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MI based Brain Signals identification using KNN and MLP Classifiers

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Abstract: Theelectroencephalogram (EEG) signals classification playsa 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 purpose. The results indicated that the performance of 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 online development of EEG classification model as well as designing the EEG based wheelchair.

Keywords: Motor-Imagery, EEG signal, KNN, MLP, ICA.

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 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 concentration [4]. In MI-based BCI, 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 reliability of the system[6].

Zip disks, hard drives, CDs and optical disks are needed for storing the recordings[7]. The format of EEG data vary from one EEG machine to another and these formats can be converted into spreadsheets by using the software like MATLAB[8], [9]. The electrodes need to work properly to record high quality and accurate data[10]. Various kinds of electrodes are used in the EEG recording system like Needle electrodes, Disposable (pre-gelled and gel

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fewer types) electrodes, Saline-based electrodes, Headbands and electrode caps, Reusable disc electrodes (gold, stainless steel, silver or tin)[11].

Any form of communication or control needs muscles and peripheral nerves[12], [13]. The process starts with the intention of the user [12]. 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 into the production of the desired movement for the control or communication task [14]. This process leads to generate an action known as efferent output or motor output. Efferent output communicates the impulses to the peripheral nervous system from the central nervous system and then to the effectors (muscles)[15]. 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[16], [17]. 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 [18], [19].

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

MATERIALS AND METHODS

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[20]. The subjects were asked to sit in a comfortable armchair with a distance of 150 cm in front of the computer monitor[21]. Subjects were provided with all necessary instruction for data recordings [22]like the concept of MI and BCI setup, full-body relaxation and no movements during data acquisition[23]–[25][26].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.

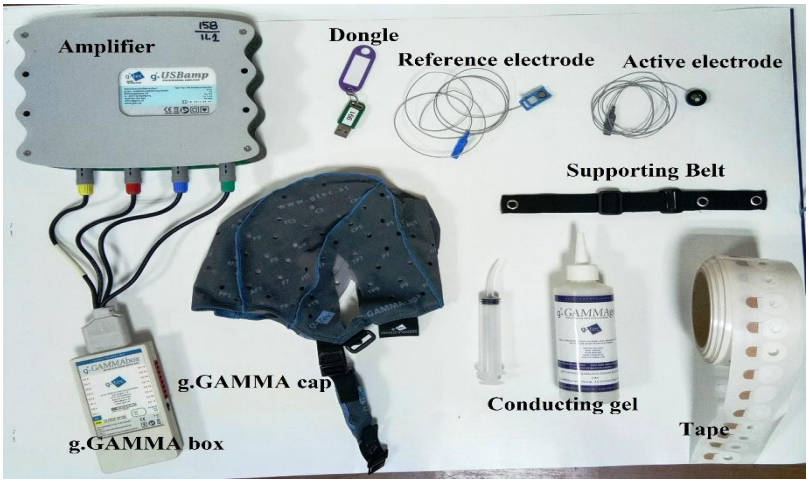

Fig. 1. Experiment accessories used during the EEG signals recording

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analogue-to-digital converters (ADC) was employed for converting analogue EEG signals in the digital form[27]. The minimum of 200 samples/sec sampling frequency was required for maintaining the all appropriate information of EEG signal having the bandwidth 100 Hz[28].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[29].

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[30]. Fig. 2 represents an EEG acquisitionsetup which has an EEG cap with active electrodes that transfer signals to the bio-signal amplifier [31]. It also consists of a computer that processes the data and runs the BCI application[32]. The bio-signal amplifier converts the signal from analogue to digital form for further processing and utilization[33]. Table 1 shows the 12 different time-domain features utilized in this work for evaluating the performance of MLP and KNN classifier.

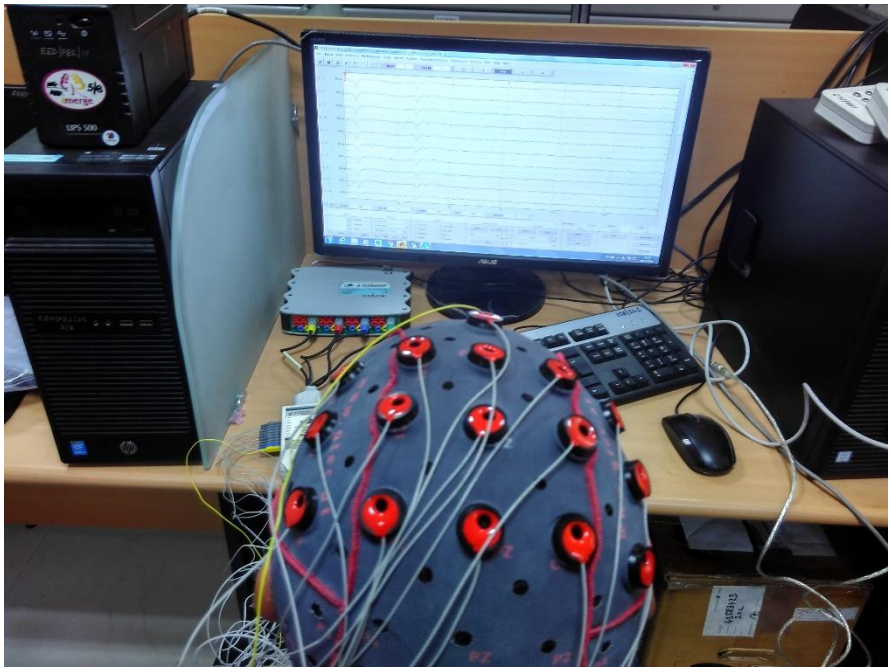

Fig. 3 EEG acquisition setup for EEG data recording from a healthy human subject

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)	$MAV = \frac{1}{N} \sum_{i=1}^{N} \lvert X_i \rvert$

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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)	$SSC = \sum_{i=2}^{N-1} [\, f[(X_i - X_{i-1}) * (X_i - X_{i-1})]$ $f(X) = \begin{cases} 1 & if\ X \geq threshold \\ 0 & otherwise \end{cases}$

Classifiers

Classification is the process in which different items or objects are identified, distinguished and then comprehended [34]. In simple words, it is a process of division of various items or objects into groups based on some similarities or properties[35], [36]. In this study,MLP and KNN classifier were compared to each other with three different sessions EEG dataset [37]. Individual features were applied in the form of input to the classifier and their classification accuracies were noted down for comparison purpose. Fivefold cross-validation method was adopted for classification accuracy computation.

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RESULTS AND DISCUSSION

In this work, two classifiers namely KNN and MLP classifier were compared using 12 time-domain features in terms of classification accuracy. The classification accuracy can be defined as the ratio of the true samples to the total number of samples. 20 healthy human subjects participated in three sessions of EEG data recording at 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 were exploited for obtaining the simulation results of classifiers. Fivefold cross-validation method was employed for dividing the whole EEG dataset into training and testing purpose. In the Fivefold cross-validation method, 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 term of classification accuracy during session 1 by 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 as compared to 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 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. Best performing feature was always suggested whereas lowest-performing features should be avoided while forming the final feature vector. The performance of MLP classifier was found better than the KNN classifier for classifying the left and right-hand motor-imagery EEG dataset.

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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 lowest-performing features were found as SD, KUT, SSC, IAV and AAC. It was clear from Table 2 to Table 4 that performance of MLP classifier was found better than the KNN classifier for classifying the left and right-hand motor-imagery EEG dataset. MLP classifier achieved 95% classification accuracy when all features combined in the form of the feature vector. So, MLP classifier was the best classification method and suggested for 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

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CONCLUSION

This work reported the comparative analysis of 12-time domain features by employing the MLP and KNN classifier in term of classification accuracy. 20 healthy human subjects were participated in three EEG data recording sessions in they imagine right and left-hand movements. After data acquisition, pre-processing and feature extraction was done followed by the classification. Results showed that the performance of MLP classifier was better than the KNN classifier and top five best features were RMS, MAV, LD, SSI and VAR whereas top lest 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. The finding of this study would be useful for online EEG classification model development towards the rehabilitation robotic designing.

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