IOP Conference Series: Materials Science and Engineering

**PAPER • OPEN ACCESS**

Brain robot interface using artificial neural network To cite this article: D Buvaneash and M R Stalin John 2018 IOP Conf. Ser.: Mater. Sci. Eng. **402** 012017

View the article online for updates and enhancements.

This content was downloaded from IP address 45.73.173.37 on 21/09/2018 at 01:49

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

**Brain robot interface using artificial neural network**

**D Buvaneash1, M R Stalin John1**

1Department of Mechanical Engineering, SRM Institute of Science and Technology, Kattankulathur.

\*Corresponding author: buvaneash\_duraisamy@srmuniv.edu.in and

mrstalinjohn@gmail.com

**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

Content from this work may be used under the terms of theCreative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Published under licence by IOP Publishing Ltd

1

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

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)

2

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

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.

3

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

|  |
| --- |
| **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.

4

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

|  |
| --- |
| **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.

5

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

|  |  |
| --- | --- |
| **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.

6

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

*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.

7

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

| ����  2− ����Hz  ����  4−����2Hz  ���� Hz  ����  8−����  4Hz D3  0 −����2Hz  0 −����  ����  8−����  4Hz  16Hz D4  0 −����  8Hz  ����  16−����  32Hz D5  0 −����  16Hz  0 −����  32Hz |
| --- |
| **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)

1

2 (1)

Mean Absolute Value (MAV)

�������� = (1��∑ ����2(��) ����=1 )

�������� =1��∑ |����(��)|

����=1 (2)

Integrated EEG (IEEG)

����=1 (3)

���������� = ∑ |����(��)|

Simple Square Integral (SSI)

�� 2

�������� = ∑ |����(��)|

��=1 (4)

8

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

Variance of EEG (VAR)

�������� =1

�� 2

��−1∑ (����(��) − ��(��)������)

��=1 (5)

Average Amplitude Change (AAC)

�������� =1��∑ |����(�� + 1) − ����(��)|

����=1 (6)

Power (P)

���� =1

�� 2

2��−1∑ |����(��)|

��=1 (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.

9

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

**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.

10

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

|  |
| --- |
| **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.

**9. References**

[1] Han Y and Bin H 2014 Brain–Computer Interfaces Using Sensorimotor Rhythms: CurrentState and Future Perspectives, *IEEE Transactions On Biomedical Engineering* **.61**, 1425-1435 [2] Dennis J M, William A S, and Jonathan R W 2010 Electroencephalographic (EEG) Control Of Three dimensional Movement, *Journal of Neural Engineering* **.7**,175-184

[3] Karl L, Kaitlin C, Alexander D, Kaleb S, Eitan R, and Bin H 2013 Quadcopter control in three dimensional space using a non-invasive motor imagery-based brain–computer interface *Journal of Neural Engineering* **.10,** 1-15

[4] Ethan B, Cornelia W, Leonardo G C, Christoph B, Michael A D, Tyler A, Jurgen M, Andrea C, Surjo S, Alissa F, and Niels B 2008 Think to Move: a Neuromagnetic Brain-Computer Interface (BCI) System for Chronic Stroke, *Journal of Stroke* **.39**, 910–917

[5] José R M, Frédéric R, Josep M, and Wulfram G 2004 Noninvasive Brain-Actuated Control of a Mobile Robot by Human EEG,*IEEE Transactions On Biomedical Engineering* **.51**,1026-1033 [6] Na L, Tengfei L, Xiaodong R, and Hongyu M 2017 A Deep Learning Scheme for Motor Imagery Classification based on Restricted Boltzmann Machines*, IEEE Transactions on Neural Systems and Rehabilitation Engineering* **.25**,566-576

[7] Wei H, Yue Z, Haoyue T, Changyin S, and Wei F 2016 A Wireless BCI and BMI System for Wearable Robots, *IEEE Transactions on Systems, Manand Cybernetics: Systems* **.46**,936-946

11

2nd International conference on Advances in Mechanical Engineering (ICAME 2018) IOP Publishing IOP Conf. Series: Materials Science and Engineering **402** (2018) 012017 doi:10.1088/1757-899X/402/1/012017

**1234567890**‘’“”

[8] Lei Q and Bin H 2005 A wavelet-based time–frequency analysis approach for classification of motor imagery for brain–computer interface applications*, Journal of Neural Engineering* **.2,** 65–72

[9] Caglar U and Turker T E 2017 Analysis of Time – Frequency EEG Feature Extraction Methods for Mental Task Classification *International Journal of Computational Intelligence Systems***.10**,31–39

[10] Pawel H, Girijesh P, Thomas M M, and Damien C 2008 Comparative Analysis of Spectral Approaches to Feature Extraction for EEG-Based Motor Imagery Classification, *IEEE Transactions On Neural Systems And Rehabilitation Engineering* **.16**,317-326

[11] Kavita M, Vargantwar M R, and Sangita M R 2012 Classification of EEG using PCA, ICA and Neural Network, *International Journal of Computer Applications* **. 6**,1-6.

[12] Eltaf A M, Mohd Z Y, Dalia M, and Aamir M 2016 Classification of Thoughts into Wheelchair Control Commands using Neural Network *International Journal of Sciences: Basic and Applied Research* ***.*25**,119-127

[13] Mohammad H A, Emad A A, Aya S , and Khaled A 2014 Wavelet -Based Feature Extraction for the Analysis of EEG Signals Associated with Imagined Fists and Feet Movements ,*Journal of Computer and Information Science* **.7**,17-27

[14] Yang B , Yan G, Yan R, and Wu T 2007 Adaptive subject-based feature extraction in brain– computer interfaces using wavelet packet best basis decomposition, *Medical Engineering & Physics***.29**, 48–53

[15] Zhichuan T, Chao L, and Shouqian S 2017 Single-trial EEG classification of motor imagery using deep convolutional neural networks, *International Journal of Optik* **.130**,11–18

12