2014 CMBEC37 Conference
Vancouver, BC
May 21 – 23, 2014

FACILITATING INDEPENDENT LIVING OF INDIVIDUALS WITH NEUROLOGICAL DISORDERS

Mojgan Tavakolan and Carlo Menon*
*MENRVA Group, School of Engineering Science, Faculty of Applied Science, Simon Fraser University (*Correspondence: cmenon@sfu.ca)*

ABSTRACT

Facilitating independent living of individuals with neurological disorders, who have upper extremity (UE) impairment, is a compelling goal for our society. The degree of impairment could be reduced by using Electroencephalography (EEG) controlled assistive devices. The successful implementation of EEG controlled devices strongly relies on the capability of properly determining individuals' actions. Therefore a preliminary study was conducted to evaluate the performance of a classification scheme based on extracting time domain features of the EEG signal. Specifically, the feature vectors were built by extracting root mean square (RMS), autoregressive (AR) coefficients and waveform length from EEG signals. Multi-class support vector machine (SVM) was used as a classifier and an acceptable classification error rate (less than 14%) on average was obtained. It was observed that the classification of three right-arm movements, namely rest, grasp and elbow flexion, was possible in principle.

BACKGROUND

Simple tasks of daily living, such as picking up, holding and placing an object or opening and closing the door can be challenging tasks for individuals with impaired upper extremities [1]. Brain-Computer-Interface (BCI) systems facilitate detecting the presence of specific patterns in the EEG signals related to brain activities such as specific movements [2]. EEG signals are correlated to tasks performed by individuals such as imagining motor movements, mental computation or imagining speech [3-6]. BCIs have shown to be potentially suitable for controlling assistive devices according to the users' intention.

Several EEG classification schemes have been proposed for controlling assistive robotic devices. Empirical mode decomposition for feature extraction was used in [7] and an accuracy of 91±5% and 87±5% were achieved when linear discriminant analysis and multilayer perceptron network were used. Extracted power of the spectral frequencies using a fuzzy classifier for classification of five mental tasks was also proposed in [8]. The classification efficiency of 65% to 100% was obtained. Multilayer perceptron back propagation was used in [9] and an accuracy of 81.80% was obtained using adaptive auto regression. The Elman Neural Network trained by the resilient back propagation algorithm was used for classification of mental tasks and an accuracy of 86% was obtained [10].

In this study, the EEG classification scheme was proposed to be potentially suitable for controlling robotic devices to assist individuals with impaired upper extremity specifically, right arm impairment. Time domain features such as AR model coefficients, RMS and waveform length were used to extract the patterns of the EEG signals corresponding to the specific UE motor movements. The extracted features were then used for the pattern recognition using machine-learning techniques.

METHODS

<u>Emotiv based EEG data collection</u>

This study was approved by the Office of Research Ethics, Simon Fraser University. Five healthy volunteers signed a consent form and participated in this study. The EEG signals were collected by the wireless Emotiv headset (see Figure 1). The Emotiv headset consists of 14 EEG channels (www.emotiv.com). The placements of the electrodes used in this study were based on the International 10-20 locations: O2, P8, T8, FC6, F4, F8, AF4, AF3, F7, F3, FC5, T7, P7, O1 [9]. The Emotiv headset is a lightweight (200 g) wireless and non-invasive headset which is potentially suitable for portable assistive devices.

Protocols

A set of three protocols were followed to collect the EEG data from the volunteers. The protocols considered a combination of three arm gesture and movements including flexing the elbow, rest and grasping. A robotic device could potentially assist a large variety of functional movements by classifying these movements. The following protocols A, B and C were defined to compare the performance of the proposed EEG classification scheme with the performance of the Emotiv EEG classification scheme. Emotiv software was designed to use eight seconds for training. In order to perform a fair comparison, eight seconds of data per person per protocol and twenty four seconds were used as training and testing data sets for the classification in this paper.

In protocol A, as shown in Figure 2-a, the volunteer was asked to keep the arm at rest position for collecting data for rest gesture (pronation position of the arm). In protocol B, as shown in Figures 2-b, the volunteer was asked to apply comfortable force while grasping for collecting data for grasping movement (pronation position of the arm). In protocol C, the volunteer was asked to lift the arm at supination position of the arm (see Figures 2-c). The volunteer repeated this protocol for collecting data for elbow flexion.

Figure 1: Wireless EEG headset

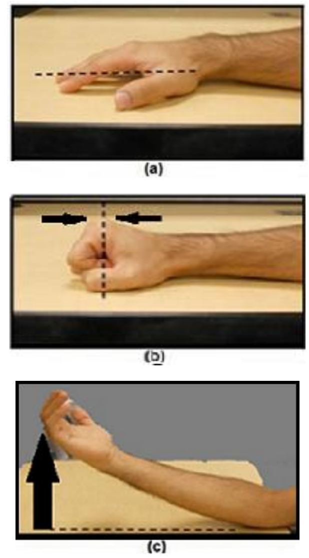

Figure 2: Functional tasks chosen for classification: (a) rest, (b) grasp, (c) lift

Feature extraction and classification

Feature extraction was used for the dimensionality reduction of the raw EEG signal. Extracting features from each sample of the raw EEG signal does not provide any useful information as the structural detail of the signal is lost [10]. The features need to be calculated by segmenting the raw EEG signal. The features were extracted from a window of predetermined length. Features were extracted from the samples by segmenting the signal into 250 ms intervals. The feature was calculated from each segment and then the segment window was incremented by 125 ms for the next feature extraction. Three types of features were extracted from each of the fourteen channels.

AR model coefficients, waveform length and RMS were used to extract six features from each channel. Waveform length and RMS and provided one feature for each channel while AR model coefficients provided four features for each channel of the EEG signal. The extracted features provided 84 dimensional feature vector. The extracted AR model coefficients from the EEG signal were a linear combination of previous samples and noise. Four AR model coefficients are adequate for modeling bio-information signals [11]. Therefore, four AR model coefficients were selected in this experiment. RMS of the raw EEG signal was also used in this experiment. RMS feature provides information regarding the amplitude of the EEG signal. The waveform length was the other extracted feature. This feature measures the waveform complexity of EEG signal in each segment.

The proposed classification scheme of EEG signal is schematically presented in Figure 3. The proposed classification scheme was performed off-line using MATLAB. The recorded EEG signal was normalized with its maximum absolute value. The features were then extracted for the classification purpose. For this experiment, SVM [12] was selected among all the other classifiers. SVM is a well-known classifier suitable for pattern recognition of bio-information signals [13]. The advantage of using SVM for the proposed EEG classification scheme is that SVM works well in high dimensional spaces. In addition SVM has shown good classification results in many practical applications [14]. SVM is a supervised learning method and produces a model which predicts the class labels of the unseen data. SVM [12] requires solving the following optimization problem presented by (1):

$$\min \quad \frac{1}{2}\|a\|^2 + c\sum_{i=1}^{N}\xi_i \qquad (1)$$

subject to

$$\mathrm{w}_i y(\mathbf{x}_i) \geq 1 - \xi_i, \qquad i = 1,\ldots,N$$

$$\xi_i \geq 0$$

where a represents adaptive model parameters, $c>0$ is the penalty factor, w_i is the label associated with a data point, y is the learned model, ξ_i is the slack variable, x_i is data point and N is the number of data points.

Radial basis function (RBF) was used as a kernel function in this experiment. The advantage of choosing RBF kernel is the superior performance of this kernel function. RBF nonlinearly maps the samples and has limited numbers of hyper parameters thus reducing the complexity of model. The mathematical representation of the RBF kernel is presented by (2):

$$k(y_i, y_j) = \exp(-\gamma\|y_i - y_j\|^2), \qquad \gamma > 0 \qquad (2)$$

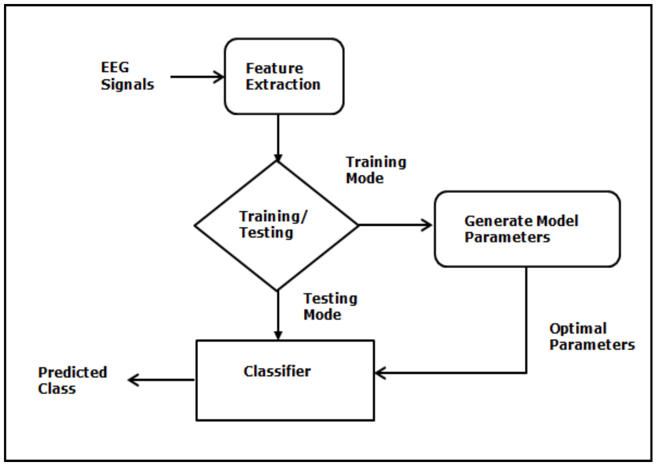

Figure 3: The proposed EEG signal classification scheme

As it is presented in Figure 3, the collected data was divided into training and testing data. The predicting model was trained using the training data to predict the test data. Grid search and eight fold cross validation was applied to train data to select the optimal model parameters for the pattern recognition. By using the cross validation procedure, we prevented the over fitting problem. Figure 4 illustrates the obtained optimal model parameters for a single participant. As it is presented in Figure 4, the highest cross validation accuracy does occur in the interval (0,100) for c parameter and (0,3) for γ parameter. The same interval was used for all the other participants.

RESULTS AND DISCUSSION

The selected optimal kernel parameters for each of the volunteers who participated in this study are presented in Table 1. The optimal kernel parameters were selected according to the highest value of the cross validation accuracy. The optimal kernel parameters were then used to build a model for classifying the arm movements of each participant. The obtained pattern recognition results for both the proposed and Emotiv classification schemes are presented in Table 1. This experiment, which was designed to compare the proposed and the Emotiv classification schemes, the average accuracies of 40.28% and 86.67% were respectively obtained for the Emotiv and the proposed classification schemes.

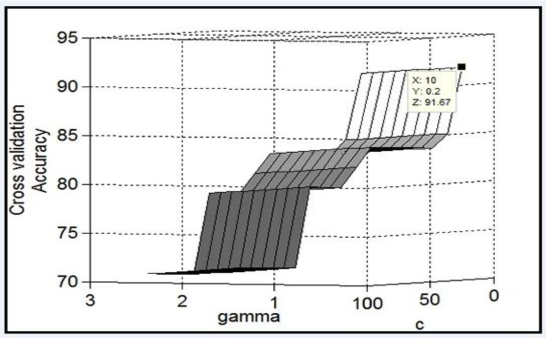

Figure 4: Cross validation accuracy based on *c* and γ

Table 1: The selected model parameters *c*, γ, cross validation error rate and the pattern recognition error rate for the proposed and Emotiv classification schemes

Volunteer	***c*, γ, Cross validation error rate (%)**	**Proposed Classification error rate (%)**	**Emotiv Classification error rate (%)**
A	10, 0.2, 8.33	17.54	60.55
B	10, 0.2, 0	17.54	58.31
C	10, 0.2, 16.67	5.26	67.17
D	10, 0.2, 8.33	21.05	70.47
E	10, 0.2, 4.17	5.26	42.11

CONCLUSION

This study presented a method of associating EEG patterns to three different right arm movements. The identified classes were grasping, elbow flexion and rest. A portable commercial EEG headset and multi-class SVM classifier were used for the pattern recognition. An acceptable classification error rate (less than 14% on average) was obtained. The obtained result proved that successful pattern recognition can be performed to distinguish different right arm movements of users. The proposed method could therefore be potentially suitable for driving an assistive device. Future work will investigate the feasibility of pattern recognition of EEG signals in stroke patients.

ACKNOWLEDGEMENTS

This research was supported by the Michael Smith Foundation for Health Research (MSFHR), the Canadian Institutes of Health Research (CIHR) and the Natural Sciences and Engineering Research Council of Canada (NSERC).

REFERENCES

[1] B.D. Adams, N.M. Grosland, D.M. Murphy and M. McCullough, "Impact of impaired wrist motion on hand and upper-extremity performance," *J. Hand Surgery*, vol. 28, pp. 898-903, 2003.

[2] K.K. Ang, C. Guan, K. S. G. Chua, B.T. Ang, C. Kuah, C. Wang, K. S. Phua, Z. Y. Chin and H. Zhang, "A clinical evaluation on the spatial patterns of non-invasive motor imagery-based brain-computer interface in stroke," *30th Annual International IEEE EMBS Conference, Vancouver, Canada,* 2008.

[3] Z. A. Keirn and J. I. Aunon, "A New Mode of Communication Between Man and His Surroundings," *IEEE Transactions on Biomedical Engineering*, vol. 37 pp. 1209-1214, 1990.

[4] S. Sun, "Multitask Learning for EEG-Based Biometrics," *19th ICPR* pp. 1-4, 2008.

[5] K. Brigham and B.V.K.V. Kumar, "Subject Identification from Electroencephalogram (EEG) Signals During Imagined Speech, "*4th BTAS,* 2010.

[6] R. Palaniappan, "Two-Stage Biometric Authentication Method Using Thought Activity Brain Waves," *Int. J. Neural Systems*, vol. 18, pp. 59-66, 2008.

[7] B. Hudgins, P. Parker and R. N. Scott,"A new strategy for multifunction myoelectric control, " *IEEE Trans Biomed Eng,* vol. 40, pp. 82-94. 1993.

[8] A. T. Campbell, T. Choudhury, S. Hu, H. Lu, M. K. Mukerjee, M. Rabbi, R.D.S. Raizada, "Neurophone: Brain-mobile phone interface using a wireless eeg headset," In *Proceedings of The Second ACM SIGCOMM Workshop on Networking, Systems, and Applications on Mobile Handhelds (MobiHeld10), ACM New York, NY,* USA, 2010.

[9] H. Nai-Jen, R. Palaniappan, "Classification of mental tasks using fixed and adaptive autoressive models of EEG signals, " *26th Annual International Conference of the IEEE EMBS, San Franscisco, CA, USA,* 2004.

[10] C. R. Hema, M. P. Paulraj, R. Nagarajan, S. Yaacob and H. Adom, "Fuzzy based Classification of EEG Mental Tasks for a Brain Machine Interface,", *Third international conference on Intelligent Information Hiding and Multimedia Signal Processing,* vol. 1, pp. 53-56, 2007.

[11] H. P. Huang, C. *Y. Chen, "Development of a myoelectric discrimination system for a multi-degree prosthetic hand, " In Proceedings of the International Conference on Robotics and Automation, pp.* 2392-2397, 1999.

[12] V. Vapnik, "The support vector method of function *estimation ", In: Nonlinear modelling: Advanced black-box techniques. Edited* by Sukens JAK, Vandewalle J. Kluwer academic publishers, Boston, pp. 55-85, 1998.

[13] I. Guler, E. D. Ubeyli, "Multiclass support vector machines for EEG-signals classification, "*IEEE Trans Inf Tech Biomedicine*, vol. 11, pp. 117-126, 2007.

[14] U. H. G. Kreßel, "Pairwise classification and support vector machines," In *B. Sch¨olkopf, C. J. C. Burges and A. J. Smola, editors, Advances in Kernel Methods: Support Vector Learning. The MIT Press, Cambridge, MA,* pp. 255–268, 1999.