Classification of EEG Signals for Brain-Computer Interface Applications: Performance Comparison*

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***Abstract*— This paper presents a comparison of Electroencephalogram (EEG) signals classification for Brain Computer-Interfaces (BCI). At present, it is a challenging task to extract the meaningful EEG signal patterns from a large volume of poor quality data and simultaneously with the presence of artifacts noises. Selection of the effective classification technique of the EEG signals at classification stage is very important to get the robust BCI system. Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) and Logistic Regression (LR) were evaluated in this paper. A BCI competition IV - Dataset 1 is used for testing the classifiers. It is shown that LR and SVM are the most efficient classifier with the highest accuracy of 73.03% and 68.97%.**

Keywords—Brain-computer Interfaces, Electroencephalogram, Support Vector Machine

I. INTRODUCTION

A Brain Computer-Interfaces (BCI) aims to provide an alternative communication system that gives human brain a way to control a machines or devices without involving any muscle movements. BCI converts electroencephalography (EEG) signals generated from brain activity into control command using machine learning technique [1-3]. BCI can be highly benefitted for those who are suffering a neuromuscular disease by using their brain thought to access multiple tasks such as controlling computer, accessing communication and means of research. Moreover, based on nowadays technologies a computer can control various electronic devices such as wheel chairs, doors, lights and home appliances[2]. Although in the early stage BCI have been studied for the main objective of providing assistive technologies for those with severe disabilities to improve their quality of life. However, due to the rapid improvement of computer and biosensor technologies it has gained attention to other non-medical applications such as to control smart mobile phone personal computer and smart home for healthy users [3, 4].

*Research supported by the Fundamental Research Grant Scheme (FRGS), Ministry of Higher Education, Malaysia (Grant No. FRGS/1/2015/ICT02/UNIMAP/01/1).

General BCI consist of five different phases. The first phase is brain activity measurement, second phase is preprocessing, third phase is feature extraction, fourth phase is classification and final phase is control interface which converts the classified signals into meaningful information for devices such as computer or wheelchair [1, 5]. Features that obtained from the feature extraction stage were classified using classification technique and at this stage, a choice of good discriminative features is very important for getting effective classification result that reflect the user's intentions. There are no specific approach to compare the results between different techniques due to different experiment settings and different environments. However, studies have shown that various factors such as preprocessing, feature extraction and classification stage are most important part that highly influence the performance accuracy. It is very important to determine the appropriate technique in these stages to get a high accuracy results [6, 7].

This paper compare four different machine learning technique that commonly used in BCI classification. Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), Multi-Layer Artificial Neural Network (MLP-ANN) and Logistic Regression (LR) are selected to be used in this experiment. The objective in this paper is to find the most efficient classifier for motor imagery BCI. The classifiers are evaluated using BCI competition IV- dataset 1 [8, 9].

II. CLASSIFICATION OF EEG SIGNALS

A. SVM

In 1963, Support Vector Machine (SVM) algorithm was proposed by Vapnik by constructing linear classifier. However, in 1992 Boser, Guyon and Vapnik proposed a procedure to develop a nonlinear classifiers by using the kernel trick to maximum-margin hyperplanes [10]. The algorithm is almost similar except for dot product is replaced by a nonlinear kernel function enables the algorithm to fit the maximum-margin hyperplane in a transformed feature space. The classifier may be nonlinear in the original input space although it hyperplane in the transformed feature space. SVM algorithm still performs well if enough samples are provided but it is known that working in a higher-dimensional feature space can cause higher generalization error of SVM [11]. This experiment implements John Platt's sequential minimal optimization algorithm for training a support vector classifier. This implementation globally replaces all missing values and transforms nominal attributes into binary ones. It also normalizes all attributes by default [12, 13]. For a multi-class case, pairwise classification is used to solve the problems[14].

B. k-NN

k-Nearest Neighbour (k-NN) algorithm is a nonparametric method that utilize for classification and regression. k-NN approach is widely use in supervised learning classification and very well studied in the machine learning problems. Nearest neighbour classifier assign a feature vector to a class based on its nearest neighbours and if the feature vector is from the training set, it is called as k-Nearest Neighbours (k-NN) classifiers [15]. k-NN is not very popular in BCI research because of the dimensionality of the feature vector sensitivity. However, k-NN has been proven to be efficient with low dimension of feature vectors and also has been tested in a multiclass environments [1].This experiment using k-NN algorithm which able to select an appropriate value of k based on cross-validation and has ability to do distance weighting [13].

C. MLP-ANN

Artificial Neural Network (ANN) is a non-linear classifiers widely used in variety of disciplines such as physics, computer sciences and neuroscience. ANN construct from a large of interconnected elements called neurons. Each neuron in ANN imitates the biological neuron and is able to perform classification tasks. Multi-Layer Perceptron Neural Network (MLP-NN) is extensively be used neural network structure. It has three layers (input layer, hidden layer and output layer) and backpropagation algorithm is used for training neural network. MLP-NN is able to provide a useful procedure for motor imagery classification. MLP-NN is very flexible classifier that can classify any number of classes and adapt to various kind of problems[1].

D. LR

Logistic regression (LR) is a classifier for building linear logistic regression models. To fit the logistic models, simple regression functions as base learners is used in LogitBoost algorithm. The most favorable number of LogitBoost iterations to perform is cross-validated, which leads to automatic attribute selection [16]. Logistic regression evaluates the relationship between the dependent variables and independent variables using a logistic function by estimating probabilities. It was widely used in medical and social sciences.

III. MATERIALS AND METHODS

A. BCI competition IV - Dataset 1

The BCI dataset used in this analysis is BCI competition IV dataset 1 provided by Berlin BCI group. The datasets consists of two classes of motor imagery data (left hand, right hand, foot). These datasets were recorded from four healthy subjects and three artificially computer generated subjects. Only four real subject data are use in this experiment. Dataset 1 contains of continuous signals with 59 channels. Two classes of motor imagery were selected from three classes for each subject. In calibration session, data are provided with complete markers. These markers indicate the corresponding target classes and the time points of cue presentation. Arrows pointing left, right, or down were presented as visual cues on a computer screen for the first two runs of calibration data. It takes 4 seconds to finish a task when subject was instructed to perform the cued motor imagery task. These periods were interleaved with 2 seconds of blank screen and with 2 seconds of fixation cross shown in the screen. The fixation cross was lay over another on the cues. Each subject performed a total of 200 motor imagery tasks. Evaluation session followed a different procedure and comes without a complete target markers therefore it was not used in this experiments [8, 9, 17] . Table 1 summarizes BCI Competition IV - dataset 1.

TABLE I. BCI COMPETITION IV - DATASET 1

Type	Motor Imagery
Subject	4 (healthy subject)
Channel	59 EEG channels
Class	2 classes (left hand,right hand and foot)
Frequency	100Hz/1000Hz
Size	85.8MB/857MB
Time	±30 minutes for each subject
Equipment	BrainAmp MR plus

B. Fast Fourier Transform (FFT)

Fourier analysis converts signals from time domain to frequency domain. Fast Fourier transform (FFT) algorithm calculates Discrete Fourier transform (DFT) of a sequence. FFT quickly calculate the transformations by factorizing the DFT matrix into a product of sparse factors and produces exactly the same result as DFT. The difference is that FFT is much faster than DFT. The N-point DFT of N-point sequence $\{x_n, n = 0,1,..., n-1\}$ is defined by

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \quad k = 0,..., N-1 \qquad (1)$$

where k is the current frequency and X_k is the energy of the current frequency k [18].

C. Experimental Setup

Classification of BCI experiments were carried out using the BCI competition IV – dataset 1. The dataset was preprocessed using EEGLAB [19, 20]. Only 11 channels (FC5 FCz FC6 C5 C3 Cz C4 C6 CP5 CPz CP6) which related to the most prominent electrode location for left/right hand and foot movements are chosen to be preprocessed [21]. The raw EEG data was processed using Fast Fourier Transform (FFT) to extract the selected features. The values obtained were formatted in Attribute-Relation File Format (ARFF). This file format will be used as an input file for the WEKA data mining tool [13]. Each subject in the dataset was classified using machine learning classifier available in WEKA. During the classification process, the classifier was trained to classify 0 or 1 values as correctly classified. In all experiments, 10 fold cross validation with 10 times repetitions are used. Default parameter values as implemented in WEKA are used for all the experiments.

D. Result and discussion

The results from classifying the BCI data for all four subjects with four classifiers are presented in Fig 1. For S1, the highest accuracy was obtained with LR (66.78%) followed by SVM (65.80%), ANN (61.60%) and k-NN (54.40%). For S2, although accuracy of all techniques are degraded compared to S1 but still the highest accuracy was obtained with LR (55.36%) followed by SVM (63.66%), ANN (52.80%) and k-NN (47.81%). For S3, accuracy of all classification techniques is increased compared to S2. However, the trends still same with S1 and S2. LR gives the highest accuracy (62.39%) followed by SVM (59.93%), ANN (58.77%) and k-NN (51.84%). For S4, although the trend is similar with S1, S2 and S3 however the classification accuracy of all techniques achieved the highest results. LR gives (73.03%) followed by SVM (68.97%), ANN (66.42%) and k-NN (56.71%). Figure 1 shows the performance comparison of each subject.

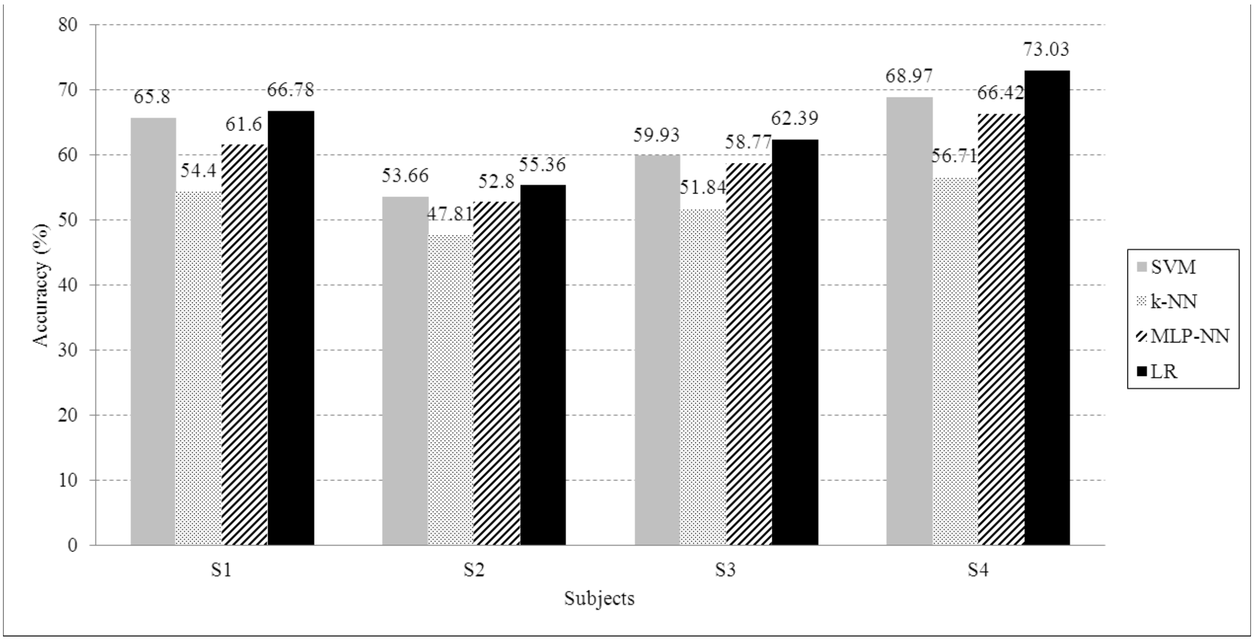

Fig. 1. Performance Comparison of four subjects using SVM, k-NN, MLP-NN and LR

Based on the results LR and SVM seemed to be good choices of classifier, however it is depends to the features as mentioned by Sohaib et al. The accuracy also can be improved for some technique such as k-NN and ANN when highly correlated feature were used, while degraded for others [6].

IV. CONCLUSION

This paper has evaluated four different machine learning techniques of classifier using motor imagery dataset 1 from BCI competition IV. Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), Artificial Neural Network (ANN) and Logistic Regression (LR) were tested to find the most efficient classifier in terms of accuracy results. It has been shown LR and SVM are the most efficient classifier with the highest accuracy of 73.03% and 68.97%.

REFERENCES

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," *Sensors,* vol. 12, pp. 1211-1279, 2012.

[2] M. Fouad, K. Amin, N. El-Bendary, and A. Hassanien, "Brain Computer Interface: A Review," in *Brain-Computer Interfaces*. vol. 74, A. E. Hassanien and A. T. Azar, Eds., ed: Springer International Publishing, 2015, pp. 3-30.

[3] G. Edlinger, B. Allison, and C. Guger, "How Many People Can Use a BCI System?," in *Clinical Systems Neuroscience*, K. Kansaku, L. G. Cohen, and N. Birbaumer, Eds., ed: Springer Japan, 2015, pp. 33-66.

[4] M. Moore Jackson and R. Mappus, "Applications for Brain-Computer Interfaces," in *Brain-Computer Interfaces*, D. S. Tan and A. Nijholt, Eds., ed: Springer London, 2010, pp. 89-103.

[5] G. Pfurtscheller, C. Brunner, R. Leeb, R. Scherer, G. Müller-Putz, and C. Neuper, "The Graz Brain-Computer Interface," in *Brain-Computer Interfaces SE - 5*, B. Graimann, G. Pfurtscheller, and B. Allison, Eds., ed: Springer Berlin Heidelberg, 2010, pp. 79-96.

[6] A. Sohaib, S. Qureshi, J. Hagelbäck, O. Hilborn, and P. Jerčić, "Evaluating Classifiers for Emotion Recognition Using EEG," in *Foundations of Augmented Cognition*. vol. 8027, D. Schmorrow and C. Fidopiastis, Eds., ed: Springer Berlin Heidelberg, 2013, pp. 492-501.

[7] P. Georgieva, F. Silva, M. Milanova, and N. Kasabov, "EEG Signal Processing for Brain–Computer Interfaces," in *Springer Handbook of Bio-/Neuroinformatics*, N. Kasabov, Ed., ed: Springer Berlin Heidelberg, 2014, pp. 797-812.

[8] K.-R. Müller, B. Blankertz, C. Vidaurre, G. Nolte, and C. B. Franklin. (2008, 12-January-2016). *BCI Competition IV*. Available: http://www.bbci.de/competition/iv/

[9] P. Sajda, A. Gerson, K. R. Muller, B. Blankertz, and L. Parra, "A data analysis competition to evaluate machine learning algorithms for use in brain-computer interfaces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, pp. 184-185, 2003.

[10] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," presented at the Proceedings of the fifth annual workshop on Computational learning theory, Pittsburgh, Pennsylvania, USA, 1992.

[11] C. Jin and L. Wang, "Dimensionality dependent PAC-Bayes margin bound," in *Advances in Neural Information Processing Systems*, 2012, pp. 1034-1042.

[12] J. C. Platt, "12 fast training of support vector machines using sequential minimal optimization," *Advances in kernel methods,* pp. 185-208, 1999.

[13] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD explorations newsletter,* vol. 11, pp. 10-18, 2009.

[14] T. Hastie and R. Tibshirani, "Classification by pairwise coupling," *The annals of statistics,* vol. 26, pp. 451-471, 1998.

[15] J. Won Yoon and N. Friel, "Efficient model selection for probabilistic K nearest neighbour classification," *Neurocomputing,* vol. 149, Part B, pp. 1098-1108, 2/3/ 2015.

[16] N. Landwehr, M. Hall, and E. Frank, "Logistic Model Trees," *Machine Learning* vol. 59, pp. 161-205, 2005.

[17] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, "The non-invasive Berlin Brain–Computer Interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage,* vol. 37, pp. 539-550, 8/15/ 2007.

[18] D. G. Manolakis, V. K. Ingle, and S. M. Kogon, *Statistical and adaptive signal processing*. Boston, London: Artech House, 2005.

[19] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of neuroscience methods,* vol. 134, pp. 9-21, 2004.

[20] A. Delorme, T. Mullen, C. Kothe, Z. Akalin Acar, N. Bigdely-Shamlo, A. Vankov*, et al.*, "EEGLAB, SIFT, NFT, BCILAB, and ERICA: New Tools for Advanced EEG Processing," *Computational Intelligence and Neuroscience,* vol. 2011, p. 12, 2011.

[21] B. Graimann, B. Allison, and G. Pfurtscheller, "Brain–Computer Interfaces: A Gentle Introduction," in *Brain-Computer Interfaces*, B. Graimann, G. Pfurtscheller, and B. Allison, Eds., ed: Springer Berlin Heidelberg, 2010, pp. 1-27.