Study of an EEG based Brain Machine Interface System for Controlling a Robotic Arm

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Abstract: We present a methodology to explore the capabilities of an existing interface for controlling a robotic arm with information extracted from brainwaves. Brainwaves are collected through the use of an Emotiv EPOC headset. The headset utilizes electroencephalography (EEG) technology to collect active brain signals. We employ the Emotiv software suites to classify the thoughts of a subject representing specific actions. The system then sends an appropriate signal to a robotic interface to control the robotic arm. We identified several actions for mapping, implemented these chosen actions, and evaluated the system's performance. We also present the limitations of the proposed system and provide groundwork for future research.

1 INTRODUCTION

The term Brain Machine Interface (BMI) refers to a system which uses sensors to collect data from the brain, classifies the data, and encodes the data as control signals for a computer or machine (Shenoy, 2006). At the beginning of this research project, we started with an existing BMI system (Ouyang, 2013). This uses an affordable Emotiv electroencephalograph (EEG) headset to interface with and control a 7 degrees of freedom (DoF) robotic arm, the Robai Cyton Veta.

The raw EEG data collected through the 14 electrode headset is analyzed and used to signal the robot to execute commands. Figure 1 below illustrates a current BMI system, and the process used to encode the action.

Figure 1: The 3 Phase BMI System.

The goals of this research project, beyond refining the system, are as follows: to test different thought patterns and determine the best method of creating and detecting unique brainwave signatures, to create a universal profile (one folder containing several subjects' data) and test this against the individual subject's folder, and to examine the feasibility of using pure EEG data in conjunction with facial expressions, which create electromyography (EMG) and electrooculography (EOG) signals (Baztarrica, 2002).

2 INTERFACE CRITERIA

A sequence of actions selected from the pool of available commands are generated randomly. For each set of trials, a maximum number of attempts are set to prevent the user from attempting an unlimited number of trials. The maximum number of attempts is determined to be at least double the length of the sequence to ensure a consistent accuracy.

To test the system the following test plan was executed for each trial:

1. Train the neutral state and train actions 5 times
2. Each tested user performs the following for both the personal profile and universal profile:

- The test subject attempts to execute an action
- The test subject stops attempting to execute the action once the robot has started moving
- The output of EmoKey is be recorded
- The output of the robot console which displays executed actions will be recorded
- The previous 3 steps are repeated for each action until there are no more actions remaining or until the maximum numbers of attempts is reached

In this experiment, four different trials were

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tested. The difficulty of each trial is increased by adding more actions to the trial and thereby decreasing the accuracy. The first trial tests two individual EEG actions, Left (L) and Right (R), in the sequence LRRL with a maximum of 9 attempts. The second trial repeats the first trial test but aids the Left and Right actions by clenching the appropriate fist to test the impact of the cognitive execution physical actions on EEG signals. The third trial adds two more actions, Smirking Left (A) and Smirking Right (B), to the first trial test in the sequence of BLABRA with a maximum of 12 attempts. The final trial tests a total of seven actions by adding three additional actions, Winking Left (X), Jaw Clenching (J), and Raising Eyebrows (W), to trial three in the sequence of LJWBABRLRXAJXW with a maximum of 28 attempts.

In the former BMI system, the robot console could receive keystrokes from the EmoKey software during the execution of the previous command. These extra keystrokes were stored within a buffer and would be executed after its previous robotic command was finished. The buffer reduces the accuracy of the system by storing and later executing these unintended keystrokes. As an improvement, a filter is implemented to clear the console buffer, so the console only reads input from the headset and implements the action when the last robotic action is completed. The Microsoft Windowing API command used was:

```
FlushConsoleInputBuffer (Handle h);
```

3 EVALUATION STRATEGY

When testing the design of the system, a user attempts to execute a specific sequence in a given order. A user is allowed a maximum number of attempts for each trial. During testing, the user will attempt to execute the given sequence and will only move onto the next action when the current action is executed properly. The user continues this process until either he or she has reached the maximum number of attempts for that trial or has fully executed the correct sequence. The testing accuracy is defined as the ratio of the number of actions that are successfully executed to the number of attempts that are made to complete a trail.

4 TEST DATA AND RESULTS

Below are the results from the four rounds of testing. As shown in the following figures, satisfactory results were achieved in the first round of testing, and the accuracy lowered as more actions were added.

Figure 2 below illustrates the first round of testing which consists of Left and Right actions.

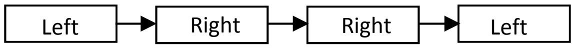

Figure 2: First round of Testing Sequence.

Tables 1 and 2 show the results from the first round of testing. Table 1 has data for each subject when they were using the Universal Profile and Table 2 shows each subject's accuracy on their own individual profile. Each separate bar corresponds with a different subject, and the rightmost bar is the average of all subject's results. The number above the bar shows the percentage accuracy.

Table 1: Universal Profile Results (Left and Right).

Subject	1	2	3	4	5	Average
Accuracy(%)	95	63.45	67.5	100	90	83.19

Table 2: Personal Profile Results (Left and Right).

Subject	1	2	3	4	5	Average
Accuracy (%)	78.3	40.4	41.7	83.3	95	67.75

Figure 3 below illustrates the second round of testing determined by the team which consists of Left and Right aided with clenching fists.

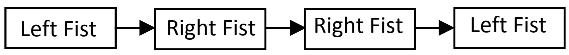

Figure 3: Second Round of Testing Sequence.

Figures 3 and 4 show the accuracy results for the second round of testing. In this set of testing the subject was instructed to physically clench their right or left fist when thinking right or left.

Table 3: Universal Profile Results (Left and Right) Aided with Clenching Fists.

Subject	1	2	3	4	5	Average
Accuracy(%)	90	65.2	81	95	95	85.24

Table 4: Personal Profile (Left and Right) Aided with Clenching Fists.

Subject	1	2	3	4	5	Average
Accuracy(%)	71.8	51.1	81.7	100	95	79.91

Figure 4 below illustrates the second and third round of testing determined by the team which consists of Left, Right, Left Smirk, and Right Smirk.

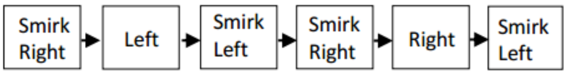

Figure 4: Third Round of Testing Sequence.

Tables 5 and 6 show the results when the users had a sequence that included left movement, right movement, and two facial expression actions. This round of testing also included the implementation of a filter which caught and discarded superfluous facial expression signals.

Table 5: Universal Profile Results (Left and Right and Facial Expressions) with Implemented Filter.

Subject	1	2	3	4	5	Average
Accuracy (%)	18.8	36.6	45.3	50.6	40	38.24

Table 6: Personal Profile Results (Left and Right and Facial Expressions) with Implemented Filter.

Subject	1	2	3	4	5	Average
Accuracy (%)	42	20.8	31.3	39.6	45.8	35.92

The Sequences of the final round of testing is left, clenching, raise eyebrows, smirk right, smirk left, smirk right, right, left, right, looking left, smirk left, clenching, looking left, and raise eyebrow.

Tables 7 and 8 show the results for the final round of testing. During this test each user attempted to perform a sequence with all seven actions. This included two EEG actions and five facial expression actions.

Table 7: Universal Results of 7 Actions with Filter.

Subject	1	2	3	4	5	Average
Accuracy (%)	25	32.1	31.3	37.5	35.1	32.2

Table 8: Individual Results of 7 Actions with Filter.

Subject	1	2	3	4	5	Average
Accuracy (%)	34.2	33.9	33	30.4	46	35.5

5 DATA ANALYSIS AND RECOMMENDATIONS

This section discusses the research findings concluded from the testing.

5.1 Recognizable and Consistent Thoughts

From the results of testing, the team hypothesized that thoughts related to muscle movement are much more distinguishable than abstract thoughts. Furthermore, thoughts related to muscle movements and movements around the head are much more recognizable than physically clenching the fists. The comparison can be shown in Figure 5 below.

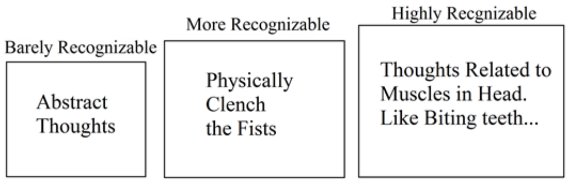

Figure 5: Thought Classification.

Reasons why thoughts related to muscle movements are more recognizable can be summarized as:

A) The thoughts related to the muscle movements are more consistent. This would mean that the brain activities of abstract thoughts such as moving a cube in the user's mind are not consistent or not strong enough for the headset to detect. It can become very difficult for the user to think about an abstract thought in a consistent way. However the brain activities caused by muscle movements are very consistent.

B) By utilizing software called Emotiv Brain Activity Mapping, the brain activity is shown to be stronger when using muscle movements rather than only using pure thoughts.

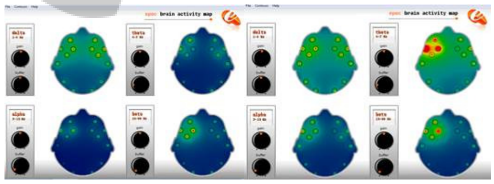

Figure 6: Thinking Left (Left) vs. Left Thinking and Biting Cheek (Right).

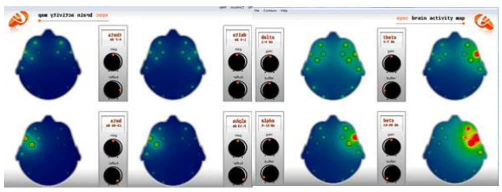

Figure 7: Thinking Right (Up) vs. Right Thinking and Biting Cheek (Down).

From the figures above, there exists more brain activity when using muscle movements. This increased activity is due to the EMG signals that result from the muscle movement. These are typically far more distinct than EEG signals, and have higher amplitudes (Baztarrica, 2002). As a result, thoughts using facial muscle movements are more recognizable for the current system.

5.2 Interference between Different Thoughts

The following are the results of the 4 test trials with 2 aided with physical movement, 2, 4 and 7 thoughts.

Table 9: Accuracy of Universal vs. Individual Profiles.

Number of Commands	Average Accuracy (Universal)	Average Accuracy (Individual)
2 Thoughts (Pure)	83.19%	67.75%
2 Thoughts (Aided with Fists)	85.24%	79.91%
4 Thoughts (Cognitive and Expression)	38.24%	35.92%
7 Thoughts (Cognitive and Expression)	32.20%	35.45%

The results shown in Table 1 above, shows a decrease in accuracy as more commands are implemented. A modeled setup is created to analyze this phenomenon. In Figure 8 below, take point A to be the thought from the profile data saved in the system (system thought) and point B is the thought detected from the user (user thought). Let the circle be the system's range to match thoughts within its bounds and the area of the circle will be defined as the detection sensitivity of the thought. To allow a uniform range of the system thought with the sensitivity, point A will be defined as the center of circle A. The system then needs to match the current thought, B, to the saved thought, A. Once the user's thought is inside the circle, the system will successfully match the user's thought to system thought.

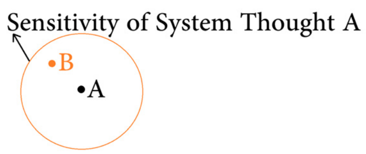

Figure 8: System Thought A and User Thought B.

Now take an implementation of two thoughts as shown in Figure 9 below. The system thought, A, will be duplicated into another system thought, B, contained within its own circle B on the left. If a user's thought, C, exists, then there will be a chance that the user's thought C happens to occur at the intersection of Circle A and Circle B. In this case, the user's thought can be similar enough to be matched to both system thought A and system thought B.

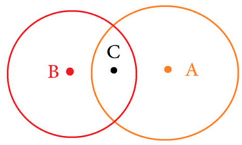

Figure 9: Interference Problem.

As a result, in determining a user's thought between two system thoughts, the phenomenon causes an interference problem. If more thoughts are implemented, this phenomenon will become more complex and cause the system's accuracy to drop rapidly.

<u>Reduced Sensitivity Solution</u>: A solution to the interference problem is to reduce the range of the circle for either or both system thoughts A and B such that no thought interference occurs. This requires a reduction to the sensitivity of either Circle A or Circle B or both such that no interference occurs as shown in Figure 10 below. As a result, a distinct match of user thought C can be matched to either system thought A or system thought B without conflicts. As a result of lowering the sensitivity, it becomes more difficult for the system to detect a user's thought causing the user to think harder.

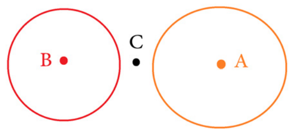

Figure 10: Reduced Sensitivity Solution.

<u>Dynamic Sensitivity Solution</u>: As discussed previously, once a user has executed a certain thought successfully, it is much easier for the user to think about the same thought than to switch to another thought or across multiple thoughts. Referring to figure 20, utilizing this property, we implemented the following matching algorithm.

Assuming the user's current thought C resides in the intersection of A and B.

```
IF((A is the last thought) AND
   (C is contained in A and B))
THEN MATCH C to B;
IF((B is the last thought) AND
   (C is contained in A and B))
THEN MATCH C to A;
```

This solution increases the system's capacity to overcome the interference problem without significantly reducing the sensitivity.

5.3 Universal User

The results of the 4 test trials with 2, 2, 4 and 7 thoughts shown in testing data and results section above are compared in Table 1 above.

From the results shown in Table 1, the universal profile shows higher accuracy than the individual profile in the majority of the test trials. Since the subjects in the universal profile tests are using similar muscle movements to create a specific brainwave activity, these signals can be considered to be consistent for different users. This is due to the brain function to plan and execute these muscle movements being similar across people (Jasper, 1949). These findings indicate the possibility of creating a BMI system that can be used by the user without any training.

5.4 Limitations of the Existing Software

By comparing the unfiltered input sequences and the desired input sequences, we discovered that the Emotiv software handles the pure EEG signals and facial expressions differently. For example, the following is a set of data of the unfiltered sequence and the desired sequences for a test trial.

The sequences and thoughts A, B, L, and R, are represented in Table 10.

Table 10: Sequences and Actions.

A	B	L	R	Desired Sequence
Left Smirk	Right Smirk	Left	Right	BLABRA

The System unfiltered input is:
BR...*LAAAALAAA*...

Examining the two sequences, the user attempts to obtain a left but he or she obtains a sequence of *LAAAALAAA*. Since the left smirk and pure EEG left thoughts have a significant interference region for this subject, the user's thought for pure EEG left is also matched as a left smirk. The user is attempting to obtain an L (Pure EEG Left) indicated by the desired sequence. However, the sequence that the system reads is LAAALAAA, indicating that the user had executed more left smirk signals than pure EEG left signals.

To examine this problem further, we analyzed the frequency of which the Emotiv software responds to the given signals and discovered a potential reason that explained the abundant matching of facial expressions compared to pure EEG. In the Emotiv software, detection of facial expressions and pure EEG signals are concurrent. However in facial expressions, if a user kept their facial expression consistent for a period of time, EmoKey would repeat the keystroke to the robot control program within that period of time. In comparison for pure EEG signals, the signaled keystroke would only be sent at the instant the user executes a specific thought from the neutral state. A future recommendation to improve this issue is to test the facial expression and pure EEG detection under the same detection system.

5.5 Disturbance Caused by Body

Throughout the test, we discovered that significant body movements, speaking, or being in an excitingly emotional state can produce a noisy signal and cause an unintended action to be performed.

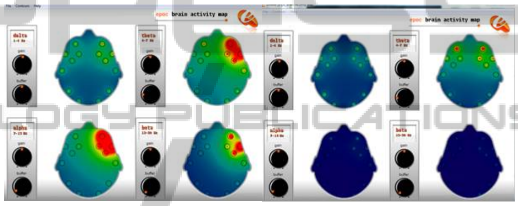

Figure 11: Brain Activity of Random Movement (Left) vs. No Movement (Right).

In this analysis, a software called Emotiv Brain Activity Mapping is used to illustrate the brain activity when executing random body movements as figure 24. Since the desired system ideally should be able to function while the user is walking, emotionally distracted, or even running, the system should be able to filter out the noisy signals generated by these movements, or emotional states. Three possible solutions can be used to help address this issue.

A) Implementing a Stop Feature: A simple stop feature would halt the system from executing any received keystrokes. This feature would also allow the user to stop or restart the system easily such that the user will not execute unintended actions while they are idled from the system. Currently a stop feature is already implemented in the current state of the project, but in the future this feature can be implemented as a facial expression based interface.

B) Sudden Strong Signal Filter: Since subjects may generate very strong and noisy brain activity when they are moving, an additional filter is needed to stop the system from executing actions when it receives a sudden, strong, and noisy signal. As a result, this would only allow the system to accept thoughts while the user is in a calm emotional state.

C) Filter out EMG Noise Signals: Noise filtering techniques such as independent component analysis (ICA) can be used to remove specific EEG channels affected by high amplitude EMG signals for the duration of the interference (Hyvärinen, 2000). This would allow the system to continue processing the pure EEG instead of stop processing altogether. However, a major challenge is filtering out the undesired noise while keeping the desired EMG signals caused by facial expressions being used as control signals. Filtering out EMG noise would result in shifting more control commands into the realm of pure EEG signals, or EEG signals aided with non-noisy muscle control such as clenching a fist.

6 CONCLUSIONS

This research project provided a significant amount of insight into the capabilities of the EEG based brain machine interface system. We tested different methods of focusing an individual's thoughts and the different methods of signal detections present within the existing software. Ultimately there were significant findings about the accuracy of the system. With minimal actions, the system performed fairly well. As more actions were added, the system performance dropped. The universal profile versus the individual profile also gave a new way of training the system which examined the idea of more focused individualization versus a broad wide sweeping approach. Research work is progressing to include more actions and activities for building a full-fledged brain machine interface system.

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