Band Decomposition of Asynchronous Electroencephalogram Signal for Upper Limb Movement Classification

Vinay Vasantao Kulkarni (✉ kulkarnivinayv@gmail.com)

Shri Guru Gobind Singhji Institute of Engineering and Technology <https://orcid.org/0000-0002-9931-6704>

Yashwant V. Joshi

Shri Guru Gobind Singhji Institute of Engineering and Technology

Ramachandra R. Manthalkar

Shri Guru Gobind Singhji Institute of Engineering and Technology

Irraivan Elamvazuthi

Universiti Teknologi Petronas: Universiti Teknologi PETRONAS

Research Article

Keywords: Gabor Elementary Function (GEF), Sensorimotor Signal, Brain Computer Interface (BCI), Electroencephalogram (EEG), ArmeoSpring, Scale Space Technique, Bi-directional Long Short-Term Memory (BiLSTM)

Posted Date: March 2nd, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1268755/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Band Decomposition of Asynchronous Electroencephalogram Signal for Upper Limb Movement Classification

VinayKulkarni^{1*}, YashwantJoshi¹, RamachandraManthalkar¹
and IrraivanElamvazuthi²

¹Electronics and Telecommunication, Shri Guru Gobind Singhji
Institute, Nanded, 431606, Maharashtra, India.

²Electrical and Electronic Engineering, Universiti Teknologi
PETRONAS, Bandar Seri Iskandar, 32610, Perak, Malaysia.

*Corresponding author(s). E-mail(s): kulkarnivianyv@gmail.com;
Contributing authors: yvjoshi@sggs.ac.in;
rrmanthalkar@sggs.ac.in; irraivan.elamvazuthi@utp.edu.my;

Abstract

Decoding Asynchronous Electroencephalogram (A-EEG) signals is a crucial challenge in the emerging field of EEG based Brain-Computer Interface (BCI). In the case of A-EEG signals, the time markers of motor activity are absent. The paper proposes a method to decompose the A-EEG signals using Gabor Elementary Function (GEF) designed with Gabor frames. The scale-space analysis extracts Gabor dominant frequencies from A-EEG signals. Statistical and temporal moment dependent features are used to create the feature vector for each estimated Gabor Band (GB). The statistical significance of the features is tested with the Kruskal-Wallis test. The deep neural network is implemented with Bi-directional Long Short-Term Memory (BiLSTM) block to classify the upper limb movement. The EEG data of healthy volunteers have been collected using the Enobio-20 electrode system and ArmeoSpring rehabilitation device. The proposed methodology has achieved an average classification accuracy of 96.83%, precision 0.96, recall 0.96, and F1-score of 0.93 on the acquired data set. The designed framework for decoding upper limb movement outperforms the

existing state-of-the-art methods. In the future, the proposed framework could increase classification performance by incorporating multiple types of biological inputs for investigating various brain functions.

Keywords: Gabor Elementary Function (GEF), Sensorimotor Signal, Brain Computer Interface (BCI), Electroencephalogram (EEG), ArneoSpring, Scale Space Technique, Bi-directional Long Short-Term Memory (BiLSTM)

1 Introduction

A brain-computer interface (BCI) is a system of communication that allows people to connect with their surroundings and control autonomous equipment by sending brain signals [1]. The BCI system can be built with a variety of biological indicators [2], but researchers mainly handle the EEG signals. This is because the non-invasive method like EEG is more suitable to handle and gives better performance at a lower cost. [3, 4]. The EEG-based BCI has been used in a variety of fields, including medical, gesture control, neurorehabilitation, video games, and education [2, 5, 6]. The EEG-based BCI technology is categorised as synchronous or asynchronous based on the kind of input EEG data [7]. In the synchronous BCI system, the EEG signals are synchronised with time markers related to motor activity, whereas time markers are absent in the Asynchronous BCI system. This paper proposes the methodology to classify upper limb movement from A-EEG signals.

Depending on the application, the EEG signals are decomposed into several frequency bands, such as alpha, beta, and gamma. The researchers mainly analyse μ (8-13 Hz) and β (13-30 Hz) bands to decode BCI activity [8]. Table 1 gives the summary of literature addressing many techniques for decomposing EEG signals into several frequency bands for classification of upper limb movement. In the EEG based BCI systems, Wavelet Packet Decomposition (WPD) [9], tunable-Q wavelet transform [10], and Discrete Wavelet Transform (DWT) [11, 12] are some of the most widely used frequency decomposition approaches for feature extraction from multiple frequency bands. Ma X. et al. [11] calculated the DWT based band energy and power spectral density features are classified with Convolution Neural Network (CNN) classifier with the accuracy of 96.21%. Riaz F. et al. [13] utilised the Empirical Mode Decomposition (EMD) for frequency band separation in terms of Intrinsic Mode Function (IMF). The spectral as well as third-order temporal moment features are derived from IMF and used to classify the Epileptic EEG data. You Y. et al. [14] extracted the statistical features from the decomposed sub-bands by using Flexible Analytical WT (FAWT), and upper limb movements are identified with an accuracy of 88.27% utilising Linear Discriminant Analysis (LDA) classifier. However, the above band decomposition methods fail to have better time and frequency resolutions at the same time [13]. Therefore, researchers

from the BCI domain have focused on sub-band decomposition techniques, which decompose EEG signals in desired frequency bands.

Table 1: Previous approaches for upper limb movement classification

Reference	Authors	Description
[10]	Taran S. et al.	Utilised tunable Q Wavelet Transform and CNN
[11]	Ma X. et al.	Used CNN on calculated DWT based band energy feature
[12]	Mirvaziri et al.	Applied DWT for feature extraction and SVM as classifier
[13]	Raiz F. et al.	Used EMD based for frequency band separation and SVM as classifier
[14]	You Y. et al.	Statistical features are extracted using FAWT with LDA classifier
[15]	Taran S. et al.	Applied Hilbert Transform in combination with EMD

Further, the coefficients from each sub-band are calculated to form the feature vector. Taran S. [15] utilised the EMD in combination with Hilbert Transform to evaluate Raw Moment of First Derivative of Instantaneous Frequency. The multiple IMFs form the feature vector and are used to classify different Motor Imagery (MI) movements. The fundamental limitations of the above methods are poor classification results, and challenges in choosing an appropriate number of boundaries for sub-band formation, mainly in the case of WPD [9]. The Empirical-wavelet-transform (EWT) is a relatively new strategy to cope with non-stationary signals like A-EEG [16]. The EWT method incorporates the advantages of wavelet-transform and the Empirical Mode Decomposition techniques. The EWT derives a sequence of Amplitude-Modulated (AM) and Frequency-Modulated (FM) signals from a single band. Employing the AM-FM modules, a portable endorsing Fourier spectrum can be provided. Differential type methods have been used to create dynamic wavelets for AM-FM modules [17]. However, the EWT algorithm has certain limitations in calculating boundaries in the presence of noisy frequency spectrum like A-EEG. As a result, the A-EEG signal is improperly segmented, employing the EWT approach.

To avoid limitations in handling A-EEG signal analysis for BCI application, the paper proposes the following contributions: 1) A protocol is designed for collecting the A-EEG motor activity data utilising the ArmeoSpring rehabilitation machine and Enobio-20. 2) The dominant frequencies are selected from prepossessed A-EEG signal employing the scale-space technique. A Gabor frame is constructed utilising the selected dominant frequencies to detect upper limb movement. 3) Each constructed Gabor band is used to obtain statistical and temporal moment-based features. 4) The deep neural network is implemented with Bi-directional Long Short-Term Memory (BiLSTM) block to classify the hand movements.

Fig. 1: Block Diagram of proposed methodology for upper limb movement classification

2 Methodology

2.1 Experimental Setup and Protocol

The A-EEG data of upper limb movement were collected from three healthy volunteers (one female). All the subjects were right-handed from the age group of 26.7 ± 1.1 . The subjects were informed about the experiment, and the consent form was collected from them. The experiment was endorsed by the Shri Guru Gobind Singhji Institute of engineering and Technology ethical committee (Ethics Approval Number: SGGsIE&T/R&D/ETHICS APPROVAL/2017-18/07/2). Figure 2 and 3a provide the idea about the experimental paradigm and the setup, respectively.

Fig. 2: Experimental Paradigm

The A-EEG data are recorded with Enobio-20 machine from standard 20 active electrodes, as shown in 3b. The ArmeoSpring interface engages the subject that helps restrict other body parts movements.

(a) Experiment Setup

(b) Electrode 10-20 system

Fig. 3: Experiment setup and 10-20 electrode placement

The volunteers are requested to sit in the chair. One of the hands of volunteers is connected to the ArmeoSpring. A cognitive load-based high-flyer game and a coin collection amusement are adopted for the experimentation. The volunteers are requested to stay relaxed during the initial four seconds. The starting hand position of the volunteer is 60° shoulder flexion, 0° abduction and about 90° elbow flexion as shown in figure 3a. The high-flyer game from the ArmeoSpring interface begins from the fifth second and continues for 120 seconds. The volunteer tries to collect a maximum number of coins by moving the hand between 30° and 145° . The A-EEG signals are recorded in six sessions as shown in table 2.

2.2 Preprocessing and Time-Framing of A-EEG signals

The artefacts are the primary source of noise produced by unwanted movements of body parts. The higher frequency noise could distinguish these artefacts from normal EEG. The epochs associated with every motor activity are initially recovered, and the average baseline value is subtracted from each channel. The A-EEG data are passed through a 50 Hz notch filter that removes the noise added due to the power supply. The BCI activity is better reflected in the alpha and beta bands (8-30 Hz). Hence, the FIR band-pass filter is designed with 7.8 Hz and 30.2 Hz cut-off frequencies. The transition of 0.2 Hz is considered to implement a band-pass filter. From the EEGLAB toolbox, the Independent-Component Analysis is utilised to separate the artefacts from the clean A-EEG signals

Table 2: Pre-processed A-EEG data recorded with the designed protocol

Subject	Session1	Session2	Session3	Session4	Session5	Session6
AA	240×20	242×20	240×20	240×20	240×20	239×20
BB	240×20	240×20	239×20	240×20	241×20	240×20
CC	240×20	241×20	240×20	240×20	240×20	240×20

This research aims to classify upper limb movements using A-EEG data that lack timing markers. Hence, time framing of A-EEG signals plays a vital role in classifying hand movements. The most commonly exploited time frame is immediately well after the occurrence of the external stimuli that direct participants to conduct motor activity [18]. The performance of the feature extraction method is strongly reliant on an average time frame for all trials of all the subjects. For further investigation, an empirically selected segment of 1000 ms with a repetition of 50% samples of A-EEG signals are used. The complete signal of samples 58000 per electrode is split into an averagely of 240 segments. The details of re-framed A-EEG data are given in table 2. Each segment contains 500 samples of the A-EEG signal. As a result, the suggested time framing approach feeds the feature extraction algorithm segmented A-EEG data of size 240×20 ($240 \times 20 \times 500$).

2.3 Dominant frequency selection using scale-space technique

This section describes the proposed framework for investigating dominant frequencies to capture upper limb movement. Figure 1 shows the structure of the proposed methodology. As shown in figure 4a, the steps are implemented for the formation of Gabor Elementary Function (GEF) for detecting boundaries in A-EEG signals.

Step 1: The Fast Fourier Transform of the input A-EEG signal is calculated. It gives the frequency contained in the A-EEG signal as high peaks.

(a) Flow chart for GEF formation

(b) Gabor Dominant Frequencies Graph

Fig. 4: Gabor Dominant Frequency Analysis

Step 2: To remove the global trend from A-EEG signals, the polynomial interpolation method is implemented. $P(X) = P(1) \times X^N + P(2) \times X^{(N-1)} + \dots + P(N) \times X + P(N+1)$, here $P(X)$ forms a $N+1$ row vector representing the algebraic coefficients of decreasing order. This calculated interpolation is subtracted from the original signal.

Step 3: The Gaussian filter is applied to the A-EEG signals as spectrum regularisation. The filtered A-EEG data are segmented over the interval $[0, e_{max}]$, where $e_{max} = 500$ is the maximum length of the segment, and the normalised 1D Gaussian kernel is defined as follows. The value of σ_b indicates the level of smoothness to regularise the EEG spectrum.

$$g(e; \sigma_b) = \frac{1}{\sqrt{2\pi\sigma_b}} e^{-\frac{e^2}{2\sigma_b}} \quad (1)$$

Scale-space Technique: The scale-space representation (F) for A-EEG signal is defined by,

$$F(e, \sigma) = g(e, \sigma) \otimes f(e) \quad (2)$$

operator $\otimes$ denotes convolution product. It smooths all patterns of characteristic length σ , i.e., as σ increases, $F(e, \sigma)$ becomes smoother. This operator fulfils a semi-group property:

$$g(e, \sigma_1 + \sigma_2) = g(e, \sigma_1) \otimes g(e, \sigma_2) \quad (3)$$

Step 4: For boundaries detection, the algorithm based on local maxima is preferred. The border of each segment i.e. f_c ,

$$f_c = \frac{f_i + f_{i+1}}{2} \quad (4)$$

(f_i, f_{i+1}) are two consecutive frequencies. The captured dominant centre frequencies (9.98 Hz, 18.34 Hz, and 26.39 Hz) are indicated in figure 4b.

2.4 Gabor Elementary Function

A Gabor Elementary Function (GEF) can be defined as the product of a Gaussian window and sinusoidal signal of frequency f_c . The GEF has both real and imaginary components,

$$R_{GEF} = \cos(2\pi f_c t) \times e^{-\frac{t^2}{2s_b^2}} \quad ; \quad I_{GEF} = \sin(2\pi f_c t) \times e^{-\frac{t^2}{2s_b^2}} \quad (5)$$

where $s_b = \frac{p}{2\pi f_c}$, p determines the number of oscillations. The implemented GEF tuned itself to the GDF present in the A-EEG signal. To regulate the effect of variable p , the work in [19] have suggested a slight change in defining p . The below Eq.(6) illustrates a new parameter, F_G .

$$F_G = \frac{p\sqrt{2\ln 2}}{\pi f_c} \quad (6)$$

Table 3: Gabor Frames inner product

Gabor Band	<GB1-R>	<GB2-R>	<GB3-R>
<GB1-I>	4.05	0.05	2.10×10^{-8}
<GB2-I>	0.07	3.95	0.03
<GB3-I>	3.83×10^{-8}	0.03	3.98

The experimental value of F_G is determined by deducting the value of time point on later -3db time point from first -3db time point in frequency peak graph. The above Eqs.(5) can be modified with F_G as follows,

$$R_{GEF} = \cos(2\pi f_c t) \times e^{-\frac{4\ln(2)t^2}{F_G^2}} ; \quad I_{GEF} = \sin(2\pi f_c t) \times e^{-\frac{4\ln(2)t^2}{F_G^2}} \quad (7)$$

The Gabor Band (GB) by GEF can be seen as loosely bounded Gabor frames. As shown in table 3, the property of GEF is observed by estimating the GEF coefficients with inner product [20]. This leads to capturing the upper limb movement from the recorded A-EEG signal. The condition for a tight frame is checked with the following equation,

$$\langle GB(\sigma_i, f_{c1}), GB(\sigma_j, f_{c2}) \rangle = \sum_{i,j} |\langle GB(\sigma_i, f_{c1}), GB(\sigma_j, f_{c2}) \rangle| \quad (8)$$

The proposed methodology employs the scale-space technique to generate the GEF from the retrieved Gabor Dominant Frequency (GDF). The constructed GB with three f_c is implied on filtered A-EEG data. Figure 5 and figure 6 show the effect of left and right-hand movements on the contralateral side of the brain, i.e. at C3 and C4 channels.

2.5 Feature Extraction and Normalization

The corresponding Gabor Band (GB) characteristics are assessed by incorporating different statistical attributes from upper limb movements. GBs are used to obtain statistical and temporal moment-based features.

2.5.1 Root Mean Square (RMS)

The Eq. (9) represents the RMS value for discrete data,

$$RMS(x) = \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \quad (9)$$

The RMS value gives the idea about the amplitude variations across the different trials of a subject within each Gabor band.

(a) Gabor bands decomposition for C3 electrode

(b) Gabor bands decomposition for C4 electrode

Fig. 5: Gabor band decomposition with $f_{c1}=9.98$ Hz, $f_{c2}=18.34$ Hz, $f_{c3}=26.39$ Hz using Real and Imaginary GEF for Right hand Movement

2.5.2 Shannon Entropy

The Shannon entropy of GB reflects the uncertainty in a random process or quantities. It is defined as:

$$ShEn = \sum p_i \log 1/p_i \quad (10)$$

where p_i is the probability of an occurrence for every value in every GB of the A-EEG data.

(a) Gabor bands decomposition for C3 electrode

(b) Gabor bands decomposition for C4 electrode

Fig. 6: Gabor band decomposition with $f_{c1}=9.98$ Hz, $f_{c2}=18.34$ Hz, $f_{c3}=26.39$ Hz using Real and Imaginary GEF for Left hand Movement

2.5.3 Average Gabor Band Power

The Average GB power is calculated for every GB and averaged over different frequency points within a trial.

$$AGBP = \frac{1}{N-1} \sum_{i=1}^N (x_{ij} - \bar{x}_j)^2 \quad (11)$$

where x_{ij} is sample from i^{th} time instance and j^{th} Gabor band, $\bar{x}_j$ is the mean of j^{th} Gabor band.

2.5.4 Temporal Moments

Here, the Temporal Moments (TM) is used as a feature in classifying A-EEG signals. Out of all moments, only 3rd (TM3), 4th (TM4) and 5th (TM5) order moments are found to be sufficient for classifying upper limb movement [21, 22].

$$TM3 = \frac{1}{M} \sum_{i=1}^M |x_i^3| \quad (12)$$

$$TM4 = \frac{1}{M} \sum_{i=1}^M x_i^4 \quad (13)$$

$$TM5 = \frac{1}{M} \sum_{i=1}^M |x_i^5| \quad (14)$$

where x = GB and M = number of samples in a GB.

2.5.5 Feature normalization

The distribution of original EEG samples fluctuates beyond the standard range. Hence, specific optimisation algorithms might not perform effectively without normalization [23]. Therefore, the normalisation of calculated features is carry out with the root mean square method. The process normalises the RMS norm of the signal to be 1.

Table 4: p value comparison for each GB using Kruskal-Wallis statistical test

Feature Set	GB1	GB2	GB3
RMS	2.91×10^{-07}	8.00×10^{-04}	3.00×10^{-04}
AGBP	1.58×10^{-22}	1.49×10^{-22}	1.49×10^{-22}
ShEn	2.82×10^{-06}	2.82×10^{-06}	3.45×10^{-03}
TM3	6.34×10^{-10}	3.26×10^{-21}	1.49×10^{-22}
TM4	2.02×10^{-27}	1.04×10^{-28}	1.76×10^{-28}
TM5	8.00×10^{-03}	4.00×10^{-03}	9.10×10^{-04}

2.6 Kruskal-Wallis statistical test

The GB-based features are extracted for the classification of upper limb movement. In addition, the Kruskal-Wallis statistical test was conducted and obtained p -values are listed in table 4. It signifies that the features extracted with the proposed algorithm are statistically significant, leading to better classification results.

Fig. 7: Basic BiLSTM Block

2.7 Classification

The choice of a classifier determines the efficacy of any classification network. For the classification of A-EEG signals, the classifier with a multi-layer BiLSTM network is preferred over traditional classifiers (KNN, SVM, naive Bayes, etc.) [24]. Figure 7 shows one forward-reverse BiLSTM model and a basic LSTM cell.

The Eqs. (15)-(17) give the result of three basic gates (forget, input and output gate). f_t (forget gate) is activated if and only if c_{t-1} is preserved previously as input block. The i_{t-1} input terminal confirms if the position was upgraded with present input x_t . If h_{t-1} is streamed to next cell block, the output gate o_t is activated. The a_t would be an agent for modifying the cell state for every iteration t . Eqs.(18)-(20) is used to measure the contribution of the existing LSTM cell c_t and the existing hidden value h_t .

$$i_t = \delta(X_i x_{t-1} + H_i h_{t-1} + C_i c_{t-1} + b_i) \quad (15)$$

$$o_t = \delta(X_o x_{t-1} + H_o h_{t-1} + C_o c_{t-1} + b_o) \quad (16)$$

$$f_t = \delta(X_f x_{t-1} + H_f h_{t-1} + C_f c_{t-1} + b_f) \quad (17)$$

$$a_t = \delta(X_a x_{t-1} + H_a h_{t-1} + C_a c_{t-1} + b_a) \quad (18)$$

$$c_t = f_t * c_{t-1} + i_t * a_t \quad (19)$$

$$h_t = o_t * \tanh(c_t) \quad (20)$$

$$h_t = \delta(W_h [\vec{h}, \overleftarrow{h}] + b_h) \quad (21)$$

Here $*$ indicates element by element multiplication operation. H, C are weights and b is bias in a network. The BiLSTM gives h_t as final output calculates the whole output from Eq.(21). Parameter tuning is a vital step in classification tasks in the case of deep neural networks. Table 5 describes the parameters used to design the BiLSTM network. In the design of BiLSTM network, three layers of BiLSTM with decreasing number of hidden units from 128 to 32 are inserted between other units, which improves the classifier's performance.

Fig. 8: Proposed BiLSTM network for analysis of A-EEG signal

Table 5: Model parameters details

Parameter	Value
Layers	3
Feature Size	15
Hidden Units	128, 64, 32
Output Layer	2
Mini-batch Size	50
Optimizer	Adam
Learning Rate	10^{-5}
Dropout	0.3

A dropout layer with a value of 0.5 is added to improve the model's classification accuracy after each BiLSTM layer. Mini-batch sizes with a maximum weight of 250 are used to train the network. The batch normalisation layer standardises the input layer for each mini-batch size. The process stabilises the learning process and significantly reduces the number of training epochs required to train BiLSTM classifier networks. Finally, the designed network ends with a fully connected layer to classify upper limb movement. Because a high learning rate may result in the perfect response, the learning rate is set at 10^{-5} in the gradient descent algorithm.

3 Results

3.1 Performance Evaluation

The deep network classifier networks are prone to overfitting when handling a small dataset. To minimise overfitting, 70% of the features were chosen for training and 30% to validate the proposed method's performance. The feature vector comprises 720 trials (360 for each class) for each session. Hence, the data from 504 trials (252 trials $\times$ 2 classes) were assigned for training, and the

data from the remaining 216 trials were designated as test data to improve decoding performance.

The results obtained by the proposed methodology are evaluated with the following parameters. Although classification accuracy is a preferable metric when assessing results, it is insufficient. As a result, classification performance is validated with the measures such as Precision, Recall, F1-score and Classification Accuracy.

3.1.1 Classification Accuracy (A_{cc})

The classification accuracy is mostly utilised to examine the overall performance of the proposed approach where all the classes have an equal number of samples. The hand movement classification results with the BiLSTM classifier are comprised of true positive (TP), false positive (FP), true negative (TN), false negative (FN).

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN} \quad (22)$$

3.1.2 Precision and recall

Precision indicates result significance in feature extraction, whereas recall measures how many accurate features are presented.

$$Precision = \frac{TP}{TP + FP} \quad ; \quad Recall = \frac{TP}{TP + FN} \quad (23)$$

3.1.3 F1-Score

The F1-score conveys the balance between positive predictive value and true positive rate. F1-score is calculated by,

$$F1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (24)$$

Table 6: Classification performance of proposed methodology with Imaginary and Real GEF

	Accuracy(%)		Precision		Recall		F1-Score	
Session	Imag.	Real	Imag.	Real	Imag.	Real	Imag.	Real
1	96.72	96.72	0.96	0.96	0.96	0.96	0.93	0.93
2	94.26	95.90	0.91	0.95	0.93	0.95	0.88	0.92
3	93.62	98.56	0.92	0.97	0.92	0.98	0.85	0.97
4	97.54	97.52	0.97	0.96	0.97	0.96	0.95	0.95
5	95.23	95.94	0.95	0.95	0.95	0.95	0.92	0.91
6	97.56	96.87	0.97	0.97	0.97	0.96	0.95	0.94
Mean	95.82	96.83	0.94	0.96	0.95	0.96	0.91	0.93

The proposed methodology designs the feature vectors from preprocessed A-EEG signals. The results of the classification of upper limb movements are

Fig. 9: Classification performance of proposed network

shown in table 6. The results are obtained with both real (R-GEF) and imaginary (I-GEF) parts of GEF. The bold value in table 6 indicates the highest average classification accuracy (96.83%) in the table. The precision parameter is better (0.97) with the R-GEF than the I-GEF (0.94) kernel. The best precision value is achieved (0.97) for the sixth session. The F1-score gives the proper distribution of binary-valued feature vectors. The classifier provides a higher F1-score (0.97) for features collected with R-GEF.

Figure 9 depicts the accuracy and loss rate of the proposed methodology during the classification of A-EEG signals in session three. The figure 9a shows the classification accuracy is constant after 50 iterations. In the same way, in figure 9b after 50 iterations, the loss rate remains constant.

Table 7: Performance of different lobes in analysis of hand movements

Brain Lobes	EEG Channels	Accuracy(%)
Parietal + Temporal	P7, P8, P3, P4, Pz, T7, T8	83.25
Frontal	Fp1, Fp2, F3, F4, Fz, F7, F8	68.12
Temporal + Occipital	T7, T8, O1, O2, Oz	63.89
Occipital	O1, O2, Oz	89.42
Occipital + Central	P7, P8, P3, P4, Pz, C3, C4, Cz	94.73
Occipital+ Central + Temporal	O1, O2, C3, C4, Cz, Oz, T7, T8	96.91

3.2 Effect of hand movement on brain lobes

According to its function, the human brain can be partitioned into five portions (Parietal, Temporal, Occipital, Frontal, and central). Every part of the brain is affected while doing motor activities. Table 7 shows the proposed classifier estimates classification accuracy by incorporating multiple electrode combinations across different lobes.

Fig. 10: Role of individual feature in upper limb movement classification

The central lobe covers the electrodes from the brain's motor cortex region, and hence the results are much better than other lobe combinations (96.91%). Adversely, the occipital lobe has a minor role in upper limb movement. As a result, classification accuracy is dropped to 74.42%. As the subject concentrates on playing the game, involvement of the occipital lobe plays a vital role. It gives higher classification accuracy (94.73%) for Occipital and Central lobes.

3.3 Performance of individual feature set to classify of upper limb movement

The GEF extracts the features from three GBs and feeds them to the classifier to classify the upper limb movement. The features, RMS value, Average Gabor band power, Temporal movements, Shannon entropy from each Gabor band are used to classify the upper limb movement. Figure 10 illustrates the importance of each unique feature in classifying upper limb movement. The performance of each feature is verified with classification results from all six sessions. The Temporal Moment (TM) feature set captures the upper limb movement from the A-EEG signal with better accuracy of 95.76%. On the other hand, the Shannon entropy (ShEn) feature set only achieves a classification accuracy of around 66.37%. The combination gives the highest accuracy (98.31%) in the sixth session, as shown in figure 10.

3.4 Crosschecking of the proposed classifier with others

The performance of the different classifiers is cross-checked with others in terms of classification accuracy. The Support Vector Machine (SVM) classifier with Quadratic kernel and Naive Bayes (NB) classifier give the lesser classification result compared to proposed as well as other classifiers (average Classification accuracy is 80%). On the other hand, the classification results with the proposed classifier are improved in all sessions. The best classification result is

Fig. 11: Comparison of different classifiers with multiple kernels to the BiLSTM network

(96.83%) obtained with the proposed classifier. The SVM with both fine Gaussian and quadratic kernel gives the classification accuracy of 75.7% and 71.1% respectively.

4 Discussion

The main focus of the work in this paper is to implement a robust methodology to classify upper limb movement from Asynchronous-EEG (A-EEG) data. For the analysis of A-EEG signals, the Gabor Elementary function is designed, and results with both R-GEF and I-GEF are compared in table 6. The classification results obtained with R-GEF are superior to I-GEF. The R-GEF filter coefficients adjust to motor activity and help classify A-EEG data efficiently. Gabor Bands (GBs) are used to capture motor activity as shown in figure 5 and 6. The highest classification accuracy and recall value are observed for session 3. The parameters like F1-Score, Precision, etc., mostly show better values with R-GEF kernel. The robustness of the classifier network is illustrated in figure 9. Compared to the training loss, the validation loss decreases quickly, indicating that the classifier's results have improved. The practical loss function never touches the zero line, as shown in the graph.

The findings in table 7 look at the effects of upper-limb movement on several brain lobes. The combination with central lobe electrodes gives better results in upper limb classification as the Central lobe covers the sensorimotor region. Only the Frontal and Occipital lobes exhibit the least classification results because the involvement of the frontal lobe is less in upper limb movement. The left hand or right-hand movement causes the sensorimotor neurons to follow Event-Related Desynchronisation (ERD) effect and supports the classifier to classify hand movements. Therefore the sensorimotor area plays a significant role. As a result, classification accuracy is improved by combining the three lobes to 96.91%.

Table 8: Comparison with state-of-the-art works

Proposed By	Year	Methodology	Electrodes	Trials	Results
Sahar Selim, et al. [25]	2018	CSP-AM/BA+SVM	118	280	86.60%
Kais Belwafi et al. [26]	2019	DSAA+KNN, SVM	22	240	89.78%
M. Tariq et al. [27]	2019	EWT+PSD+LS-SVM	118	210	94.60%
Liwei Cheng et al. [28]	2020	PCA+DBN+DBN	118	280	91.71%
Yang You et al. [14]	2020	FAWT+PCA+LDA	3	240	94.29%
Proposed Method		GEF+GB+BiLSTM	20	720	96.83%

From the collected GBs of upper limb movement, statistical as well as temporal moment features are derived. In figure 10, the contribution of every feature in the classification of left hand and right hand movement is checked with the results of classifier. It is observed that the ShEn feature set is more effective for data with higher coherence, whereas the A-EEG data are less coherent. The ShEn feature set gives poor performance, and hence, ShEn features are removed from the final set of features. Finally, the feature-set comprises Band Power (BP), RMS value, and Temporal Moment (TM) given to the BiLSTM network. Only Temporal moment-based features are effective in classifying motor activity from EEG signals.

The figure 11 gives the comparison of different classifiers with variations in kernels like Support Vector Machine (SVM) with kernels Fine Gaussian (FG), Quadratic (Q), K-Nearest Neighbor having kernels Fine (F) and Cosine (C). The BiLSTM classifier performs best to classify the A-EEG signal, which gives higher classification accuracy of 96.83%. The NB classifier depends on null correlation, which means that the estimated features are independent of one another. The recorded A-EEG data have correlated features, so the NB classifier gives poor classification results (70.6%). The KNN classifier with the Fine kernel gives better classification accuracy than the cosine kernel and other classifiers.

• Comparison with state-of-the-art works

Table 8 compares the result of the proposed methodology to previously published research in the literature [14, 25–27]. The comparison indicates that the Gabor frame-based feature extraction approach outperforms other approaches, with a classification accuracy of 96.83% employing the BiLSTM classifier. The authors Liwei Cheng et.al [28] used Principal Component Analysis (PCA) for feature extraction. The features are classified using Deep Belief Network (DBN). This method gives a classification accuracy of 91.71% which can be improved with a slight modification in the frequency decomposition method. For feature vector calculation, the Common Spatial Pattern has mostly employed methodology. The researchers Sahar Selion et.al [25] used the CSP technique to acquire features, and then AM/BA is appended to refine features. The advanced features are classified with an SVM classifier that improves classification accuracy up to 85%. The Gabor Elementary Function accurately captures the upper limb movement by extracting more efficient frequency bands than other techniques.

5 Conclusions

The work presented in this paper focuses on using asynchronous EEG signals to classify upper limb movement. The proposed technique provides the Gabor Frame-based frequency decomposition technique to handle A-EEG signals. The Gabor Elementary Function (GEF) encapsulates the upper limb movement with three Gabor Bands (GBs) obtained from preprocessed A-EEG data. The feature sets like Band power, Temporal moments, RMS are extracted with designed GEF considering real and imaginary parts. The Kruskal-Wallis statistical test is used to assess the produced feature sets, which has been demonstrated to help accurately categorise hand movements. The BiLSTM based classifier learns the connectivity between adjacent frames from non-stationary A-EEG signals. Hence, the proposed framework achieves better classification results in terms of statistical parameters like classification accuracy, Precision, recall, and F1-Score. Furthermore, the central lobe or Sensorimotor region has more impact while performing hand movement tasks. Thus, the proposed work contributes to achieving better performance in the BCI field.

References

- [1] Nicolas-Alonso, L.F., Gomez-Gil, J.: Brain computer interfaces, a review. *sensors* **12**(2), 1211–1279 (2012)
- [2] Shih, J.J., Krusienski, D.J., Wolpaw, J.R.: Brain-computer interfaces in medicine. In: Mayo Clinic Proceedings, vol. 87, pp. 268–279 (2012). Elsevier
- [3] Shin, J., von Lühmann, A., Blankertz, B., Kim, D.-W., Jeong, J., Hwang, H.-J., Müller, K.-R.: Open access dataset for eeg+ nirs single-trial classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **25**(10), 1735–1745 (2016)
- [4] Graimann, B., Allison, B., Mandel, C., Lüth, T., Valbuena, D., Gräser, A.: Non-invasive brain-computer interfaces for semi-autonomous assistive devices. In: Robust Intelligent Systems, pp. 113–138. Springer, ??? (2008)
- [5] Van Erp, J., Lotte, F., Tangermann, M.: Brain-computer interfaces: beyond medical applications. *Computer* **45**(4), 26–34 (2012)
- [6] Ahn, M., Lee, M., Choi, J., Jun, S.C.: A review of brain-computer interface games and an opinion survey from researchers, developers and users. *Sensors* **14**(8), 14601–14633 (2014)
- [7] Chae, Y., Jeong, J., Jo, S.: Toward brain-actuated humanoid robots: asynchronous direct control using an eeg-based bci. *IEEE Transactions on Robotics* **28**(5), 1131–1144 (2012)
- [8] Göksu, H.: Bci oriented eeg analysis using log energy entropy of wavelet packets. *Biomedical Signal Processing and Control* **44**, 101–109 (2018)
- [9] Kevric, J., Subasi, A.: Comparison of signal decomposition methods in classification of eeg signals for motor-imagery bci system. *Biomedical Signal Processing and Control* **31**, 398–406 (2017)

- [10] Taran, S., Bajaj, V.: Motor imagery tasks-based eeg signals classification using tunable-q wavelet transform. *Neural Computing and Applications* **31**(11), 6925–6932 (2019)
- [11] Ma, X., Wang, D., Liu, D., Yang, J.: Dwt and cnn based multi-class motor imagery electroencephalographic signal recognition. *Journal of neural engineering* **17**(1), 016073 (2020)
- [12] Mirvaziri, H., Mobarakeh, Z.S.: Improvement of eeg-based motor imagery classification using ring topology-based particle swarm optimization. *Biomedical Signal Processing and Control* **32**, 69–75 (2017)
- [13] Riaz, F., Hassan, A., Rehman, S., Niazi, I.K., Dremstrup, K.: Emd-based temporal and spectral features for the classification of eeg signals using supervised learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **24**(1), 28–35 (2015)
- [14] You, Y., Chen, W., Zhang, T.: Motor imagery eeg classification based on flexible analytic wavelet transform. *Biomedical Signal Processing and Control* **62**, 102069 (2020)
- [15] Taran, S., Bajaj, V., Sharma, D., Siuly, S., Sengur, A.: Features based on analytic imf for classifying motor imagery eeg signals in bci applications. *Measurement* **116**, 68–76 (2018)
- [16] Gilles, J.: Empirical wavelet transform. *IEEE transactions on signal processing* **61**(16), 3999–4010 (2013)
- [17] Deng, W., Zhang, S., Zhao, H., Yang, X.: A novel fault diagnosis method based on integrating empirical wavelet transform and fuzzy entropy for motor bearing. *IEEE Access* **6**, 35042–35056 (2018)
- [18] Ang, K.K., Chin, Z.Y., Zhang, H., Guan, C.: Mutual information-based selection of optimal spatial-temporal patterns for single-trial eeg-based bcis. *Pattern Recognition* **45**(6), 2137–2144 (2012)
- [19] Cohen, M.X.: A better way to define and describe morlet wavelets for time-frequency analysis. *NeuroImage* **199**, 81–86 (2019)
- [20] Sokic, M.: Gabor representations. <https://www.coursehero.com/file/36557198/GaborLocalizationpdf/>
- [21] Saridis, G.N., Gootee, T.P.: Emg pattern analysis and classification for a prosthetic arm. *IEEE Transactions on Biomedical Engineering* (6), 403–412 (1982)
- [22] Chaudhary, S., Taran, S., Bajaj, V., Siuly, S.: A flexible analytic wavelet transform based approach for motor-imagery tasks classification in bci applications. *Computer methods and programs in biomedicine* **187**, 105325 (2020)
- [23] Aksoy, S., Haralick, R.M.: Feature normalization and likelihood-based similarity measures for image retrieval. *Pattern recognition letters* **22**(5), 563–582 (2001)
- [24] Bengio, Y., Simard, P., Frasconi, P.: Learning long-term dependencies with gradient descent is difficult. *IEEE transactions on neural networks* **5**(2), 157–166 (1994)
- [25] Selim, S., Tantawi, M.M., Shedeed, H.A., Badr, A.: A csp\am-ba-svm

approach for motor imagery bci system. *IEEE Access* **6**, 49192–49208 (2018)

[26] Belwafi, K., Gannouni, S., Aboalsamh, H., Mathkour, H., Belghith, A.: A dynamic and self-adaptive classification algorithm for motor imagery eeg signals. *Journal of neuroscience methods* **327**, 108346 (2019)

[27] Sadiq, M.T., Yu, X., Yuan, Z., Zeming, F., Rehman, A.U., Ullah, I., Li, G., Xiao, G.: Motor imagery eeg signals decoding by multivariate empirical wavelet transform-based framework for robust brain–computer interfaces. *IEEE Access* **7**, 171431–171451 (2019)

[28] Cheng, L., Li, D., Yu, G., Zhang, Z., Li, X., Yu, S.: A motor imagery eeg feature extraction method based on energy principal component analysis and deep belief networks. *IEEE Access* **8**, 21453–21472 (2020)

Statements and Declarations

Competing Interests

The authors of this manuscript declare that they have no conflict of interest with any person or organisation for carrying out this research work.

Ethics approval

The experiment conducted was endorsed by the The experiment was endorsed by the Shri Guru Gobind Singhji Institute of engineering and Technology ethical committee and no human being is harmed during data collection. (Ethics Approval Number: SGGSI&T/R&D/ETHICS APPROVAL/2017-18/07/2)