IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

Brain robot interface using artificial neural network

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Abstract. Recent researches in Brain Computer Interface (BCI) that can decode brain EEG signals has aided in an effective robot control which has led to the raise of Brain Robot Interface (BRI). This project focuses on the accurate classification of the user's Action/Cognitive thoughts, where successful decoding of EEG signals can provide a higher degree of freedom control in BRI applications. The EEG signals from the user's scalp are recorded through a non-invasive electrode and prepossessed to produce a noise free EEG signals. Time-Frequency Analysis techniques are used to extract featured from the EEG signal. In this work an Artificial Neural Network (ANN) machine learning algorithm is used as classifier to learn the EEG signal features for effective output classification. This work presents a performance analysis on the accuracy of the system for the proposed combination of Time-Frequency analysis and ANN algorithm for the EEG feature extraction and classifier respectively.

1. Introduction

Over a last few decades, neural engineering have led to the field of neurotechnology that links computer systems and brain activities from a human being directly called the Brain computer Interface (BCI). A BCI system recognizes the user's intent by reading the brain activity through different method of recording modalities such as electrophysiological signals acquired over the scalp [electroencephalography (EEG)], over the cortical surface [electrocorticography (ECoG)], and within the brain [single-neuron action potentials (single units) and local field potentials (LFPs)] and converts it into a control signal that bridges the communication gap between a human and a computer system [1]. A BCI technology holds promise of assisting severely disables people with their day-to-day tasks and human machine interface applications. In a BCI system, the number of independent degree of freedom (DOF) derived from user's brain signals is the key attribute that determines the extent to which a BCI system can execute or the user is able to control a system effectively [2].

Robots have not only been used in automation and industrial applications, but also slowly entering into human machine interface applications to improve the quality of life. Assistive robots can deliver assistive support for disabled people in performing their daily tasks in day-to-day life and professional life as well, thus creating a rising demands for them. In general Human Machine Interface, a healthy users can control the robots with a various conventional input control device such

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as a keyboard, a mouse, kinect sensor, motion sensor or a teach pendent. These devices, however, pose extreme difficulties to be used by elderly or disabled individuals with the multiple sclerosis (MS), amyotrophic lateral sclerosis (ALS), or strokes.

For this reason, a Brain Robot Interface emerges which is an EEG-based brain controlled robot system which arise from an EEG-based BCI system to receive human intent controls directly and convert it into a control signal to the robot [3, 4, 5]. The major possible classes of brain-controlled robot are brain-controlled manipulator for self-assisting with personal tasks, mobile robots for mobility control for the user and neruoprosthesis to compensate for lost limb functionalities as shown in figure 2.

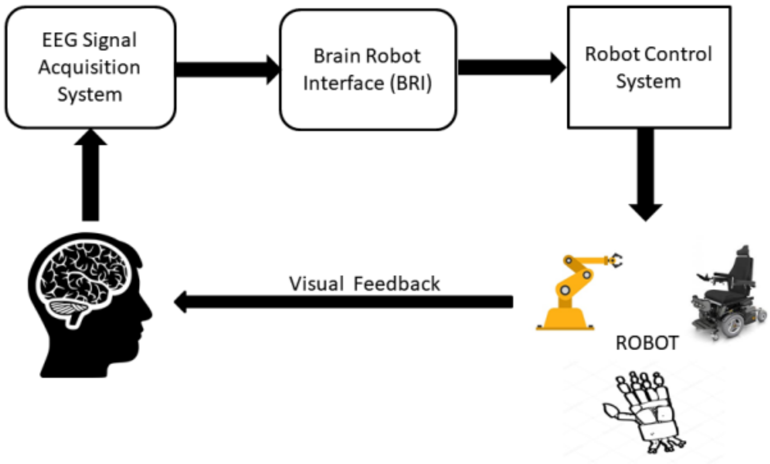

Figure 1. Brain robot interface schematics

2. Related Works

This is mainly focused on the extraction of features from the EEG within two frequency bands: alpha (8-13 Hz) and beta (13-30 Hz) using Discrete Wavelet Transform (DWT) and classification of the EEG rhythms using an Artificial Neural Network (ANN). In this section, some of related works are discussed as follows. Na Lu et al., [6] proposed a novel deep learning scheme based on Restricted Boltzmann machine (RBM) to classify two EEG mental thoughts from Mu (8-12Hz) and Beta (16-30Hz) Rhythms using Time-Frequency analysis for feature extraction. Whereas Wei et al., [7] has investigated the a combination of EEG signals analysis algorithm and methods such as wavelet transform for signal de-noising, Common Spatial Pattern feature extraction on Event Related De-synchronization (ERD) / synchronization (ERS) phenomenon of the Mu and Beta Rhythms and Linear Discriminant Analysis Classifier to control a two motion upper limb robotic arm. Similarly Lei et al., [8] has worked with Time-Frequency analysis on ERD/ERS rhythms to classify left/right motor imagery tasks. Caglar et al., [9] has conducted a comparative study between different Time frequency analysis of feature extraction techniques such as Wavelet Packet Decomposition (WPD), Morlet Wavelet Transform (MWT), Short Time Fourier Transform (STFT) and Wavelet Filter Bank (WFB)

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for classifying EEG signals of two class Motor imagination using Multi-Layer Perceptron Neural network (MLP-NN). Pawel et al., [10] has performed a comparative analysis of different EEG signal spectral representation approaches and found that the Power Spectral Density (PSD) feature extraction method showed consistent performance followed by DWT method. Kavita et al., [11] has carried out the analysis of effective EEG signal classification using discrete wavelet transform feature extraction method on epilepsy diagnosing BCI system, from the experimental analysis both ANN and SVM showed a comparable accuracy level around 98%. Eltaf et al., [12] experimented with DWT using different mother wavelets and a MLP-NN on Mu and Beta rhythms for motor classification. Similarly Mohammad et al., [13] has performed an analysis on the performance of wavelet based feature extraction of EEG signal and NN classification of fist and feet movement with statistical measures of the DWT coefficients as features for NN inputs. Yang et al., [14] made an study on subject based wavelet packet decomposition method of feature extraction technique which uses best basis for each subject and used Probabilistic Neural Network (PNN) in Bayesian estimation theory, which concluded that subject-based adaptation can provide more accuracy and performance than the non- subject-based method. Zhichuan et al., [15] has proposed a new method of Motor Imagery (MI) EEG signal classification system based on deep convolutional neural network (CNN) that extract features and classify motor imagery EEG signals.

From the above studies it is evident that a combination of Time-frequency analysis such as DWT and DPT method of feature extraction and an Deep Artificial Neural Networks has a significant classification accuracies and performance over EEG motor imaginary classes compared to other methods. This work is a further forwarding towards the application of Brain Robot Interface.

3. Method

3.1. Methodology of work

The approach towards to making a Brain Robot Interface consists of different processes that aid in effective control mechanism for the user. The different process steps such as EEG data acquisition, Pre-processing, Feature Extraction, Feature Dimensionality reduction, classifier model and Robot Interface are depicted in figure 2.

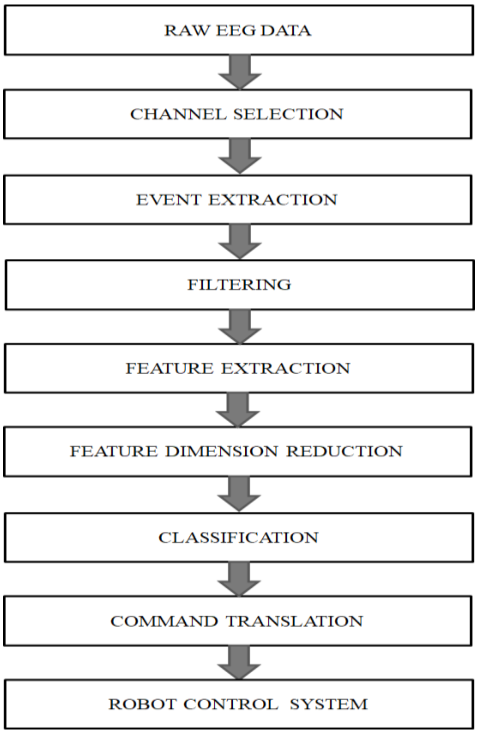

Figure 2. Process step flow diagram

3.2. Experimental offline data set

An offline analysis of the proposed methodology is performed on the pre-recorded EEG signal data obtained from the Berlin BCI Competition IV – Graz data set 2A. The EEG data were collected from 9 healthy subjects with 22 EEG channels and 3 EOG channels connected to the subject. The recording was conducted in sessions each containing 288 trials of data, i.e., 2592 sample data from total 9 subjects. Each trial consisted of directing the subject to imagine a motor out of four motor imagery task such as Left hand, Right hand, Both feet and Tongue according to the cue displayed on a monitor as per the timing scheme of the trial paradigm shown in figure 3. The EEG data were sampled at 250 Hz and bandpass filtered between 0.5-100Hz and additional 50Hz notch filter was applied to suppress power line noise.

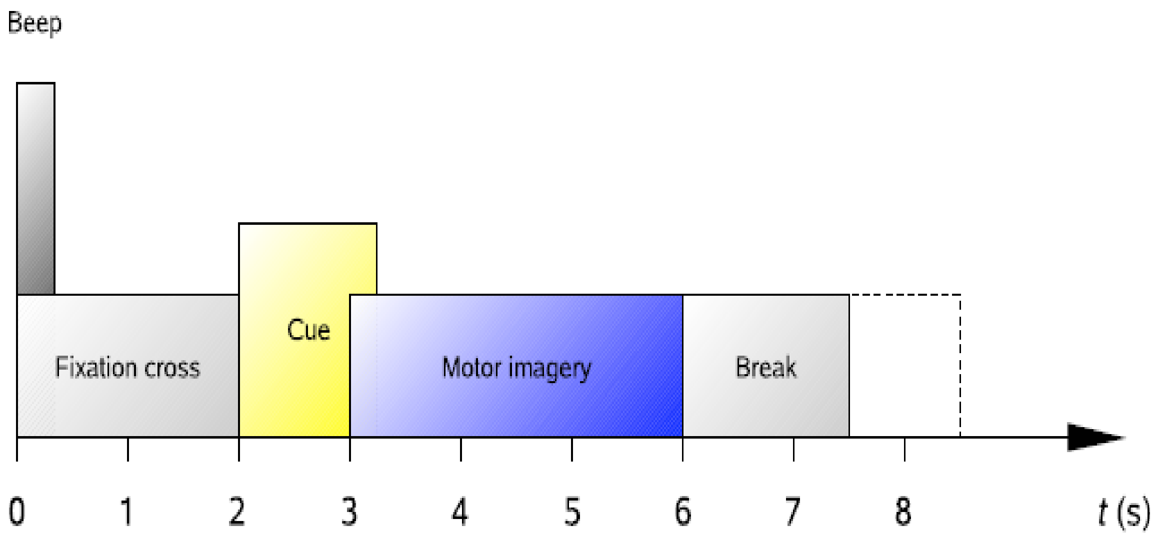

Figure 3. Timing scheme of each trial paradigm

4. Preprocessing

4.1. Channel selection

It was shown in the literature survey that most of the EEG channels signals are representing redundant information about the brain activity. The neural activity that is closely correlated with limb movement were almost exclusively found within the channels C3, C4 and CZ of the EEG channels as found in the figure 4. So the analysis were performed on reduced 3 channel sets and all the 22 channel sets separately to find the performance of the selected channels against all.

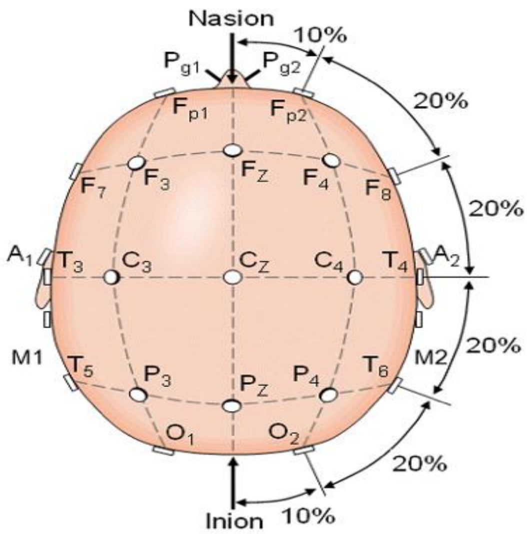

Figure 4. EEG channel locations based on 10-20 standard system

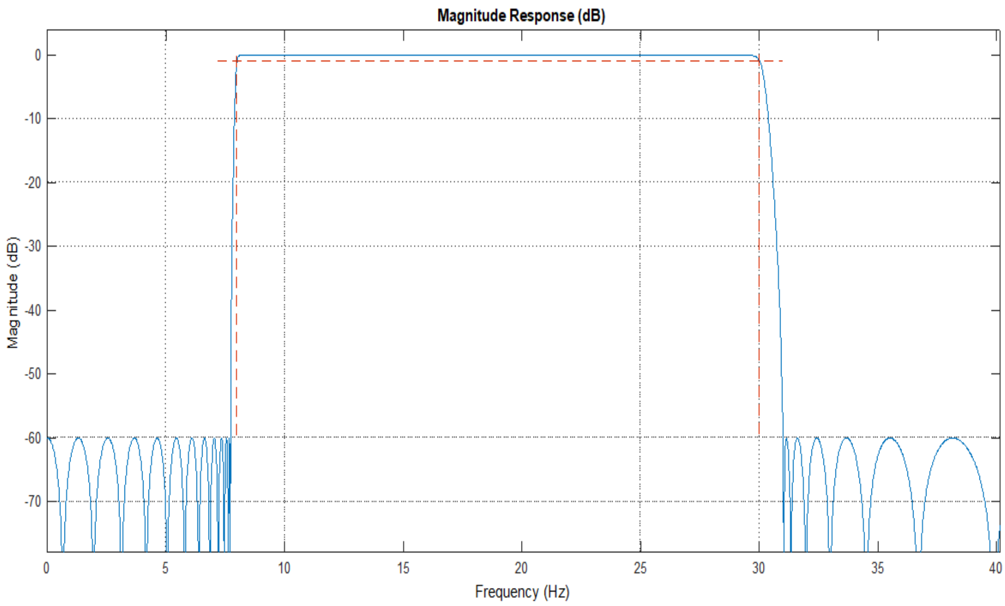

Figure 5. Bandpass filter magnitude response

4.2. Event extraction

As described in previously according to timing scheme paradigm as shown in figure 3, for each trial for four motor imagery tasks, 3 second of EEG signal data out of 8 second trial duration were extracted from each channels. Since the EEG data were sampled at 250Hz, each event extracted presented a total of 750 data points that spanned over a 3 second.

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4.3. Filtering

EEG signals are noisy and non-stationary signals contains artifacts such as eye blinks, eye movement, cardiac signals and muscle movement that needs to be filtered to get rid of the noises from the raw EEG signal which are vital for maximizing signal-to-noise ratio. Common Spatial Filter is applied to remove the noise from EEG signal. Since most of the brain activity information Event related De-synchronization / synchronization (ERD/ERS) related to motor imagery tasks lies in the Mu (8-12Hz) and Beta (12-30Hz) Rhythms, a chebyshev Type II bandpass filter between 8-30Hz with a stopband attenuation of 60dB and passband ripple of 1dB as shown in figure 5, was applied to the extracted EEG signals.

5. Feature Extraction

5.1. Discrete wavelet transform

Discrete Wavelet Transform (DWT) is a time-frequency signal analysis that inherits multi-resolution nature. DWT samples the signal in discrete wavelets, where its key advantage over the Fourier Transform is that it has temporal resolution along with the frequency resolution information, hence called a time-frequency analysis.

Single level DWT of a signal is calculated by passing the signal through lowpass and highpass filters which produces approximate coefficients and detailed coefficients respectively, according to Nyquist's rule half the samples are discarded by subsampling by 2. For N multi-level DWT, the approximate coefficients from each level is decomposed further by repeatedly passing through lowpass and highpass filters till nth level approximate and detailed coefficients are obtained as shown in figure 6.

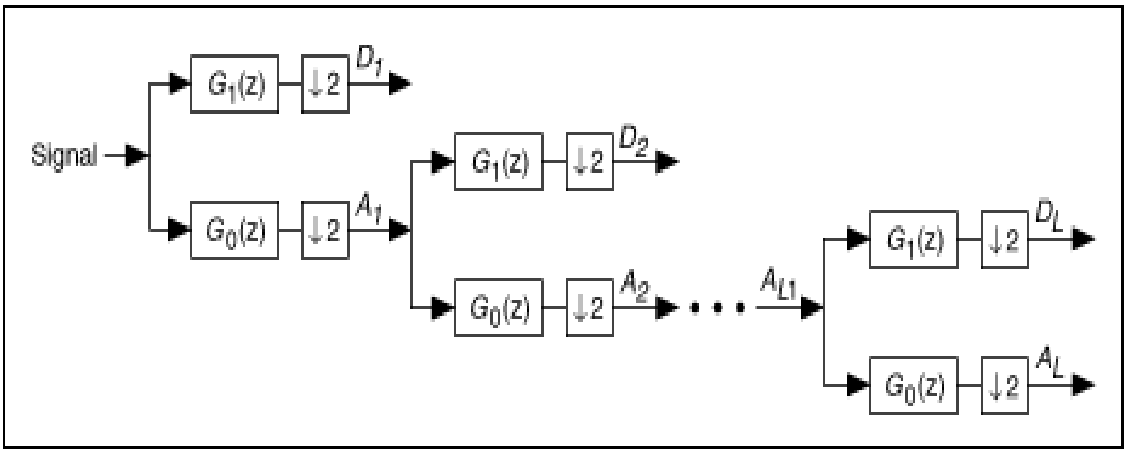

Figure 6. DWT signal decomposition

For the proposed method, a 2 level DWT with a mother wavelet of 'dB4' was applied on the filtered EEG signals which produced 3 sets of detailed coefficients D3, D4,D5 from the decomposed EEG signal. The decomposed EEG signal in the frequency resolution is shown in figure 7.

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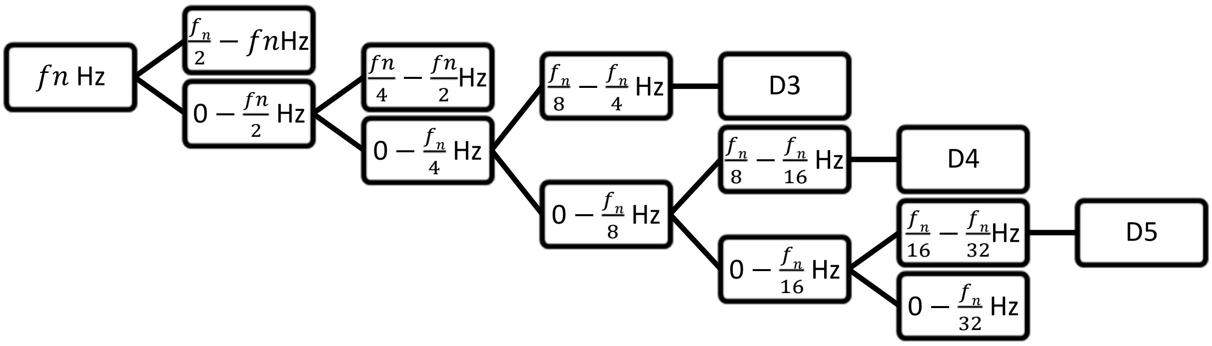

Figure 7. EEG signal DWT decomposition

5.2. Feature vector dimension reduction

Sometimes due to high dimensionality of the features vector, the classifier suffers from more computational time, redundant information, and over-fitting, which in turn has a detrimental effect on the performance of the BRI system. To avoid this problem, mathematical definitions are extracted from the decomposed signals. If nth sample of a wavelet decomposed coefficient at level i is assumed as Di (n), then we can define the following features:

Root Mean Square (RMS)

$$RMS_i = \left(\frac{1}{N}\sum_{n=1}^{N} D_i^2(n)\right)^{\frac{1}{2}} \tag{1}$$

Mean Absolute Value (MAV)

$$MAV_i = \frac{1}{N}\sum_{n=1}^{N} |D_i(n)| \tag{2}$$

Integrated EEG (IEEG)

$$IEEG_i = \sum_{n=1}^{N} |D_i(n)| \tag{3}$$

Simple Square Integral (SSI)

$$SSI_i = \sum_{n=1}^{N} |D_i(n)|^2 \tag{4}$$

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Variance of EEG (VAR)

$$VAR_i = \frac{1}{N-1}\sum_{n=1}^{N}(D_i(n) - D(n)_{avg})^2 \tag{5}$$

Average Amplitude Change (AAC)

$$AAC_i = \frac{1}{N}\sum_{n=1}^{N}|D_i(n+1) - D_i(n)| \tag{6}$$

Power (P)

$$P_i = \frac{1}{2N-1}\sum_{n=1}^{N}|D_i(n)|^2 \tag{7}$$

6. Classification Algorithm

To classify the feature vector extracted from the EEG signal for four motor imagery tasks, an Artificial Neural Network is used as the classification algorithm. The neural network is constructed as a feed-forward perceptron neural network with a hidden layer of 100. The DWT extracted features are fed to the neural network and trained using Gradient descent w/momentum & backpropagation algorithm. Data samples of 288 were taken to train and validate the performance of the classification decoder.

The output matrix for neural network is of 4x288, four motor imagery tasks for 288 data samples. The input matrix for the neural network was taken in various manner such as for 22 channel consideration with all earlier mentioned features is 399x288 and while considering only single feature at a time is 57x288. The results and performance analysis can be seen in the next chapter.

7. Experimental Results

7.1. Results

The overall and average accuracy percentage of the neural network for all subjects over different statistical features is calculated by means of 10 Fold Cross Validation method. Table 1 presents the overall classification accuracy for different statistics feature extracted from 22 channels trained in the neural network for 9 subjects. Similarly Table 2 presents the average classification accuracy per class for different statistics feature extracted from 22 channels.

From the neural network output data, it was inferred that all features as input produced an overall accuracy mean of 68.7886% for the ANN model and all feature as input produced an average accuracy mean of 84.3364% for the ANN model.

From the overall and average accuracy for all subjects over different features, it is seen that both the accuracies varies with respect to the subject. It clearly points out that the control of BCI/BRI system depends on the user’s/subject’s ability to maintain a mental concentration that produce an output efficiently.

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Table 1. Overall Accuracy for different statistics feature

Feature	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Mean
ALL	75.3472	63.1944	82.2917	57.2917	51.7361	57.6389	77.7778	86.8056	67.0139	68.7886
RMS	72.9167	65.2778	81.25	59.7222	49.6528	59.0278	76.7361	84.375	67.0139	68.4414
MEAN	75	65.2778	84.375	57.2917	48.2639	55.2083	77.4306	85.0694	66.6667	68.287
VAR	71.5278	60.7639	80.9028	55.9028	49.3056	56.25	79.1667	82.6389	65.9722	66.9367
IEEG	75.6944	62.8472	84.375	59.375	49.6528	55.9028	79.5139	85.0694	65.625	68.6728
SSI	71.875	62.1528	80.2083	56.9444	45.1389	53.125	77.7778	81.9444	65.2778	66.0494
AAC	72.5694	62.8472	84.7222	50.6944	47.5694	58.3333	74.3056	86.1111	65.625	66.9753
POWER	71.875	62.8472	80.5556	58.6806	49.3056	55.9028	83.3333	83.3333	66.6667	68.0556

Table 2. Average Accuracy per class for different statistics feature

Feature	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Mean
ALL	87.1528	81.5972	91.1458	78.6458	75.8681	78.8194	88.8889	93.4028	83.5069	84.3364
RMS	86.4583	82.6389	90.625	79.8611	74.8264	79.5139	88.3681	92.1875	83.5069	84.2207
MEAN	87.5	82.6389	92.1875	78.6458	74.1319	77.6042	88.7153	92.5347	83.3333	84.1435
VAR	85.7639	80.3819	90.4514	77.9514	74.6528	78.125	89.5833	91.3194	82.9861	83.4684
IEEG	87.8472	81.4236	92.1875	79.6875	74.8264	77.9514	89.7569	92.5347	82.8125	84.3364
SSI	85.9375	81.0764	90.1042	78.4722	72.5694	76.5625	88.8889	90.9722	82.6389	83.0247
AAC	86.2847	81.4236	92.3611	75.3472	73.7847	79.1667	87.1528	93.0556	82.8125	83.4877
POWER	85.9375	81.4236	90.2778	79.3403	74.6528	77.9514	91.6667	91.6667	83.3333	84.0278

7.2. Robot interface

A quadruped robot of similar to a spider as shown in figure 8 designed by Regis Hsu under the GNU-GPL license Published on September 11, 2015: www.thingiverse.com/thing:1009659, was used as the end robot interface in this work. The quadruped robot is programed to follow a mechanism similar to that of the salamander locomotion. The neural network trained output signal is interfaced with the quadruped robot. The motion and the direction of the robot depend on the classified output.

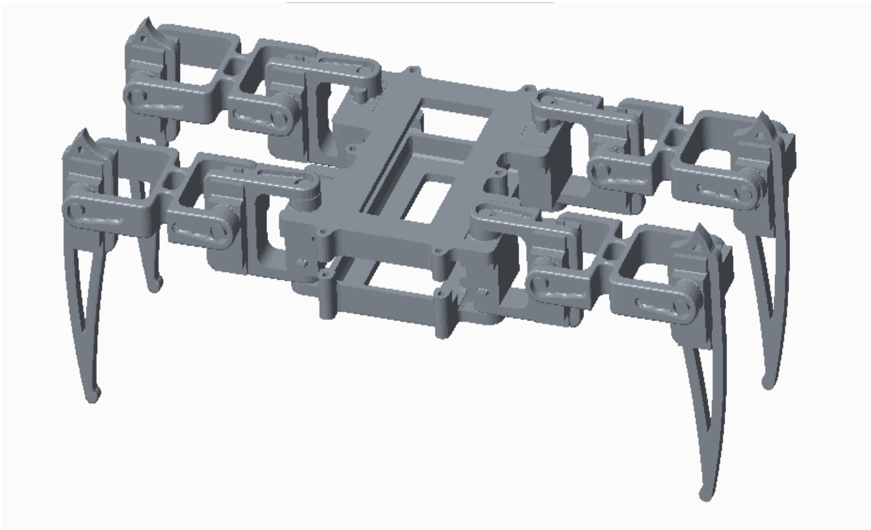

Figure 8. Quadruped Robot

8. Conclusion

This shows that there still exists future prospect towards optimization in the feature selection and network architecture, where a fixed architecture was used for this study analysis. Consideration of optimally selecting the correct bandwidth of the frequency range of the EEG signal that is to be filtered is to be studied and analyzed. Further along with the optimization of the feature selection and neural network architecture, the study can to be carried out in an online training of the neural network and real time control of the robot to be experimented and analyzed for multiple degrees of robot control.

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