6-2015

Brain Machine Interface Using Emotiv EPOC to Control Robai Cyton Robotic Arm

Daniel P. Prince
University of Dayton

Mark J. Edmonds
University of Dayton

Andrew J. Sutter
University of Dayton

Matthew Thomas Cusumano
University of Dayton

Wenjie Lu
University of Dayton

See next page for additional authors

Author(s)
Daniel P. Prince, Mark J. Edmonds, Andrew J. Sutter, Matthew Thomas Cusumano, Wenjie Lu, and Vijayan K. Asari

Brain Machine Interface Using Emotiv EPOC To Control Robai Cyton Robotic Arm

Daniel Prince, Mark Edmonds, Andrew Sutter, Matthew Cusumano, Wenjie Lu, 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 controlling a robotic arm. Raw EEG brain activity data is collected using an Emotiv EPOC headset. The EEG data is processed through linear discriminant analysis (LDA), 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. Future goals for this research include recognition of more gestures, and enabling of real time processing.**

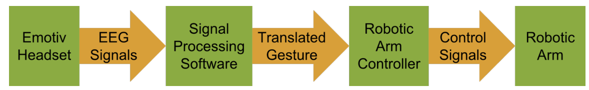

Fig. 1. EEG Signal Processing Steps

Fig. 2. The Emotiv EPOC EEG headset

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 [1], [2]. While previous work from the group involves optimizing Emotiv's own software suite for use in processing EEG signals for controlling a robotic arm, this paper presents the development of an original EEG signal processing suite. The signal processing suite 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 in this system.

The BMI system includes separate phases for recording signals, extracting features, classifying the features, 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 a 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 [3], [4]. fMRI offers high spatial resolution, but the system is very expensive and not portable. 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. The Emotiv EPOC headset used in this experiment is shown in Figure 2.

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 secure it 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 in this research.

Several researchers have developed Brain Computer Interfaces (BCI) to encode brain data for various applications [5]-[11]. We extensively studied various aspects in order to select the most effective for our application. Many techniques were found to be effective in processing EEG signals including the P300 potential [5], [6], and an approach using support vector machines that out performs Emotiv's own EPOC Control Panel [7]. These works constitute a solid foundation of research to build a EEG classifier for the Emotiv EPOC. Other generalized feature extraction techniques such as linear feature extraction and principal component analysis were considered, but linear discriminant analysis was selected as the primary feature extraction technique for this research due to its relative simplicity

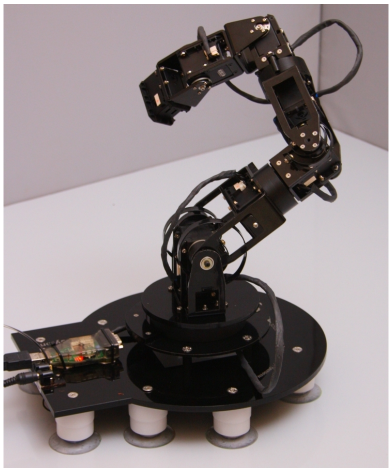

Fig. 3. The Robai Cyton Veta robotic arm

and effectiveness [12], [13].

While much previous work also uses the Emotiv EPOC, we believed there was room for significant improvement. This research 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, we 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 subject moves his or her left index and left thumb as close together as possible without touching them together, holding that position for 1 to 2 seconds.

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

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

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 subjects 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 4. 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 [13]. 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 research work, 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. 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 Σ_i represents the covariance matrices for each class, μ_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

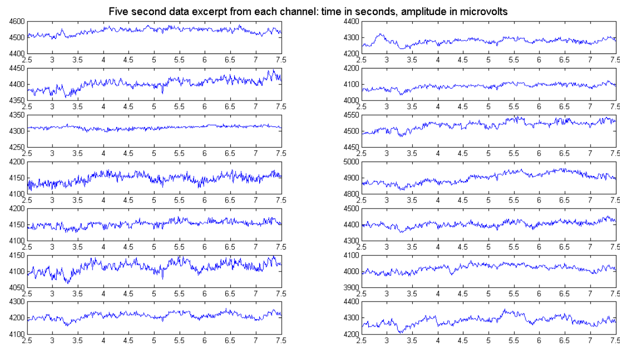

Fig. 4. Example of the signals collected from the Emotiv headset

whether a given data set more closely represents one of the 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 4 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 5 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 6 and 7, 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.

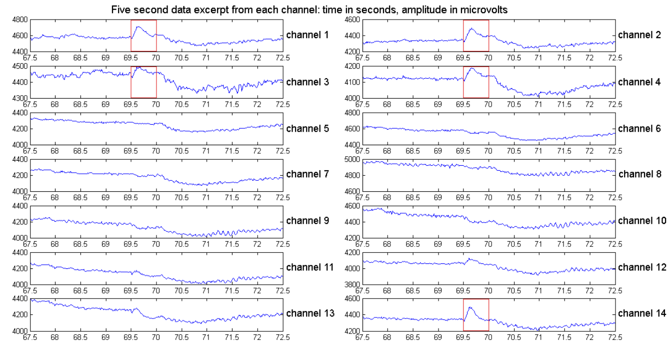

Fig. 5. Visual identification of impulses on the channels characterize the gestures tested

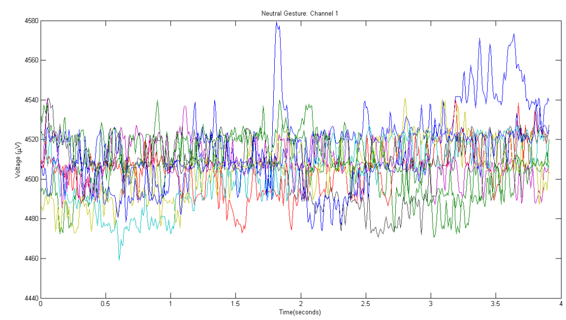

Fig. 6. Channel 1 aligned neutral gestures

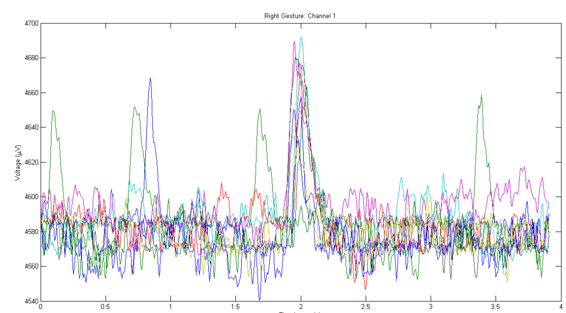

Fig. 7. Channel 1 aligned right gestures

Following the manual sample alignment, each data set is then downsampled by a factor of 50 to create signals that 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 8 and 9.

In Figure 10, 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.

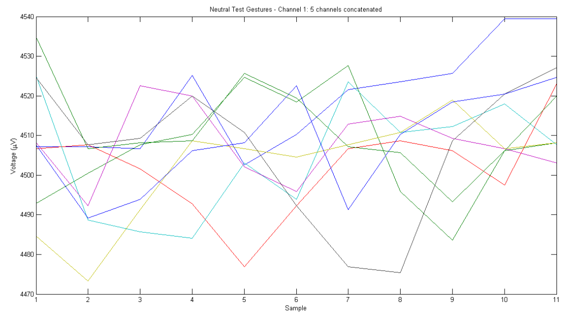

Fig. 8. Channel 1 aligned and downsampled neutral gestures

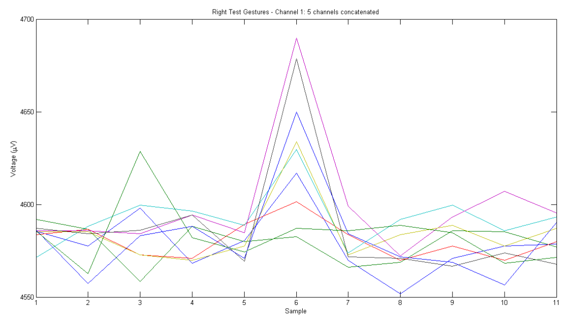

Fig. 9. Channel 1 aligned and downsampled right gestures

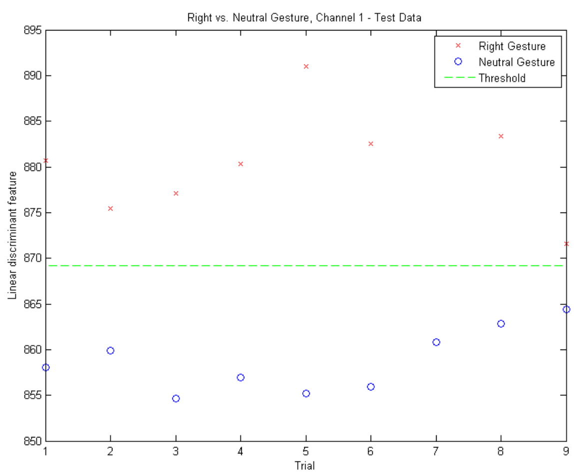

Fig. 10. Resulting linear discriminant analysis plots for channel 1 in a classification of a right gesture versus a neutral gesture

IV. Conclusion

The EEG classifier successfully classified two separate sets of distinct gestures. As the results indicate, the classification accuracy of the best channels between two classes is 100%, even when using a discriminant value 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 offline processing, and a maximum of two classes can be distinguished at once.

Our ongoing work includes customizing the EEG classification system 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.

As part of future work, we are experimenting with holding each gesture for a longer period of time to increase the clarity of the resulting EEG data. We are also developing 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.

Acknowledgment

The authors would like to thank Weisong Wang and John Hageman of the University of Dayton for providing guidance during the research, Dr. Russel Hardie for assistance in implementing LDA, as well as Yicong Gong for for helping the team with the previous BMI research in Vision Lab.

References

[1] W. Ouyang, K. Cashion, and V.K. Asari, "Electroencephelograph based brain machine interface for controlling a robotic arm," IEEE Computer Society Workshop on Applied Imagery Pattern Recognition - AIPR 2013, Washington DC, 23-25 October 2013.

[2] Y. Gong, C. Gross, D. Fan, A. Nasrallah, N. Maas, K. Cashion, and V.K. Asari, "Study of an EEG based brain machine interface system for controlling a robotic arm," Proceedings of the 6th International Conference on Neural Computations Theory and Applications - NCTA 2014, 339-344, 22-24 October 2014.

[3] L.L. Emberson, and D. Amso, "Learning to sample: eye tracking and fMRI indices of changes in object perception", Journal of Cognitive Neuroscience 24, 2030-2042, October 2012.

[4] D. Zumsteg, and H.G. Wieser, "Presurgical evaluation: current role of invasive EEG", Epilepsia, 41: S55S60, 1528-1157, March 2000.

[5] B. Choi, and S. Jo, "A low-cost EEG system-based hybrid brain-computer interface for humanoid robot navigation and recognition", PLOS One, September 2013.

[6] M. Duvinage, et al, "Performance of the Emotiv Epoc headset for P300-based applications", Biomed Eng Online 12, 56, June 2013.

[7] J. O'Connor, "Real-time Control of a Robot Arm Using an Inexpensive System for Electroencephalography Aided by Artificial Intelligence", Computer Science Honors Papers, paper 3, January 2013.

[8] Y. Chae, J. Jeong, and S. Jo, "Toward brain-actuated humanoid robots: asynchronous direct control using an EEG-based BCI", IEEE Transactions on Robotics, 28.5, 1131-1144, June 2012.

[9] R. Kottaimalai, et al. "EEG signal classification using principal component analysis with neural network in brain computer interface applications", IEEE International Conference on Emerging Trends in Computing, Communication and Nanotechnology, 227-231, March 2013.

[10] J.R. Millan, et al, "Noninvasive brain-actuated control of a mobile robot by human EEG" IEEE Transactions on Biomedical Engineering, 51.6, 1026-1033, June 2004.

[11] N.Q. Nguyen, and T.D. Bui, "Improvement of Single-Trial EEG Classifier Accuracy Based on Combination of Optimal Spatial Filters and Time-Domain Features", IEEE International Conference on Knowledge and Systems Engineering, 252-257, October 2011.

[12] R. Nevatia, and K.R. Babu, "Linear feature extraction and description", Computer Graphics and Image Processing, 13.3, 257-269, October 1979.

[13] A.M. Martnez and A.C. Kak, "PCA versus LDA", IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 23, No. 2, 228-233, February 2001.