International Journal of Engineering Trends and Technology Volume 69 Issue 1, 121-125, January 2021
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I1P219 © 2021 Seventh Sense Research Group®

Motor-Imagery based EEG Signals Classification using MLP and KNN Classifiers

Yogendra Narayan
Department of ECE, Chandigarh University, Gharuan, Mohali, Punjab-140413, India
narayan.yogendra1986@gmail.com

Abstract: *The electroencephalogram (EEG) signals classification plays a major role in developing assistive rehabilitation devices for physically disabled performs. In this context, EEG data were acquired from 20 healthy humans followed by the pre-processing and feature extraction process. After extracting the 12-time domain features, two well-known classifiers, namely K-nearest neighbor (KNN) and multi-layer perceptron (MLP), were employed. The fivefold cross-validation approach was utilized for dividing data into training and testing purposes. The results indicated that the performance of the MLP classifier was found better than the KNN classifier. MLP classifier achieved 95% classifier accuracy, which is the best. The outcome of this study would be very useful for the online development of the EEG classification model and designing the EEG based wheelchair.*

Keywords: *Motor-Imagery, EEG signal, KNN, MLP, ICA, Innovation*

I. INTRODUCTION

The BCI system consists of four different units: (a) signal acquisition unit, (b) signal processing and classification unit, which extracts the features of brain signals and converts those feature into device commands, (c) an output device, and (d) an operating mechanism for guiding operation [1]. The implementation of such a BCI system is based on four basic techniques (i) P300, (ii) slow cortical potentials, (iii) steady-state visually evoked potentials (SSVEP), and (iv) motor imagery (MI) [2]. Among these techniques, only two BCI techniques, namely SSVEP and MI, have been mainly utilized for controlling the orthoses, exoskeleton, and neuroprostheses [3]. The SSVEP technique requires the external stimuli for generating the evoked potentials and thereby producing a higher rate of false-positive detections in long resting periods, whereas MI-based BCI does not need any external stimulus but depends on the subject's concentration [4]. In MI-based BCI, the subject thinks either right or left-hand movement, and this motor imagery activity of brain signal is recognized and recorded by the BCI system [5]. Although, the MI-based method has limited classification accuracy and results in poor system reliability [6] [7].

Zip disks, hard drives, CDs, and optical disks are needed for storing the recordings [8]. EEG data format varies from one EEG machine to another, and these formats can be converted into spreadsheets by using software like MATLAB [9], [10]. The electrodes need to work properly to record high quality and accurate data [11]. Various kinds of electrodes are used in the EEG recording system like Needle electrodes, Disposable (pre-gelled and gel fewer types) electrodes, Saline-based electrodes, Headbands and electrode caps, Reusable disc electrodes (gold, stainless steel, silver, or tin) [12].

Any form of communication or control needs muscles and peripheral nerves [13], [14]. The process starts with the intention of the user [13]. This intention gives a spark to a complex process that activates some areas of the brain, and hence, signals are transmitted to the muscles via the peripheral nervous system, which resulted in the production of the desired movement for the control or communication task [15]. This process leads to generate an action known as efferent output or motor output. Efferent output communicates the impulses to the central nervous system's peripheral nervous system and then to the effectors (muscles) [16]. Afferent is the opposite of efferent. In other words, it can be said that it conveys a message to the central nervous system from sensory receptors [17], [18]. The efferent (motor) pathway is necessary for controlling the motion, while the afferent (sensory) pathway is necessary for dexterous tasks like playing the piano or violin or typing and learning motor skills [19], [20].

This paper is distributed into four parts, and the first part is the introduction, which provides the information related to the classification of EEG signals. The second part explores the materials and methods, including the EEG acquisition, feature extraction, and classification technique. The third part discusses the results obtained from the MATLAB© 2020 simulation, whereas the fourth part demonstrates the conclusion of work followed with future directions.

II. MATERIALS AND METHODS

A. EEG data acquisition and pre-processing

20 healthy human subjects participated in two recording sessions in which they imagined 20 right-hand movements and 20 left-hand movements per session [21]. The subjects were asked to sit in a comfortable armchair with a distance of 150 cm in front of the computer monitor [22]. Subjects were provided with all necessary instruction for data recordings like the concept of MI and BCI setup, full-body

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

relaxation, and no movements during data acquisition [23]. Fig. 1 shows the experimental accessories in which g.LADYbird active electrodes (g.GAMMAcap) are placed on the scalp of a subject for EEG data recording.

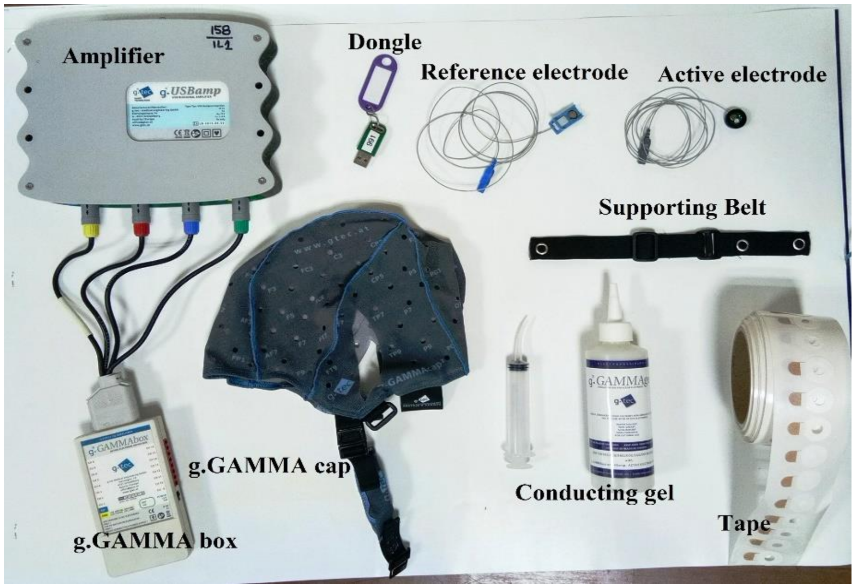

Fig. 1. Experiment accessories used during the EEG signals recording

analog-to-digital converters (ADC) were employed to convert analog EEG signals in the digital form [24]. A minimum of 200 samples/sec sampling frequency was required for maintaining the all appropriate information of EEG signal having the bandwidth 100 Hz [25]. After the pre-processing steps, feature extraction was done by employing the CSP technique, EOG artifacts were removed by the ICA method, whereas dimension reduction was performed by the PCA technique [26].

B. EEG feature extraction

Feature extraction is an essential process for better classification results. To achieve a good performance of the classifier, one must utilize the robust feature set [27]. Fig. 2 represents an EEG acquisition setup with an EEG cap with active electrodes that transfer signals to the bio-signal amplifier [28]. It also consists of a computer that processes the data and runs the BCI application [29]. The bio-signal amplifier converts the signal from analog to digital form for further processing and utilization [30]. Table 1 shows the 12 different time-domain features utilized in this work for evaluating the performance of MLP and KNN classifier.

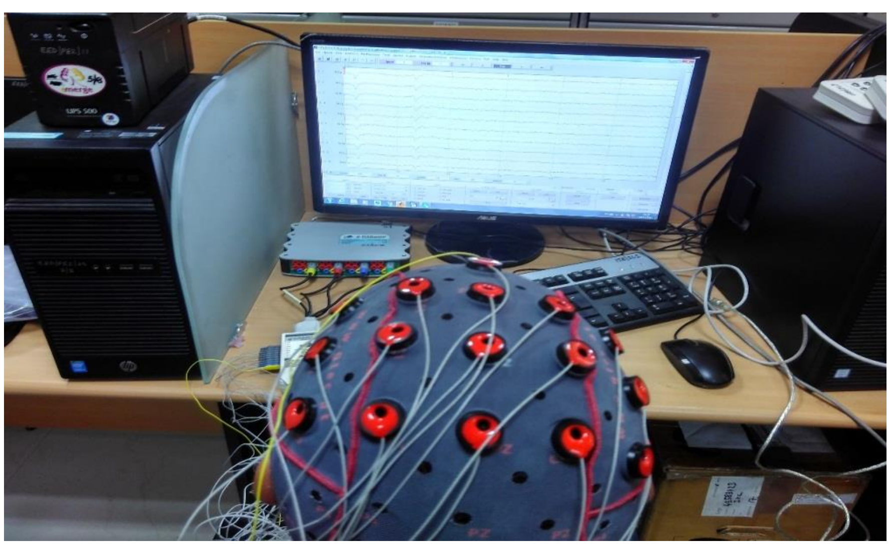

Fig. 3 EEG acquisition setup for EEG data recording from a healthy human subject

Table 1. Mathematical Definitions of Features

Sr. No.	Name of the Feature	Equation
1	Integrated Absolute Value (IAV)	$IAV = \sum_{i=1}^{N} \lvert X_i \rvert$
2	Mean Absolute Value (MAV)	$MAV = \frac{1}{N}\sum_{i=1}^{N} \lvert X_i \rvert$
3	Simple Square Integral (SSI)	$SSI = \sum_{i=1}^{N} (X_i)^2$
4	Variance (VAR)	$VAR = \frac{1}{N-1}\sum_{i=1}^{N} (X_i)^2$
5	Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {X_i}^2}$
6	LOG Detector (LD)	$LOG = e^{\sqrt{\frac{1}{N}\sum_{i=1}^{N} {X_i}^2}}$
7	Waveform Length (WL)	$WL = \sum_{i=1}^{N-1} \lvert X_{i+1} - X_i \rvert$
8	Average Amplitude Change (AAC)	$AAC = \frac{1}{N}\sum_{i=1}^{N-1} \lvert X_{i+1} - X_i \rvert$
9	Zero Crossing (ZC)	$ZC = \sum_{i=1}^{N-1} [sgn(X_i * X_{i+1}) \cap \lvert X_i - X_{i+1} \rvert \geq Threshold]$ $sgn(X) = \begin{cases} 1 & if\ X \geq threshold \\ 0 & otherwise \end{cases}$
10	Standard Deviation (SD)	$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} x_n}$
11	Kurtosis (KUT)	$\sum_{n=1}^{N} \frac{E(x_0-\mu)^4}{\sigma^4}$
12	Slope Sign Change (SSC)	$SSC = \sum_{i=2}^{N-1} [f[(X_i - X_{i-1}) * (X_i - X_{i-1})]$ $f(X) = \begin{cases} 1 & if\ X \geq threshold \\ 0 & otherwise \end{cases}$

C. Classifiers

Classification is when different items or objects are identified, distinguished, and then comprehended [31]. In simple words, it is a process of division of various items or objects into groups based on some similarities or properties [32], [33], [34]. In this study, MLP and KNN classifiers were compared with three different sessions EEG dataset [35]. Individual features were applied in the form of input to the classifier, and their classification accuracy was noted for comparison purposes. The Fivefold cross-validation method was adopted for classification accuracy computation.

III. RESULTS AND DISCUSSION

In this work, two classifiers, namely KNN and MLP classifiers, were compared using 12 time-domain features in classification accuracy. The classification accuracy can be defined as the true samples ratio to the total number of samples. 20 healthy human subjects participated in three EEG data recording sessions at the Bio-Medical Laboratory of NITTTR Chandigarh, India. Individual features accuracy were compared using KNN and MLP classifier in all three sessions with corresponding standard deviation. MATLAB© 2020 was exploited for obtaining the simulation results of classifiers. The Fivefold cross-validation method was employed for dividing the whole EEG dataset into training and testing purposes. In the Fivefold cross-validation method, the whole EEG dataset was divided into five equal parts, and one part was utilized for testing while four parts were utilized for training the classifier.

Table 2 showed the results in terms of classification accuracy during session 1 using MLP and KNN classifier. Standard deviation was computed per subject. The results showed that the top five best features were RMS, MAV, LD, SSI, and VAR with the accuracy of 66.8±4.6%, 65.6±5.5 %, 64.9±5.1%, 58.5±3.6%, and 57.7±3.4% with MLP classifier, respectively. The least five features, namely SD, KUT, SSC, IAV, and AAC, performed lower than all features. The least performance features could be avoided for better results or replaced by other useful features.

Table 2. Performance of KNN and MLP classifier for session 1 to discriminate left and right-hand movement

Feature Rank	Features	KNN (% ACC+SD)	MLP (% ACC+SD)
1	RMS	63.3±4.5	66.8±4.6
2	MAV	62.5±4.7	65.6±5.5
3	LD	61.6±3.6	64.9±5.1
4	SSI	55.8±3.4	58.5±3.6
5	VAR	54.3±3.2	57.7±3.4
6	WL	51.4±6.0	54.5±6.2
7	ZC	48.9±2.5	51.6±3.1
8	SD	40.8±5.1	44.4±5.4
9	KUT	38.6±9.1	41.7±10.3
10	SSC	36.5±2.4	39.6±3.2
11	IAV	31.5±3.7	34.4±3.8
12	AAC	25.2±2.4	31.6±2.0

The performance of the second session EEG dataset was demonstrated by Table 3 for MLP and KNN classifier. RMS feature was found best feature followed by MAV, LD, SSI, and VAR, whereas lowest-performing features were found as SD, KUT, SSC, IAV, and AAC. The best performing feature was always suggested, whereas the lowest-performing features should be avoided while forming the final feature vector. MLP classifier's performance was found better than the KNN classifier for classifying the left and right-hand motor-imagery EEG datasets.

Table 3. Performance of KNN and MLP classifier for session 2 to discriminate left and right-hand movement

Feature Rank	Features	KNN (% ACC+SD)	MLP (% ACC+SD)
1	RMS	63.5±4.1	66.5±4.8
2	MAV	62.8±4.4	65.2±5.6
3	LD	61.7±3.8	64.5±5.5
4	SSI	55.9±3.2	58.2±3.3
5	VAR	54.5±3.6	57.4±3.2
6	WL	51.7±5.5	54.2±6.6
7	ZC	48.8±2.8	51.8±3.7
8	SD	40.7±4.5	44.8±5.7
9	KUT	38.5±8.8	40.5±9.3
10	SSC	36.5±2.6	36.9±2.7
11	IAV	31.8±3.4	34.1±3.1
12	AAC	25.4±2.6	31.7±2.8

Similarly, the performance of the third session EEG dataset was demonstrated in Table 4. Again the RMS feature was found best feature followed by MAV, LD, SSI, and VAR, whereas the lowest-performing features were found as SD, KUT, SSC, IAV, and AAC. It was clear from Table 2 to Table 4 that the performance of the MLP classifier was found better than the KNN classifier for classifying the left and right-hand motor-imagery EEG datasets. MLP classifier achieved 95% classification accuracy when all features combined in the form of the feature vector. So, the MLP classifier was the best classification method and suggested developing the online model for classifying the EEG dataset.

Table 4. Performance of KNN and MLP classifier for session 3 to discriminate left and right-hand movement

Feature Rank	Features	KNN (% ACC+SD)	MLP (% ACC+SD)
1	RMS	64.6±4.3	67.4±4.7
2	MAV	63.7±4.6	66.5±5.5
3	LD	62.6±3.7	65.8±5.4
4	SSI	56.8±3.4	59.6±3.2
5	VAR	55.7±3.8	58.4±3.1
6	WL	53.2±5.6	55.2±6.5
7	ZC	49.7±2.2	53.3±3.6
8	SD	43.4±4.4	45.6±5.9
9	KUT	40.4±8.5	42.8±9.2
10	SSC	38.8±2.5	40.7±2.6
11	IAV	33.9±3.7	35.8±3.4
12	AAC	27.5±2.3	33.1±2.6

IV. CONCLUSION

This work reported the comparative analysis of 12-time domain features by employing the MLP and KNN classifier to classify accuracy. 20 healthy human subjects participated in three EEG data recording sessions to imagine right and left-hand movements. After data acquisition, pre-processing and feature extraction was done, followed by the classification. Results showed that the MLP classifier's performance was better than the KNN classifier, and the top five best features were RMS, MAV, LD, SSI, and VAR, whereas the top least performing features were SD, KUT, SSC, IAV, and AAC. Further, the classification accuracy could be improved if more robust and novel features were utilized for forming the final feature vector. This study's finding would be useful for online EEG classification model development towards robotic rehabilitation designing.

Reference

[1] A. Vourvopoulos and S. Bermúdez i Badia., Motor priming in virtual reality can augment motor-imagery training efficacy in restorative brain-computer interaction: a within-subject analysis., J. Neuroeng. Rehabil., 13(1)(2016) 69.

[2] N. Hooda, R. Das, and N. Kumar., Fusion of EEG and EMG signals for classification of unilateral foot movements," Biomed. Signal Process. Control, 60(2020) 101990.

[3] M. Wang, J. Hu, and H. A. Abbass., BrainPrint : EEG Biometric Identification based on Analyzing Brain Connectivity Graphs," Pattern Recognit., 300(5)(2020) 107381.

[4] J. Ortega, J. Asensio-Cubero, J. Q. Gan, and A. Ortiz., Classification of motor imagery tasks for BCI with multiresolution analysis and multiobjective feature selection., Biomed. Eng. Online, 15(73)(2016) S1.

[5] O. W. Samuel, Y. Geng, X. Li, and G. Li., Towards Efficient Decoding of Multiple Classes of Motor Imagery Limb Movements Based on EEG Spectral and Time Domain Descriptors., J. Med. Syst., 41(12)(2017).

[6] E. Monge-Pereira, J. Ibañez-Pereda, I. M. Alguacil-Diego, J. I. Serrano, M. P. Spottorno-Rubio, and F. Molina-Rueda, "Use of Electroencephalography Brain-Computer Interface Systems as a Rehabilitative Approach for Upper Limb Function After a Stroke: A Systematic Review., PM&R,9(9)(2017) 918–932.

[7] M. Kaur and V. Wasson.,ROI Based Medical Image Compression for Telemedicine Application., in Procedia Computer Science, 70(2015) 579–585.

[8] J. Minguillon, M. A. Lopez-Gordo, and F. Pelayo., Trends in EEG-BCI for daily-life: Requirements for artifact removal," Biomed. Signal Process. Control, 31(2017) 407–418.

[9] According to movement intention state, Cogn, B. Kim, L. Kim, Y. H. Kim, and S. K. Yoo., Cross-association analysis of EEG and EMG signals. Syst. Res., 44(2017) 1–9.

[10] W. Y. Hsu, "Brain-computer interface connected to telemedicine and telecommunication in virtual reality applications," Telemat. Informatics, 34(4)(2017) 224–238.

[11] S. Çınar and N. Acır, A novel system for automatic removal of ocular artifacts in EEG using outlier detection methods and independent component analysis, Expert Syst. Appl., 68(2017) 36–44.

[12] Z. Yin and J. Zhang., Cross-session classification of mental workload levels using EEG and an adaptive deep learning model," Biomed. Signal Process. Control, 33(2017) 30–47.

[13] A. Arunkumar et al., Classification of focal and non-focal EEG using entropies, Pattern Recognit. Lett., 94((2017) 112–117.

[14] Y. Narayan, L. Mathew, and S. Chatterji., SEMG signal classification with novel feature extraction using different machine learning approaches," J. Intell. Fuzzy Syst., 35(5)(2018) 5099–5109.

[15] P. Martín-Smith, J. Ortega, J. Asensio-Cubero, J. Q. Gan, and A.

Ortiz., A supervised filter method for multiobjective feature selection in EEG classification based on multi-resolution analysis for BCI., Neurocomputing, 250(12) 45–56.

[16] S. M. Park, X. Yu, P. Chum, W. Y. Lee, and K. B. Sim., Symmetrical feature for interpreting motor imagery EEG signals in the brain-computer interface," Optik (Stuttg)., 129(2017) 163–171.

[17] A. Jafarifarmand, M. A. Badamchizadeh, S. Khanmohammadi, M. A. Nazari, and B. M. Tazehkand, "A new self-regulated neuro-fuzzy framework for classification of EEG signals in motor imagery BCI," IEEE Trans. Fuzzy Syst., vol. 6706, no. 99, pp. 1–11, 2017.

[18] J. Hori and N. Okada, "Classification of tactile event-related potential elicited by Braille display for the brain-computer interface," Biocybern. Biomed. Eng., vol. 37, no. 1, pp. 135–142, 2017.

[19] F. Alimardani, R. Boostani, and B. Blankertz, "Weighted spatial based geometric scheme as an efficient algorithm for analyzing single-trial EEGS to improve cue-based BCI classification," Neural Networks, vol. 92, pp. 69–76, 2017.

[20] Y. Yang, S. Chevallier, J. Wiart, and I. Bloch, "Subject-specific time-frequency selection for multi-class motor imagery-based BCIs using few Laplacian EEG channels," Biomed. Signal Process. Control, vol. 38, pp. 302–311, 2017.

[21] N. Wang, K. Lao, and X. Zhang, "Design and Myoelectric Control of an Anthropomorphic Prosthetic Hand," J. Bionic Eng., vol. 14, no. 1, pp. 47–59, 2017.

[22] R. Zarei, J. He, S. Siuly, and Y. Zhang, "A PCA aided cross-covariance scheme for discriminative feature extraction from EEG signals," Comput. Methods Programs Biomed., vol. 146, pp. 47–57, 2017.

[23] S. CINAR and N. ACIR, "A novel system for automatic removal of ocular artifacts in EEG by using outlier detection methods and independent component analysis," Expert Syst. Appl., vol. 68, pp. 36–44, 2017.

[24] A. Schurger, S. Gale, O. Gozel, and O. Blanke, "Performance monitoring for brain-computer-interface actions," Brain Cogn., vol. 111, pp. 44–50, 2017.

[25] H. Mirvaziri and Z. S. Mobarakeh, "Improvement of EEG-based motor imagery classification using ring topology-based particle swarm optimization," Biomed. Signal Process. Control, vol. 32, pp. 69–75, 2017.

[26] R. M. Cichy and D. Pantazis, "Multivariate pattern analysis of MEG and EEG: A comparison of representational structure in time and space," Neuroimage, vol. 158, pp. 441–454, 2017.

[27] X. Li, O. W. Samuel, X. Zhang, H. Wang, P. Fang, and G. Li, "A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees," J. Neuroeng. Rehabil., vol. 14, no. 1, 2017.

[28] S. K. Satapathy, S. Dehuri, and A. K. Jagadev, "EEG signal classification using PSO trained RBF neural network for epilepsy identification," Informatics Med. Unlocked, vol. 6, pp. 1–11, 2017.

[29] N. Hamzah, N. Zaini, M. Sani, and N. Ismail, "EEG Analysis on Actual and Imaginary Left and Right-Hand Lifting using Support Vector Machine (SVM)," Int. J. Electr. Electron. Syst. Res. EEG, vol. 10, no. 6, pp. 10–17, 2017.

[30] S. Ge et al., "A Brain-Computer Interface Based on a Few-Channel EEG-fNIRS Bimodal System," IEEE Access, vol. 5, pp. 208–218, 2017.

[31] C. Y. Sai, N. Mokhtar, H. Arof, P. Cumming, and M. Iwahashi, "Automated Classification and Removal of EEG Artifacts with SVM and Wavelet-ICA," IEEE J. Biomed. Heal. Informatics, vol. 2194, no. c, pp. 1–1, 2017.

[32] M. Li, W. Chen, and T. Zhang, "Application of MODWT and log-normal distribution model for automatic epilepsy identification," Biocybern. Biomed. Eng., vol. 37, no. 4, pp. 679–689, 2017.

[33] A. Al-Ani, I. Koprinska, and G. Naik, "Dynamically identifying relevant EEG channels by utilizing channels classification behavior," Expert Syst. Appl., vol. 83, pp. 273–282, 2017.

[34] M. Kaur, H. K. Gianey, D. Singh, and M. Sabharwal, "Multiobjective differential evolution based random forest for e-health applications," Mod. Phys. Lett. B, vol. 33, no. 5, Feb. 2019.

[35] J. Kevric and A. Subasi, "Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system," Biomed. Signal Process. Control, vol. 31, pp. 398–406, 2017.