# Brain Machine Interface Using Emotiv EPOC Through Linear Discriminant Analysis

Daniel Prince, Andrew Sutter, Mark Edmonds, Matthew Cusumano, Wenjie Lu, Russell Hardie, and Vijayan Asari
Department of Electrical and Computer Engineering
University Of Dayton, Dayton, Ohio

***Abstract*—The initial framework for an electroencephalography (EEG) thought recognition software suite is developed, built, and tested. This suite is designed to recognize human thoughts and pair them to actions for a robotic arm. Raw EEG brain activity is collected using an Emotiv EPOC headset. The EEG data is processed through linear discriminant analysis, where an intended action is identified. The EEG classification suite is being developed to increase the number of distinct actions that can be identified compared to the Emotiv recognition software. The EEG classifier was able to correctly distinguish between two separate physical movements through nonreal time processing. Future goals for this project include recognition of more gestures, and enabling of real time processing.**

## I. Introduction

The work presented here is a continuation of ongoing research in the University Of Dayton's Vision Lab that utilizes the Emotiv EPOC for use in various capacities for testing the feasibility of low cost applications for EEG signal processing. While previous work from the group involves optimizing Emotiv's own software suite for use in processing EEG signals for controlling a robotic arm [1], the work presented here focuses on the development of an original EEG signal processing suite. The signal processing suite in development shares the same goal as previous work of enabling disabled people to regain a level of autonomy through the control of a robotic arm using EEG signals from the user as an input. Figure 1 illustrates the stages of control in this system.

The BMI system includes separate phases for recording signals, classifying the signals, and sending control to the robotic arm. During the recording phase, the subject's brain signals are collected and encoded into a computer-readable format. The classification phase then removes noise and classifies the thought appropriately. The controlling phase sends the classified action to the robotic arm.

The BMI system uses EEG to collect the brain signals. EEG is a non-invasive technique that offers high temporal resolution, portability, and low cost. Other methods that could have been chosen for collecting brain signals include functional Magnetic Resonance Imaging (fMRI) and invasive systems. fMRI offers high spatial resolution, but the system is not portable and very expensive. Likewise, the invasive systems involve implanting sensors into the subject's brain or using a needle to pierce the subject's scalp. Besides the discomfort of the subject, the system is not practical for quick or widespread use.

One of the most commercially viable and versatile EEG recording devices is the Emotiv EPOC headset. This EEG system offers a wide range of benefits from being market affordable to high-resolution, multichannel, and wireless EEG data acquisition. The headset comes with software detection suites that can detect the user's emotional state, facial expressions through electromyography (EMG), and user trained mental commands. Using a low-cost headset like the EPOC means research advancements can be deployed to a large number of users. A photograph of the Emotiv EPOC headset used in this experiment is shown in Figure 2.

Fig. 1. EEG Signal Processing Steps

Fig. 2. The Emotiv Epoc EEG headset

Figure 3 shows the robotic arm used, the Robai Cyton Veta. The Veta has 7 degrees of freedom, making its range of motion comparable to the human arm. The robot has suction cups on the bottom to keep it secure to the surface it is functioning on and it has safety mechanisms so that the arm does not over-rotate or hyper extend and cause damage to itself. The control software was provided by Robai and modified by the team.

The team extensively researched existing Brain Computer Interfaces (BCI) to decide which existing EEG classification methods would transfer well to the low-cost Emotiv EPOC headset. The team decided to focus on research pertaining to the Emotiv EPOC headset. The work in [3][4][9] (Choi, Duvinage, O'Connor) all describe effective EEG classification using the Emotiv EPOC headset. The work in [3] combined multiple processing methods: the P300 potential, the steady state visually evoked potential (SSVEP), and event related desynchronization (ERD). The users were tasked with moving a robot through a maze-like environment. The P300 potential represents a waveform that is closely related to decision making process. The researchers of [3] used the ERD-based

Fig. 3. The Robai Cyton Veta robotic arm

Fig. 4. A representative photograph showing the right gesture

BCI with Common Spatial Patterns (CSP) to identify features related to motor imagery presented to the user. The xDAWN spatial filter was used to filter data to evoke P300 potentials. The SVVEP-based BCI classified two actions: left and right head turns. SVVEP is useful for classifying visual information; there is an excellent signal-to-noise ratio. These turns were detected using Canonical Correlation Analysis (CCA). CCA essentially uses two sets of variables and finds the maximum correlation between those variables using weights. The authors of [3] manually found the response peaks, which is particularly relevant to the result of this work. The researchers found success using these methods.

The work in [4] utilized the P300 potentials in a similar fashion, only to conclude that the Emotiv EPOC is not a good choice for BCI applications. The authors argue that due to reliability concerns and the operational and maintenance costs, the EPOC should only be used in gaming and communication systems. The authors call for a low-cost device that meets these requirements, recognizing the medical potential of a low-cost EEG headset for a wide range of medical applications.

In [9], a Support Vector Machine (SVM), a form of Machine Learning, was used to classify the EEG data. SVM uses a supervised learning model. This model processes a set of data and predicts which classifications the inputs belong to. The SVM is trained using support vectors that separate a small amount of training data. The SVM learns how to separate the training data with the least amount of error. The results presented in [9] show the Emotiv Control Panel performing worse (success rate of 20%) than random chance for 4-inputs (success rate of 25%), highlighting the need for an alternative system. The SVM presented showed a success rate of 37%, vastly outperforming the Emotiv Control Panel. This paper effectively illustrates that the Emotiv EPOC can be classified using other methods that outperform the Emotiv Control Panel.

These works constitute a solid foundation of research to build a EEG classifier for the Emotiv EPOC. While the works all use the EPOC, the team believed there was room for significant improvement. This project is aimed at constructing another EEG classifier that outperforms previous implementations using the EPOC headset.

## II. System Design

### A. Data Collection

The design of the classifier began by collecting various gestures using the Emotiv headset and Emotiv's provided Testbench application. The Testbench records live input of EEG signals from the user wearing the headset for later processing and classification. Every data collection period was approximately two minutes long, where a user was to focus on using a single physical gesture at every five second interval. Initially, the team planned to collect a number of short, single actions. However, the Testbench requires that each recorded session be at least ten seconds long in order for it to save the data properly. Using the recording timer shown in the Emotiv Testbench, the user kept track of their own gesture timing. A separate facilitator would click the mouse to begin the data recording when the user was prepared and end the testing session after two minutes. By holding the gesture for one to two seconds, a relatively short period of time, the test data showed the signature of the EEG signals as the user transitions between the neutral state, and either the left or right gesture. For each of the gestures, the user was seated in front of the computer used to run the Emotiv Testbench software and was given a single class of gesture to use for the session. The different classes of gestures are described as the following:

Left: The user moves their left index and left thumb as close together as possible without touching them together, holding that position for 1 to 2 seconds.

Right: The user moves their right index and left thumb as close together as possible without touching them together, holding that position for 1 to 2 seconds.

Neutral: The user remains calm and still for the duration of the two minute collection session

A photograph representing the right gesture is shown in Figure 4. The index finger touching gesture was selected based on the small amount of physical movement involved, but also the strong mental sensation that is created from holding the two fingers close together but not touching them. The testing users were encouraged to remain still for the length of the two

minute collection session, but a small number of additional movements over all of the sessions did occur, presenting additional noise in the collected signals.

The data collected from the Emotiv Testbench was initially saved to the Emotiv proprietary .edf format. Emotiv's EDFConverterConsole command line application converts the .edf files to a comma separated value format, which can easily be read with Matlab. In order to automate the use of EDFConverterConsole, a Windows batch file was created to recursively converts all collected .edf files to comma separated value files. Since each gesture occurred at five second intervals, five second windows were created that plotted each gesture impulse in the center. An example of this plot is shown in Figure 5. A Matlab matrix was constructed that organizes the individual samples for each headset node for each data collection session in order to further process this information.

### B. Gesture Classification

Linear discriminant analysis (LDA) is a method that can be used to show the distance between a given data set's relationship to a "signal" class that is identified, versus a "noise" class that represents all data outside the desired set. This kind of analysis was used to separate right or left gestures from the neutral gestures that represent random EEG signals from the user.

At this phase in the project, the EEG classification system can not automatically locate time period of a single recorded gesture, so the analysis process begins by visually locating an impulse from the collected data to use in analysis. Matrix indices are manually selected in order to align multiple instances of the same gesture that is being used as the "signal" class. An example of the impulses that indicate a right gesture is shown in Figure 6, and an example of these gestures that have been aligned is shown in Figure 8. Following the alignment of the gestures, the input signals are downsampled by a factor of 50 in order to reduce the complexity of the data in them before either being used to create the discriminant via (1), or being used to compute a data set's relationship between the two classes represented by the classifying vector via (2) and (3).

Linear discriminant analysis was used to classify the gestures from the recorded data. This process allows for dimensionality reduction as well as a distinction between the signal that is being searched for and the noise that it is being separated from. Equation (1) shows the calculation used to create the discriminant.

$$w = (\Sigma_0 + \Sigma_1) - (\mu_1 - \mu_0) \tag{1}$$

Where $\Sigma_i$ represents the covariance matrices for each class, $\mu_i$ represents the mean vector for each class, and $w$ represents the discriminant used to compute the separation between the two classes, class 1 represents the right gesture, and class 0 represents the neutral gesture. Following the computation of the discriminant, it may be used to compute whether an input data set more closely correlates to one of the classes of data used to create the classifier. The computation needed to show whether a given data set more closely represents one of the

Fig. 5. Example of the signals collected from the Emotiv headset

classes used to create the classifier in (1) is shown in (2) and (3).

$$f_N = wN \tag{2}$$

$$f_R = wR \tag{3}$$

Where $N$ and $R$ are data sets representing aligned and downsampled neutral and right gestures respectively, $w$ represents the discriminant used to compute the separation between the two classes, and $f_N$ and $f_R$ are the output functions, where a higher value indicates a correlation towards the right gesture, and a lower value indicates a correlation towards the neutral gesture.

## III. Results

The EEG classification system successfully distinguished between two separate sets of actions: right and neutral, and left and neutral. Figure 5 shows an example of a single five second interval that contains signals collected using the EPOC headset, where each subplot shows the signal detected at each of the fourteen nodes of the headset.

Figure 6 shows an example of the gesture signature used to visually identify when a gesture occurred. The red bordered boxes were drawn in this plot show that impulses related to the gesture can be seen clearly on channels 1, 2, 3, 4, and 14. Because these channels consistently show a visible impulse near the times when gestures should occur, they were selected to be used as the best channels in the creation and processing for the signal classifier.

In Figures 7 and 8, the raw headset data for a right gesture and a neutral gesture are shown following the manual selection of matrix indices that allow for a visual alignment of the impulse in the center of the right gesture. In these figures, each different color line represents a different section of the session that has been aligned within the five second window shown, with nine sections of five seconds in length shown in each figure simultaneously. The neutral gestures are mostly uncorrelated, while the right gestures all feature a significant impulse at the center of the window. This simultaneous impulse occurring on many different channels will be the defining feature that the classifier uses to represent the right gesture.

Following the manual sample alignment, each data set is then downsampled by a factor of 50 to create signals that

Fig. 6. Visual identification of impulses on the channels characterize the gestures tested

Fig. 7. Channel 1 aligned neutral gestures

Fig. 8. Channel 1 aligned right gestures

represent the same trends, but with less complex data. The downsampled versions of the same neutral and right gestures from headset channel 1 are shown in Figures 9 and 10.

In Figure 11, an example output from the LDA classification is shown. A threshold value of 40% of the difference between the lowest and highest scoring values is plotted to separate the right gestures, which occur above the threshold, and the neutral gestures, which occur below the threshold. Note that in this specific scenario, the two gestures are separated at nearly 100% accuracy, even though the classifier was computed from a different user than the test data being classified. This result proves that the EEG signals proved by the tested gestures are consistent between different users.

Fig. 9. Channel 1 aligned and downsampled neutral gestures

Fig. 10. Channel 1 aligned and downsampled right gestures

Fig. 11. Resulting linear discriminant analysis plots for channel 1 in a classification of a right gesture versus a neutral gesture

## IV. Conclusion

The EEG classifier successfully classified two separate sets of two distinct gestures. As the results shown indicate, the classification accuracy of the best channels between two classes is 100%, even when using a discriminant resulting from EEG data recorded from a different user. The system is highly successful with several given conditions: the gesture indices and the optimal channels need to be identified manually in non-real time processing, and a maximum of two classes can be distinguished at once.

The future of the project is promising. The customized EEG classification system can be tailored to the requirements needed for assistance in operating a robotic arm. Now that an offline signal processing system has been designed, it can be adjusted for use in real time gesture classification.

During the data collection procedure, the team recommends that each gesture be held for a longer period of time to increase the clarity of the resulting EEG data. The team also recommends the development of an algorithm that can automatically locate the time when a gesture candidate occurs. An approach that uses LDA to distinguish between more than two classes of gestures will also be required in order to enable a more sophisticated level of communication from the user to the robotic system that is being controlled.

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