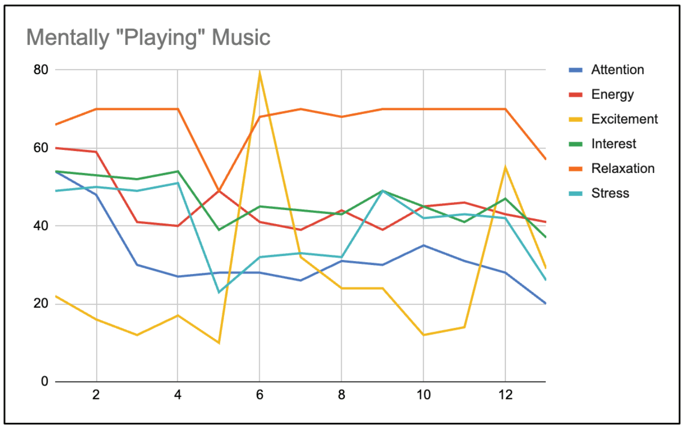

Figure 2. Shows subject mental command.

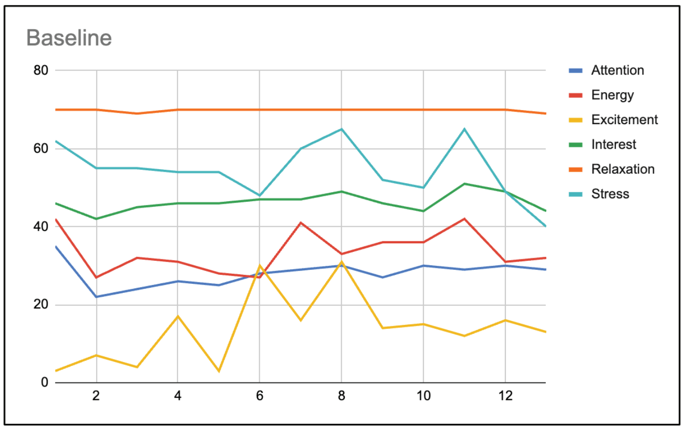

Figure 3. Shows subject mental baseline.

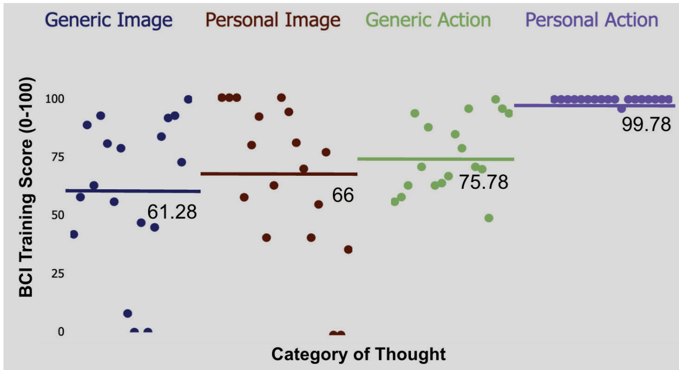

Figure 4. Every trial in the study, categorized by the type of thought (Generic Image, Personal Image, Generic Action, and Personal Action), scaled from 0-100, with 100 being the most consistent with training data.

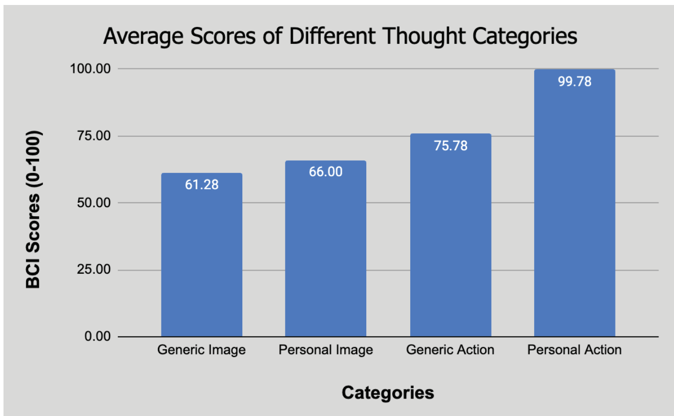

Figure 5. Comparison of the average scores given by the percent match of the training data in each category (Generic Image, Personal Image, Generic Action, and Personal Action).

generic and personal actions, with means of 61.3, 66.0, 75.8, and 99.8, respectively. These results support the hypothesis that personal images/actions will be more replicable and distinguishable than generic ones, since the mean score for both generic thoughts was 68.5, while the average score for both personal thoughts was 89.2. Not only were personal thoughts found to be more effective, but the results support the idea that imagined actions are more detectable than images, with personal action being of course, the highest-scoring category. The average score for visualized images was 63.8, while the average score for visualized actions was 87.7. Additionally, the calculated P-values for the highest scoring category, personal action, were 0.00005, 0.0002, and 0.000004 against generic image, personal image, and generic action, respectively. When using a t-critical value of 0.05 ($\alpha = 0.05$), these results prove to be significant, meaning they were not due to chance and can be acknowledged as usable data. After each subject's four tests, they moved on to the live-mode section of the experiment. In live mode, they would be prompted to visualize one of the four actions/images calibrated before. They would visualize each thought on command for a period of ten seconds, five times. The detection and accuracy of the thought they were imagining was recorded by a power meter and virtual block, that moved based on how well the designated thought was detected (Figure 6). They were prompted to "start" and "stop" every ten seconds, and the amount of time they were able to keep the block in motion out of those ten seconds was recorded.

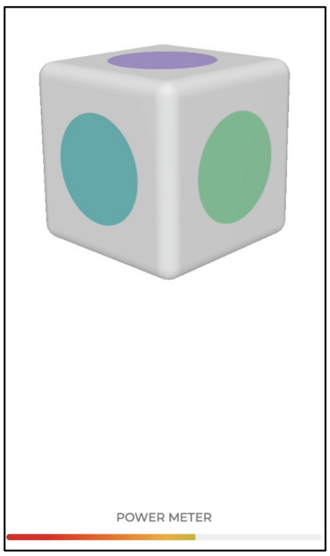

Figure 6. Virtual object that demonstrates when a thought is detected.

As seen in Figure 7, the average time of the block in motion was the highest for personal actions, with a time of 7.8 seconds. The next most maintained thought was the personal images, with an average time of 7.4 seconds. On top of the time the thought was maintained, the number of false starts and the time it took to stop the command after being instructed were measured. This was done by using screen recording software and timestamping when the block stopped moving. A false start was defined as one instance of when the block stopped during ten-second trial.

According to Figure 8, the generic image and generic action tests had the highest number of false starts per trial. Compared to Figure 9, it can be determined that the time of the block in motion is inversely proportional to

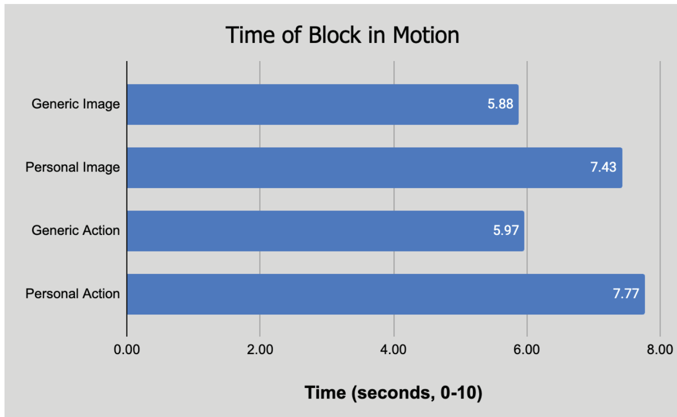

Figure 7. Average times that the thought was detected during a ten-second trial of each category (Generic Image, Personal Image, Generic Action, Personal Action).

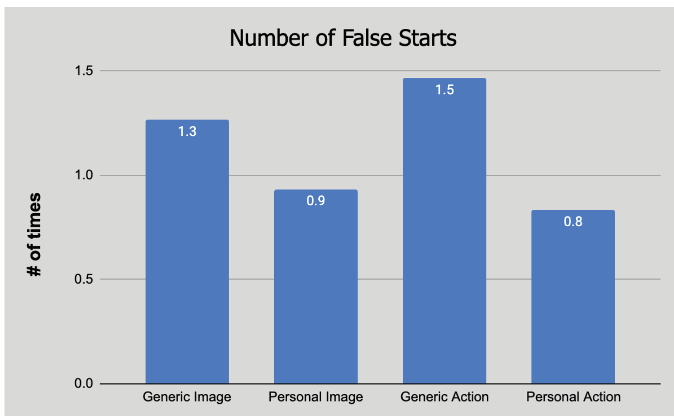

Figure 8. The average number of false starts in each category (Generic Image, Personal Image, Generic Action, Personal Action).

the number of false starts. It can therefore be concluded that images/actions that are more difficult to maintain a thought about are also hard to control on demand, leading to false starts. Figure 9, on the other hand, reveals that it took subjects the longest amount of time to stop visualizing personal actions. Though subjects were accurate and did not have many false starts during the personal action test, it took them an average of 3.1 seconds to stop visualizing the action after the ten seconds were up. This data is beneficial because it shows how personal actions were clearly detected and easy to maintain, however, further action must be taken to help mitigate this extra response time, or train subjects to stop their thoughts on command.

DISCUSSION

These results serve as a proof-of-concept for Telebot's design. First, the data displayed in Figure 6 clearly shows that personal actions can be accurately detected nearly 100% of the time. According to these results, our future studies will mainly utilize different types of personal actions, to see how the EMOTIV can distinguish between different thoughts. Our next step is to utilize personal action thoughts and program a subject's different thoughts to be associated with a physical output. Using Node-Red, a calibrated thought can be programmed to correspond with an output such as "forward" or "reverse" when detected. Additionally, since this study included only six participants, which is a relatively small sample size in a neurophysiological BCI study, future studies could include more participants.

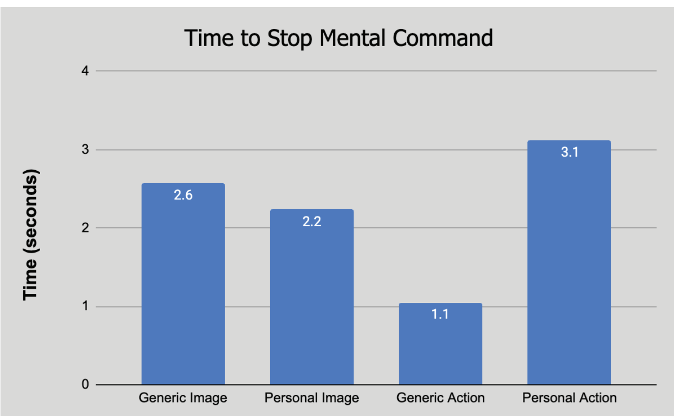

Figure 9. The average time it took to stop the mental command (Generic Image, Personal Image, Generic Action, Personal Action) after the ten-second trial.

The most promising aspect of the study was the participants' ability to match their brain-wave patterns accurately multiple times when visualizing their designated personal actions. This then translated into an average maintenance time of 7.8 out of 10 seconds, with few false starts. In the next portion of the study, the three top-scoring participants (Those with the highest maintenance scores, the fewest false starts, and the shortest stop times) will essentially repeat live mode, however, the detections will be connected to the Raspberry Pi on the Telebot through Node-Red. This means that the detection of their calibrated personal action brain pattern will trigger the Telebot to move. Instead of the block used on EMOTIV's interface (Figure 8) to virtually mimic motion output, the Telebot will move. The Telebot's specific movement can be easily changed in Node-Red, so a specific detected thought can tell it to move backward, forward, turn, etc. Participants will also attempt to calibrate multiple personal actions so that different actions can be associated with different outputs. Though it might be hard for participants to think about different actions on command, the initial data shows that visualizing one personal action led to nearly perfect success when detecting and controlling the thought. According to these results, it is expected that with some practice, participants will be able to accurately shuffle between thoughts depending on which type of output they intend for the robot to have. One obstacle that will be targeted in the next steps of the study is shortening the time it takes for participants to stop visualizing the action once commanded to. In the initial tests, participants averaged 3.1 seconds of thought detection after the ten-second test interval, which would cause the robot to move further, even when the user wants it to stop. Practice starting and stopping actions abruptly, or tinkering with the sensitivity of the EEG's nodes could mitigate this problem.

Telebot's cognitive control will promote access to high-quality physical and mental well-being in our communities by benefiting all people, no matter their ability. Telebot enables all users to be more efficient with their everyday tasks, and specifically, it could help parents care for their children, elders stay safe and healthy, and so much more. EEG mental control is a developing technology that is beginning to be used in many input/output scenarios, such as in medical technologies like prosthetics and mind-controlled wheelchairs. While the technology is being developed by many people Telebot aims to be the first application that can be on the market, widely available to all people, and to be the first mind-operated mobile manipulator. Additionally, it targets the largest audience compared to other EEG applications due to its wide array of applications; the consumer can choose to do what they wish with it. One company with a similar technology and mission is Neuralink. Neuralink is a BCI surgically implanted into the user's brain. Telebot, however, is more accessible and non-invasive, making it more appealing and less risky to everyday users.

It is shown in our research that the highest and most accurate power level obtained by participants was by visualizing personal actions such as mentally playing the flute, visualizing swimming strokes, or even one's detailed nightly routine. This supports Telebot's mission of creating devices that can be uniquely tailored to be suitable for each user. It is apparent that each individual user of Telebot will have the most success using the device when creating mental commands that correlate to the user's interests or areas of expertise.

CONCLUSION

The result uses the main metric, which measures the uptime of the mental command being above the BCI's detectable threshold, to analyze the general efficacy. In the study, the uptime is represented by the time of the block in motion, and is measured through summing the difference(s) between the timestamps of when the block started and stopped moving. The data showed that, on average, generic images are effective 58.8% of the time, individualized images 74.3%, generic actions 59.7%, and individualized actions 77.7%. This data supports our hypothesis that visualizing personalized images/actions are more effective than standardized ones. These findings contribute to the development of mobile robotic manipulators, potentially transforming the way humans interact with the world. Telebot may help users in getting a task done with no physical exertion, as the robot can complete it for them. Since Telebot is completely hands-free, it allows users to multitask, even allowing quadriplegic users to be able to fully operate it. Telebot is not only able to help users be efficient with their time, but it can also be a lifesaving medical device in the future. If an individual were to get injured, fall, get physically stuck inside a cave, and need help, they could send their robot to get help. Additionally, it could quickly get medications and perform tasks if the user is unable to. The possibilities are limitless.

In the future, we will use this data to develop the best practices for using a Telebot. The first prototype of Telebot is currently being developed and will be improved upon and updated as best seen fit in the near future.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this article.

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