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Signal processing techniques for motor imagery brain computer interface: A review

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ABSTRACT

Motor Imagery Brain Computer Interface (MI-BCI) provides a non-muscular channel for communication to those who are suffering from neuronal disorders. The designing of an accurate and reliable MI-BCI system requires the extraction of informative and discriminative features. Common Spatial Pattern (CSP) has been potent and is widely used in BCI for extracting features in motor imagery tasks. The classifiers translate these features into device commands. Many classification algorithms have been devised, among those Support Vector Machine (SVM) and

Linear Discriminate Analysis (LDA) have been widely used. In recent studies, the researchers are using deep neural networks for the classification of motor imagery tasks. This paper provides a comprehensive review of dominant feature extraction methods and classification algorithms in brain-computer interface for motor imagery tasks. Authors discuss existing challenges in the domain of motor imagery brain-computer interface and suggest possible research directions.

1. Introduction

A Brain Computer Interface (BCI) utilizes signals to establish a connection between a person's state of mind and a computer-based signal processing system, which interprets the signals [1]. BCI provides a direct communicational channel between the brain and an external device without involving any muscular activities. These systems either use electroencephalogram (EEG) activity recorded from the scalp or the activity of individual cortical neurons recorded from implanted electrodes [2].

EEG has relatively short time constants, and requires simple and inexpensive equipment; therefore at present EEG-based BCI systems are widely used [2–6]. Various forms of electrical brain activities have been used to discern EEG based BCI systems, such as mu rhythm [7,8], slow cortical potential [9], event-related p300 [10] and steady-state visual evoked potential [11,12]. Among various types of electrical brain activities, the one related to motor tasks is mu rhythm [13].

Motor imagery (MI) is defined as the cognitive process of imagining the movement of your own body part without actually moving that body part [14]. Motor imagery based Brain Computer Interface (MI BCI) provides an interface for the patients with motor impairment or those who are in completely locked-in-state to interact with the environment by controlling robotic prostheses, wheelchairs, and other devices [15].

MI BCI has a wide range of applications, such as controlling a wheelchair, virtual reality, neurorehabilitation and controlling devices such as quadcopters in 2-D/3-D space [16–19].

The EEG signal processing for MI BCI involves feature extraction and classification. In feature extraction phase the EEG signal acquired for MI BCI reveals task-specific features in both spectral domain and spatial domain [20]. Several spectral processing methods such as wavelet transform [21–23], fourier transform [24], autoregressive model [25] and spatial method such as common spatial pattern (CSP) [26–29] have been used in literature to extract the features from these EEG signals. CSP algorithm is the most successful and is widely used in MI BCI due to its high recognition rate and computational simplicity [30].

The goal of classification is to translate the signal features provided by the feature extractor into commands or orders that carry out user's intent [2]. In MI BCI, classifiers convert discriminative features into different MI tasks such as left-right hand movement, foot movement, tongue movement or word generation. Copious classification algorithms, such as support vector machines [31,32], linear discriminate analysis (LDA) [26–28] neural networks [22,33,34], and deep neural networks [23,24, 35–38] have been applied on MI BCI.

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2. Related work

The relevant reviews available on signal processing techniques mostly focus either on feature extraction methods or on classification techniques. Table 1 shows all reviews that are related to feature extraction and classification techniques. The label Yes in table implies that article presented that particular technique and label No implies vice versa.

Swati Vaid et al. [39] describe the model of BCI system. The author categorized the techniques into basic techniques and advanced techniques. The basic techniques are time domain and frequency domain techniques. Advanced techniques are classified into time frequency domain and space-time frequency domain. Further, they have summarized the features and its techniques in respective domains.

M. Rajya Lakshmi et al. [40] briefly describe the feature extraction techniques, which are Principal Component Analysis (PCA), Independent Component Analysis (ICA), Auto Regressive Model (AR), Wavelet Transform (WT) and Wavelet Packet Decomposition (WPD). Furthermore, the paper has explored the signal processing methods used in each stage of brain computer interface.

Amjed S. Al-Fahoum and Ausilah A. Al-Fraihat [25] discuss the feature extraction techniques in frequency domain and time frequency domain such as fast fourier transform, auto regressive model, wavelet transform, eigen vectors and time frequency distribution. The authors have provided recommendations based on the performance.

Lotte et al. [41] discussed the classification algorithms used for EEG based brain computer interfaces. The authors described the properties of algorithms in detail and compared the performances of the classifiers. Based on the performances the authors provide the guidelines for selecting the best-suited classifier.

Rupal Chaudhary et al. [42] described the different stages of BCI. The authors provided a review of classification of motor imagery tasks. It has provided a summary of the paper selected and studied by the author.

All the works discussed in Table 1 provide brief description about any one of the two important components of signal processing, that is feature extraction or classification. Though M. Rajya et al. has discussed both feature extraction and classification but discussion is not comprehensive. Certainly, the description and discussion of various signal-processing components needs further elaboration. It is understood that it would be more helpful if all the elements of signal processing were presented in a comprehensive and holistic manner. Based on this perspective the authors have summarized the algorithms available for feature extraction and classification for brain computer interfaces.

Authors in this paper have presented the variants available for feature extraction methods and all the components are classified appropriately. Recently Deep Learning has been introduced as the classification methods for brain computer interfaces [23,24,35–38], which has not been discussed in previous related works listed in Table 1. As benefits of deep learning in BCI has been highlighted by different researchers [35–38], authors in this paper have included a discussion on deep learning classification methods for BCI. Furthermore, the review also critically examines the various challenges of different modules of BCI.

3. Working principle of BCI system

The working of the BCI system requires three modules that are signal acquisition module, signal processing, and application module. This section describes the working of each module. Fig. 1 shows the components of BCI and their interactions.

3.1. Signal acquisition module

The Signal Acquisition Module is liable for recording the electrophysiological signals that provide input to the BCI. These signals are recorded from the scalp or from the surface of the brain or neuronal activity [43]. BCI might use either invasive methods or non-invasive methods for signal acquisition. Invasive methods are electrocardiograms (ECoG) and single-neuron recordings [43,44] and have better signal quality as compared to non-invasive methods. Non-invasive methods are Electroencephalogram (EEG), Magnetoencephalogram (MEG), Positron Emission Tomography (PET), Functional Magnetic Resonance Imaging (fMRI) and Near-Infrared Spectroscopy (NIRs) [44].

The acquired signals are amplified to enhance the strength and are digitized before they are used by any of the computer application.

3.2. Signal processing module

3.2.1. Preprocessing

The task of preprocessing is to prepare the recorded signals for processing by enhancing the signal –to- noise ratio (SNR). The part of EEG signal that comes from muscular activity of head, and eye movement generate electrical activity that is unrelated to the brain. Such part of signal is considered as artifact and should not be processed in order to preserve and exhibit the relevant information; therefore preprocessing is done to remove artifacts in EEG signals. In BCI research, the proper preprocessing of EEG signal is important in order to obtain high classification accuracy. Preprocessing of BCI is based on the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) which obtains the spatial and frequency selection filters automatically [45].

3.2.2. Feature extraction

After preprocessing the signal is fed into one or more type of feature extraction algorithms. This component extracts features in the time domain and frequency domain that encode messages or commands [43]. Wide varieties of feature extraction methods are used in BCI system;

Table 1
Signal Processing techniques presented in related work.

Category	Techniques	Article				
		Rupal Chaudhari et al. (2017) [42]	Swati Vaid et al. (2015) [39]	M. Rajya Lakshmi et al. (2014) [40]	Amjed S. Al-Fahoum1 (2014) [25]	F Lotte et al. (2007) [41]
Feature Extraction	Fast Fourier Transform		Yes	Yes	Yes	
	Short Term Fourier Transform		Yes	No	No	
	Auto Regressive Model		Yes	Yes	Yes	
	Wavelet Transform		Yes	Yes	Yes	
	Wavlet Packet Decomposition		Yes	Yes	No	
	Common Spatial Pattern		Yes	No	No	
Classification	Linear Discriminant Analysis	Yes		Yes		Yes
	Support Vector Machine		No	Yes		Yes
	Artificial Neural Network	Yes	No	Yes		Yes
	Deep Learning		No			No

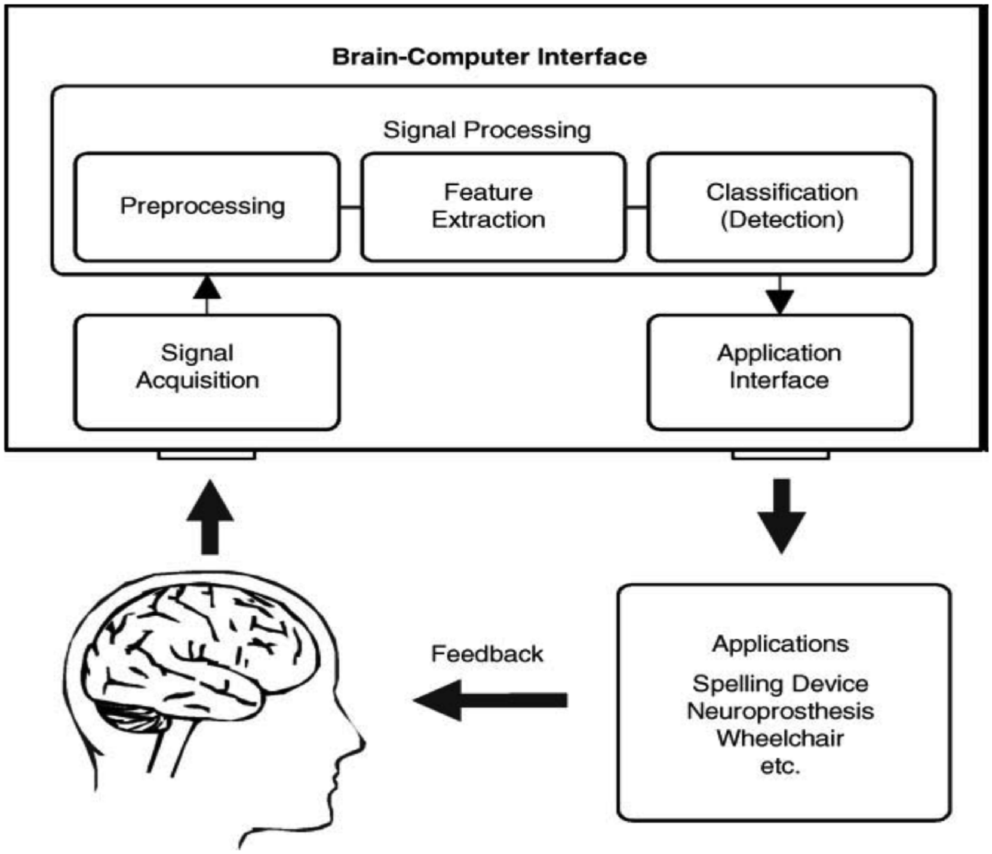

Fig. 1. Components of a BCI system [21].

some of these methods include amplitude measures, band power, Hjorth parameters, autoregressive models, and wavelets and spatial filters [9].

3.2.3. Classification

The task of the classification component is to translate the features provided by the feature extractor to a category of brain patterns; that is the independent variable is converted into the dependent variable. The classification algorithms may use linear methods like Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) or non-linear methods such as neural networks.

3.3. Application module

For most current BCIs, the output device is a computer screen and the output is the selection of targets, letters, or icons presented on it [19]. Some BCIs provide an output, such as cursor movement toward the item prior to its selection.

The output generated by the output device is the feedback provided to the user to notify the user about the recognized brain activity pattern. This pattern is then used to sustain and enhance the accuracy and speed of communication.

There are various key components in the BCI closed loop, one is feature extraction and the other is classification. There is a large diversity of feature extraction and classification methods that have been explored in BCI for motor imagery tasks. This paper gives an extensive review of these two components that are described in the following sections.

4. Feature extraction techniques

During Feature extraction, features are extracted from the signals in either time domain or frequency domain. As shown in Fig. 2 the feature extraction process involves frequency filtering, windowing in which short segments are selected, feature extractor and the feature selection which outputs the selected features that are being fed into the classifier. In BCI, frequency band power features and time domain features represent EEG signals. Band power features represent the power of EEG signals for a given frequency band averaged over a time window and time domain features are the combination of EEG signals from all channels. MI BCI extensively uses band power features. Based on the literature found and studied as shown in Table 4 it has been noticed that most of the used

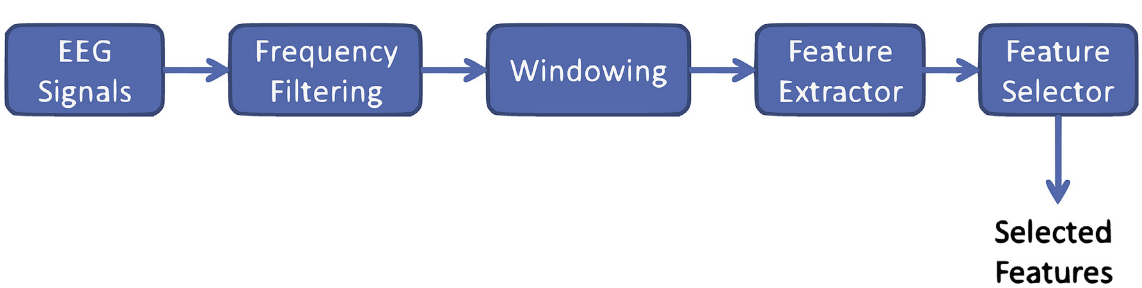

Fig. 2. Processes involved in Feature Extraction.

or referenced techniques for feature extraction in motor imagery brain computer interfaces are Short Term Fourier Transform (STFT), Auto Regressive Model (AR), Wavelet Transform (WT), and Common Spatial Pattern (CSP). This section gives detailed description of the varied feature extraction methods used for motor imagery tasks.

4.1. Fast fourier transform (FFT)

The first feature extraction method used for MI BCI was based on Fast Fourier Transform [25] that is applied to estimate the power at chosen frequency bands in FFT generated spectra. Fourier analysis decomposes the signal into its frequency components and determines their relative strengths. FFT does not consider time information, thus it is not able to analyze non-stationary EEG signals. In order to represent the non-stationary signal the author uses Short Term Fourier Transform (STFT) [25,46]. In STFT, the signal is divided into small overlapping frames on which FFT is applied by placing a window function on time axis as shown in Fig. 3.

When fixed time window function is applied to STFT, it produces fixed time-frequency resolution that limits the use of STFT. This means that one can only trade time resolution for frequency resolution or vice versa.

4.2. Autoregressive (AR) model

The Autoregressive model is the parametric approach that estimates the Power Spectrum Density (PSD) of the signal. Typically, short epochs are preferred over longer epochs for analysis in order to characterize the rapid changes that occur in EEG signal. The spectra obtained from FFT on short epochs have poor resolution when compared to an autoregressive model. Although the resolution of FFT could be improved by applying window function such as Hanning window, but still it have poor resolution as compared to autoregressive model as shown in Fig. 4. The validity of spectral estimate depends on the selection of proper model order where model order roughly determines the number of spectral peaks that need to be captured. If the model order is too low, AR yields smooth spectrum whereas, if it is too high the spectrum has spurious peaks [19]. The model order for EEG ranges from 3 to 20 [47].

4.3. Wavelet transform (WT)

Wavelet Transform is the feature extraction technique that extracts features in time-domain and is used to represent the function by an infinite number of wavelets where each wavelet has specific time-frequency characteristics. The above two techniques, FFT and AR model uncover only spectral characteristics of signals and do not obtain good performance with non-stationary EEG signal. Wavelet Transform combines frequency information and time domain information, which gives better performance as compared to FFT or AR [25]. WT uses varying size window such that high frequencies are evaluated on the shorter window and low frequencies over longer window [48,49] thus WT performs better in time resolution of high frequencies as compared to STFT as shown in Fig. 5. The other extensions of WT have also been used in MI BCI such as Wavelet Packet Transform (WPT) [50] and Wavelet Packet Best Basis Decomposition (WPBBD) [51].

4.4. Common spatial pattern (CSP)

In MI BCI, spatial information is required in multichannel EEG recordings to discriminate intent patterns and therefore, the spatial filters have been used to extract spatial information from the signal. Common Spatial Pattern generates spatial filters that minimize the variance of one class and maximize the variance of other class simultaneously. The multichannel EEG signal is passed into bandpass filter for selecting the frequency. After frequency filtering, spatial filtering is performed that uses spatial filters and FIR filters. The process of common spatial pattern

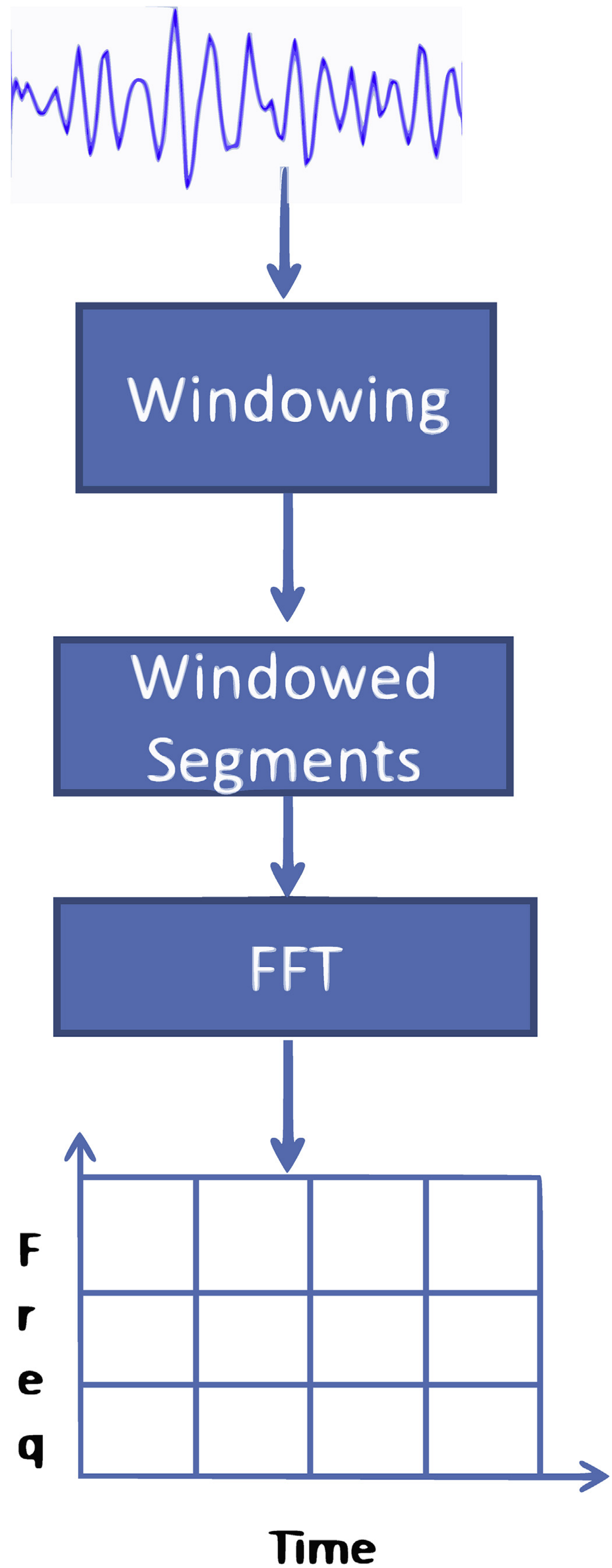

Fig. 3. Short term Fourier Transform Process.

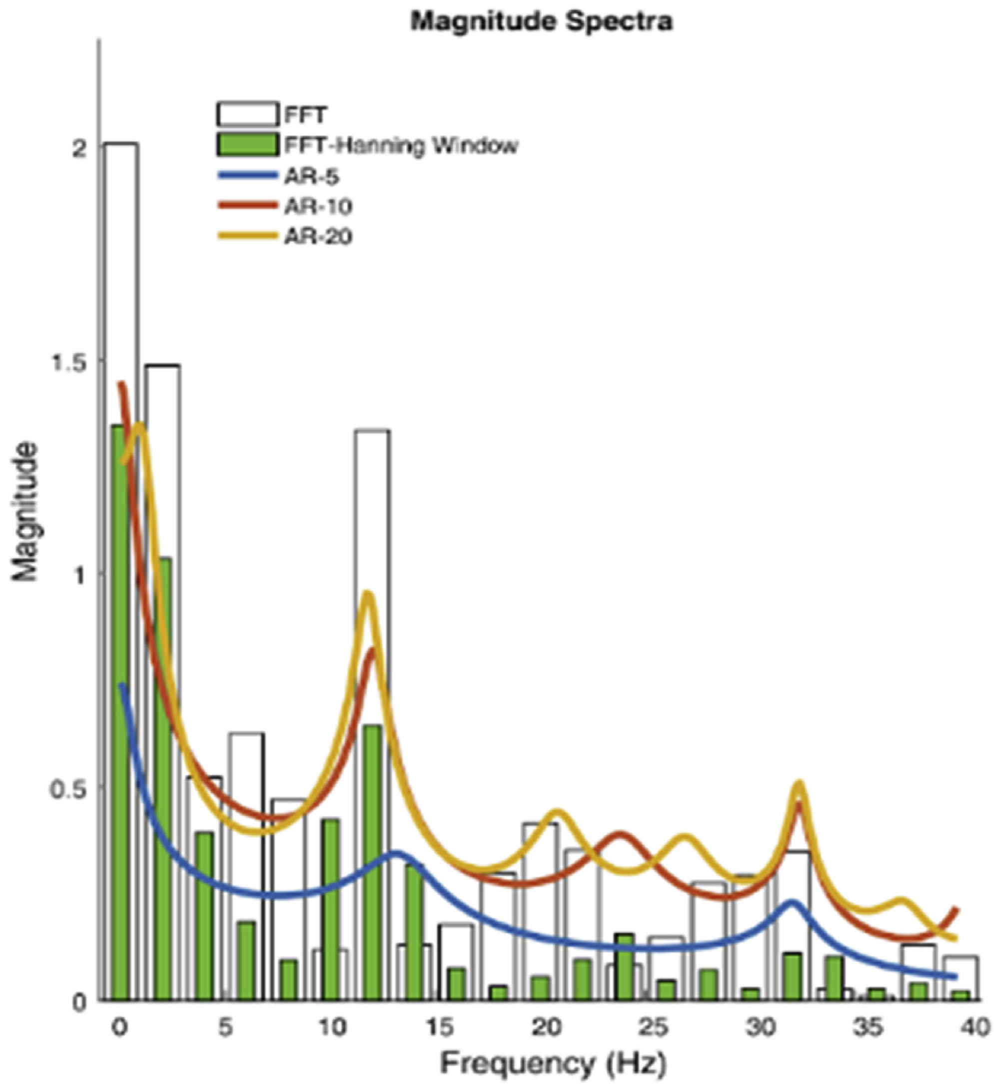

Fig. 4. Comparison of Spectra generated by FFT and AR model [47].

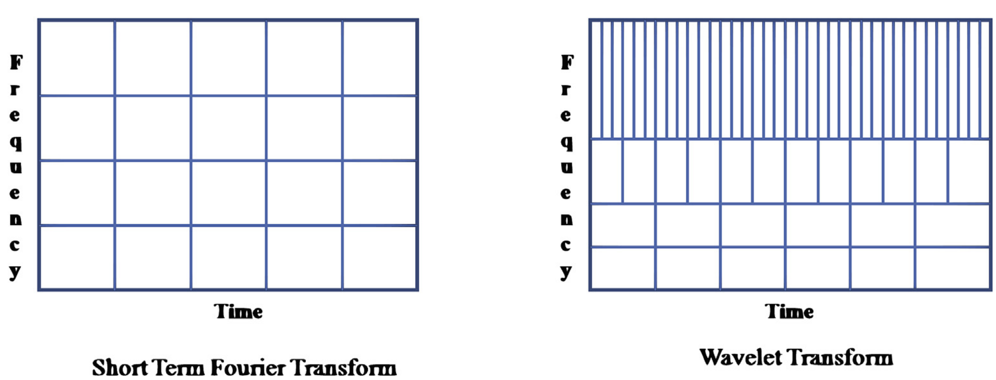

Fig. 5. Comparison of resolution obtained by STFT and WT.

is shown in Fig. 6. CSP is one of the most effective feature extraction methods used in binary motor imagery task classification.

In brain computer interface the objective of spatial filtering used by the CSP algorithm is to compute features whose variances are optimal for discriminating two classes of EEG measurements [52]. The performance of this spatial filtering depends on the operational frequency band of EEG. Several approaches have been proposed to fine-tune the subject-specific frequency range for CSP algorithm. One such approach is the Common Spatio-Spectral Pattern (CSSP) [53], which optimizes simple filters with a spatial filter. Another approach was the Common Sparse Spectral-Spatial Pattern (CSSSP) [54]. It improves the CSSP algorithm by performing simultaneous optimization of an arbitrary FIR filter within the CSP algorithm.

An alternative approach called Sub Band Common Spatial Pattern

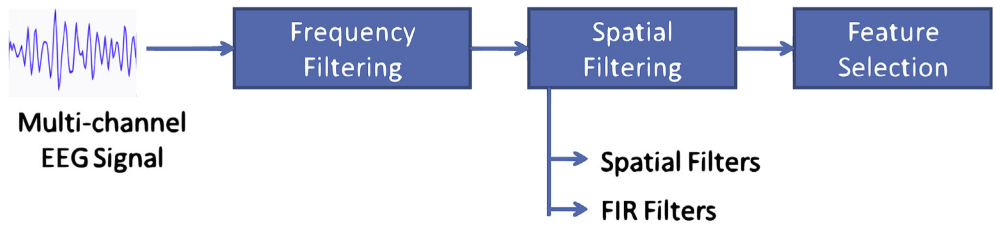

Fig. 6. Process of common spatial pattern.

(SBCSP) [55] was proposed in which EEG signals are decomposed into sub-bands. CSP is applied to each sub-band that defines sub-band score and then these scores are fused together to derive the final decision. SBCSP has improved classification accuracy when compared to CSSP and CSSSP.

As compared to SBCSP, a more generalized approach called Filter Bank Common Spatial Pattern (FBCSP) [56] was proposed that comprised of four stages: frequency filtering, spatial filtering, feature selection, and classification. It deploys a small subset of effective spatial filters that reduces computational complexity against SBCSP. A variant, named Discriminative FBCSP (DFBCSP) [57] was proposed to enhance classification accuracy. DFBCSP extracts subject specific discriminative frequency bands from the set of filters instead of using fixed frequency bands for all subjects as in FBCSP.

In 2016, Separable Common Spatio Spectral Patterns (SCSSP) [20] had been proposed that jointly processed the data in both spectral and spatial domains and had low computational cost over FBCSP. This approach was suitable for wearable mobile BCI systems. FBCSP used the fixed partition of a frequency band that leads to loss of information in the frequency domain. The augmented CSP [58] based on varying partition of the frequency band with different bandwidths had solved the problem of information loss.

Some other variants of CSP found in literature are sparse CSP [59] that impose sparsity on weights by adding regularization factor on spatial filter, stationary CSP [60] that uses stationary subspaces, divergence CSP [61] that utilizes information from other subjects and enforce different invariance formulating divergence maximization problem, and probabilistic CSP [62] that solves the problem of overfitting.

While all these variants improve the standard CSP algorithm, they are still unable to characterize temporal (time-related) dynamics; thus, more sophisticated techniques that consider time-related information are required. The features extracted from CSP are then fed into various classifiers for classification.

The different prominent feature extraction techniques used for MI BCI along with advantages and limitations are summarized in Table 2.

5. Classification techniques

The classification is a process of predicting the target variables or classes from the given input. To build the classification model, learning algorithm is applied in the training phase to adjust the parameters of the model as shown in Fig. 7. The same model is then used in the testing phase to extract the output. In motor imagery brain computer interface the features extracted by various feature extraction techniques are converted into different motor imagery tasks like hand movements, foot movement, word generation and alike through classification algorithms.

The authors have classified the classification algorithms used in the literature as linear classifiers, neural networks, non-linear classifiers, and deep neural networks. Linear Classifiers use the linear function to distinguish classes. Two main types of linear classifiers are Linear Discriminant Analysis (LDA) [26–38] and Support Vector Machine (SVM) [29,31,63] and have been commonly used in testing of BCI. Neural Network (NN) is an assembly of different artificial neurons, which enables to produce nonlinear decision boundaries. The NN specifically created and used for BCI is Gaussian Classifier [41]. Non-linear classifiers produce non-linear decision boundaries and are generative. These classifiers are not widespread and not popular as the linear classifier and neural networks in MI BCI. Deep Neural network (DNN) is an artificial network with multiple layers called as hidden layers between input and output layers and is used to model complex non-linear relationships. The classifiers based on deep neural networks have been used in MI BCI research to improve the accuracy of multiclass signal analysis.

This section gives a detailed description of the linear classifier,

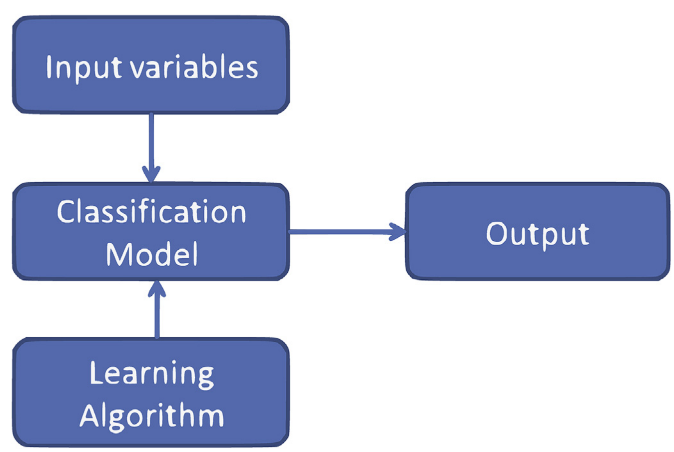

Fig. 7. Classification process.

Table 2
Comparison of Feature Extraction Techniques used for MI BCI.

Technique	Advantages	Limitations	Analysis Method
Fast Fourier Transform(FFT)	• FFT is accurate at frequency composition of a signal. • It has enhanced speed over all other methods.	• FFT is not suitable for analyzing non- linear signals. • It does not take into time information into account.	Frequency
Autoregressive Model (AR)	• It provides good frequency resolution. • It has reasonable spectral estimates for short segments.	Validity of the model depends upon the proper selection of model order.	Frequency
Wavelet Transform(WT)	• WT provides improved balance between window length and spectral resolution. • It is better suited for sudden changes in signal.	Proper selection of appropriate mother wavelet is required.	Time-Frequency
Common Spatial Pattern (CSP)	• CSP is suitable for multichannel signal analysis. • It is used to tune subject specific frequency range.	• CSP does not able to handle temporal dynamics. • It has slow convergence.	Spatial Filters

classifier based on neural network and the deep neural network that is used in the field of MI BCI.

5.1. Linear discriminative analysis (LDA)

LDA classifier has the low computational requirement that makes it a commonly used classifier in EEG based BCI applications. LDA projects data into new space using projection $y = w^T x$ that minimizes the scatter within the class and maximizes between the classes as illustrated in Fig. 8.

LDA has been successfully used for classification of right and left-hand motor imagery [41]. The main drawback of LDA is that it provides the poor result on complex nonlinear EEG data [65]. Regularized Fisher LDA [27], an enhancement of LDA has also been used for right and left-hand motor imagery that uses decision boundary or hyperplane in feature space for classifying features in distinct classes. Fisher LDA obtains better generalization capabilities and gives better results than LDA [65].

5.2. Support vector machine (SVM)

Support Vector Machine has been very popular in BCI research. SVM selects the hyperplane that maximizes the distance from the nearest training points. Linear SVM uses the linear function as decision boundaries while nonlinear SVM uses the kernel function to map the data into higher dimensional space [29]. Linear SVM and non-linear SVM is shown in Fig. 9.

Md Rabiul Islam et al. (2017) [63] uses SVM on features with reduced dimension obtained by employing multiband TSM and PCA respectively for four class classification problems. Some other flavors of SVM like Transition Detection based SVM (TD-SVM) [31] and Evolved filters based SVM [32] have been used for MI BCI. In TD-SVM, the classification problem is divided into two sub-problems: detecting class transitions and determining the class for sequences of instances between transitions. Evolved filters based SVM algorithm optimizes spatial and frequency-selection filters by means of the Covariance Matrix Adaptation Evolution Strategy. SVM is known to have good generalization properties and is insensitive to the curse-of-dimensionality [64].

5.3. Neural network (NN)

SVM gives high-quality results but is not able to handle the multiclass problem and dynamic nature of EEG signal effectively. Robust classifiers give better performance but need more time; therefore, there is a tradeoff between accuracy and speed. As the neural network provides reasonable tradeoff, it has been extensively used in BCI research. There are several NN architectures used in the field of BCI, the one that has been specifically created for BCI is the Gaussian classifier [65,66]. Each unit of this NN is a Gaussian discriminant function representing a class prototype. This classifier has been applied with success to motor imagery [22] and mental task classification [34]. Other NN architectures such as Multilayer Perceptron (MLP), neural network based on Radial Basis Function (RBF), spiking neural network [67] that uses Online Meta neuron based Learning Algorithm (OMLA) has been applied for classification of MI tasks. NN has also been successfully applied for multiclass multiuser MI tasks [22] classification.

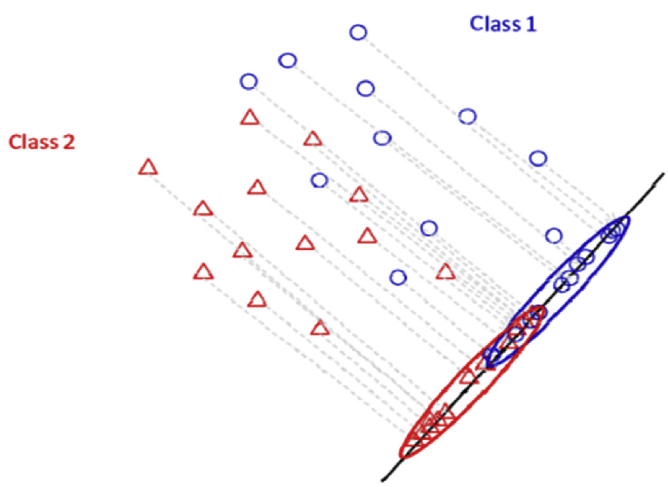

Fig. 8. Linear Discriminant Analysis (LDA) projection [26].

5.4. Deep learning

In the traditional neural network, weights have to be chosen very carefully. This is a major obstacle in the effective use of the neural network in many applications of BCI. In recent studies, researchers have been using deep learning approach as deep neural network has high descriptive power and thus improves the accuracy of the system. Deep learning has successful performance in the field of computer vision and in recent years has also been applied in classification of motor imagery tasks [24,68]. Initially, Na Lu et al. [24] proposed an approach to use manually extracted features from the channels based on FFT and then feed them into a Deep Belief Network (DBN). Among various deep learning architectures Convolutional Neural Network (CNN) is effectively used for classification of motor imagery tasks [23,35–38,69] due to its regularization structure and degree of translation invariance. The Convolutional neural network is a class of deep feed-forward artificial neural network that uses a variation of multilayer perceptrons. A simple CNN is a sequence of layers, and every layer of a CNN transforms one volume of activations to another through a differentiable function. CNN architecture consists of the input layer, convolution layer, pooling layer, fully connected layer and output layer as shown in Fig. 10. The Convolutional layer is the core building block of CNN and does most of the computation. Pooling layer reduces the spatial size of representation and neurons in fully connected layer have full connections to the previous layer.

Siavash et al. [36] and Huijuan et al. [58] proposed CNN architecture that uses dynamic energy based features for classifying multiclass motor imagery EEG signals. In Ref. [36] the author proposed a parallel architecture that uses 3 layered MLP for static energy features and CNN for dynamic energy features with dropout regularization. The predictions from both the networks are joined via averaging. The framework yields a significant increase in classification accuracy as compared to the support vector machine. In Ref. [58] the author proposed an architecture that uses augmented CSP for feature extraction. The energy features are arranged on a 2D matrix and CNN is then trained on this matrix to discriminate the features. Further, the feature maps are selected by using the map selection algorithm after the convolution.

In the past, CNN has been used for classification of left and right motor imageries that use time-frequency representation as input [23,35]. The author [23] proposed an architecture that uses Continuous Wavelet Transform with morlet and bump wavelets for feature learning. The 1D convolution is conducted at convolution layer to analyze spectral characteristics over time. The framework has achieved promising performance.

More recently, CNN has been applied for the classification of multiclass motor imagery tasks using temporal representations [38]. Another framework [37] that is applied for multiclass motor imagery task consists of temporal feature extractor, spatial feature extractor and a classifier that is learned jointly in an end-to-end manner. The framework uses recurrent convolution layers and has shown acceptable performance.

The classifiers in the field of MI BCI, along with their advantages and limitations, have been described in Table 3.

6. Literature cited

According to various studies reviewed in this paper, it has been found that most of the work is based on publicly available dataset and is limited

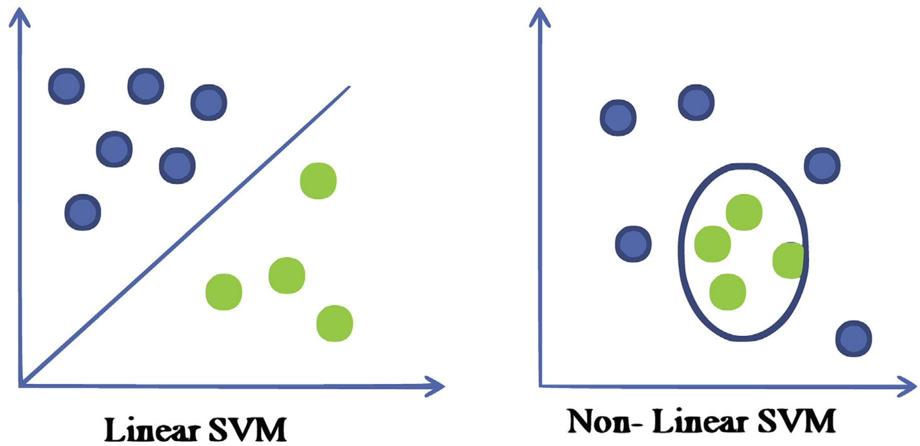

Fig. 9. Linear and non-linear support vector machine.

Fig. 10. Convolutional neural network.

Table 3
Comparison of classification algorithms used for MI BCI.

Technique	Advantages	Limitations
Linear Discriminant Analysis (LDA)	• LDA has low computational requirement. • It is Simple to use.	It is not suitable for complex non-linear EEG data.
Support Vector Machine (SVM)	• SVM has better generalisation properties. • It is insensitive to curse to dimensionality.	It is not suitable for handling dynamic nature of signal.
Neural Networks (NN)	NN provides reasonable tradeoff between accuracy and speed.	Weights have to be chosen carefully.
Deep Neural Networks (DNN)	It is able to learn discriminat features and classifier simultaneously from raw EEG data.	DNN has large computational complexity for training and testing.

to upper limb imageries. Among the classification methods, SVM is commonly used and has promising results. Although Shallow CNN has shown the promising results in MI BCI research; still the deep neural networks is lagging in performance due to unavailability of the large training dataset. The earlier studies focus on two class motor imagery that is now shifting towards multiclass and multilabel motor imageries in recent studies.

Table 4 presents the summary of the literature studied related to the motor imagery brain computer interface.

Table 5 shows the performance comparison of Common Spatial Pattern and Wavelet Transform with different classification techniques using publicly available dataset BCI Competition III. The table reveals that the Wavelet Transform has accuracy of 86.20% with CNN classifier, which is highest among all other classifiers, used with Wavelet Transform. Moreover, Common Spatial Pattern is also effective with the classification techniques that are based on Deep Learning or Deep Neural Network.

7. Challenges

Various feature extraction and classification algorithms have been applied successfully for EEG based BCI for motor imagery tasks and obtained good accuracy results, still, there are some unresolved issues and challenges that attract attention from researchers from varied domains. Pertaining to open issues and challenges are listed in Table 6.

7.1. Feature extraction

EEG signal is usually very noisy and time-variable; therefore, it is challenging to extract relevant features from EEG measurements in a very short time window. Although Common Spatial Pattern (CSP) and its variants are popular and extensively used in BCI, it does not consider the temporal structure of the signal that results in loss of temporal information (time-related information) [77]. Thus, sophisticated time series modeling techniques are required that consider temporal dynamics.

There has been some research [28,36,38] in recent years that has considered temporal dynamics and improved the classification accuracy to some extent. The author in Ref. [38] proposed a parallel MLP and CNN architecture where MLP uses log energy based features and CNN uses a temporal representation of selective EEG channels from FBCSP algorithm. The combination of architecture used by the author resulted in a small and consistent increase in all subjects. The author has suggested research directions in preprocessing of data, optimization of hyperparameter in parameter selection and in proposing a modified architecture that should be based on the combination of static and dynamic energy features.

The author in Ref. [28] presents an algorithm for determining features that used a combination of temporal, spectral and spatial information. The proposed algorithm is a four-phase method based on the static selection of subject-specific information to reduce classification error. The authors suggested that automatic subject selection and multivariate feature selection methods might be used further to enhance the accuracy of the system.

Owing to the efficiency of CSP for binary classification, it has been extensively used in brain computer interfaces to overcome the limitation of the subject-specific frequency band. However, the performance of CSP and its variants in multiclass classification remain an open challenge due to the dramatic increase in the number of feature subsets in MI tasks.

7.2. Classification

The challenges related to classification have been discussed in three articles where Na Lu et al. [24] suggested that the classification algorithms available needed large computation and are unsuitable for online

Table 4
Summary of literature studied in MI BCI.

Paper Title	Year	Feature Extraction technique	EEG Features	Class	Motor Imagery	Classification	Dataset	Accuracy
Evolving Spatial and Frequency Selection Filters for Brain-Computer Interfaces [32]	2010	CSP	Frequency based	3	Left hand, Right hand and generation of words	SVM	BCI-III competition	Evolved Filters- Subject1- 77.96%, Subject2-75.11%, Subject-3 57.76%
EEG feature comparison and classification of simple and compound limb motor imagery [71]	2013	CSP	Band Power	7	Compound(both hands, left hand + right foot, right hand + left foot), rest state	SVM	Author Prepared	70%
A Novel Classification Method for Motor Imagery Based on Brain-Computer Interface [26]	2014	CSP	Spatial features	2	Left and Right Motor Imagery	LDA	Author prepared	91.25
Increase performance of four-class classification for Motor-Imagery based Brain-Computer Interface [29]	2014	CSP	ERD/ERS	4	Left hand, right hand, foot and tongue	LDA, QDA, SVM	BCI competition 2008 (Graz data set 2A)	LDA- 78.82%
Neural Network-based Three-Class Motor Imagery Classification Using Time-Domain Features for BCI Applications [33]	2014	Root mean Square and integrated EEG	Time domain	3	Left hand, right hand and tongue	Neural network	Author Prepared	MLP RMS- 82.50%,IEEG- 81.07% RBF RMS- 84.94%, IEEG- 81.52%
Parallel Convolutional-Linear Neural Network For Motor Imagery Classification [36]	2015	FBCSP	Energy based	4	Left hand, right hand, feet and tongue	CNN	BCI competition IV dataset 2A	70.60%
On the Use of Convolutional Neural Networks and Augmented CSP Features for Multi-class Motor Imagery of EEG Signals Classification [58]	2015	Augemented CSP	Frequency based	Multi class	Left hand, right hand, both feet and tongue	CNN	BCI competition IV dataset 2A	Complementary feature map selection scheme – 68.45%, Full map scheme – 69.27%
A Multi-label Classification Method for Detection of Combined Motor Imageries [72]	2015	CSP	Band Power	4	Rest, right hand, left hand and both hands	LDA	Author Prepared	51.67%
A Deep Learning Scheme for Motor Imagery Classification based on Restricted Boltzmann Machines [24]	2016	Fast Fourier Transform and wavelet packet decomposition	Frequency domain features	2	Left and Right motor imagery	Deep Neural Network	BCI competition IV data set 2B	Not Provided
EEG Feature Extraction and Classification in Multiclass Multiuser Motor Imagery Brain Computer Interface using Bayesian Network and ANN [22]	2017	Wavelet decomposition	Sensorimotor rhythms	Multi class	Rest state, left fist, both fists, right fist, both feet movement	Neural network	Physionet dataset record	93.05%
A Deep Learning Approach for Motor Imagery EEG Signal Classification [68]	2017	Common Spatial Pattern	Variance based CSP features	2	Left and Right hand	Deep Neural Network	BCI competition III dataset 4A	Not Provided
A Convolution Neural Networks Scheme for Classification of Motor Imagery EEG based on Wavelet Time-Frequency Image [23]	2018	Continous Wavelet transform	Time -frequency Representations	2	Left and Right hand	CNN	BCI competition IV dataset 2B	Morlet- 78.93%, Bump-77.25%
Deep Convolutional Neural Network for Decoding Motor Imagery based Brain Computer Interface [35]	2017	STFT	Time -frequency Representations	2	Left and Right hand	CNN	Author Prepared	CNN(RELU)- 86.74%, CNN(ELU) – 88.92, CNN(SELU)- 92.73%
Classification of Motor Imagery for Ear-EEG	2018	CSP	Log variance features	2	Motor + ear	RLDA	Dataset 1: Author prepared, Dataset	Dataset 1: 77.71%, Dataset 2: 74.28%

(continued on next page)

Table 4 (*continued*)

Paper Title	Year	Feature Extraction technique	EEG Features	Class	Motor Imagery	Classification	Dataset	Accuracy
based Brain-Computer Interface [73]							2: BCI Competition III dataset 4A	
Learning Temporal Information for Brain-Computer Interface Using Convolutional Neural Networks [38]	2018	FBCSP	Temporal	4	Left, right, feet and tongue	CNN	BCI competition IV dataset 2A	74.46%
Deep Recurrent Spatio-Temporal Neural Network for Motor Imagery based BCI [37]	2018	Recurrent CNN	Spatial and temporal features	4	Left hand, right hand, feet and tongue	Recurrent CNN	BCI Competition IV dataset 2A	45%

Table 5
Performance Comparison of Common Spatial Pattern and Wavelet Transform on different Classifiers.

Paper Title	Feature Extraction	Classification	Dataset	Accuracy
Evolving Spatial and Frequency Selection Filters for Brain-Computer Interfaces [32]	CSP	SVM	BCI-III competition	Evolved Filters- Subject1- 77.96%, Subject2- 75.11%, Subject-3 57.76%
Classification of Motor Imagery for Ear-EEG based Brain-Computer Interface [70]	CSP	RLDA	BCI-III competition	74.28%
A Deep Learning Approach for Motor Imagery EEG Signal Classification [65]	CSP	DNN	BCI-III competition	Percentage Error- 10%
A Motor Imagery BCI Experiment using Wavelet Analysis and Spatial Patterns Feature Extraction [74]	WT	LDA	BCI III Competition	MisClassification Rate: 0.1286
Enhancing EEG Signals in Brain Computer Interface Using Wavelet Transform [75]	WT	SVM	BCI III Competition	85.54%
Enhancing EEG Signals in Brain Computer Interface Using Wavelet Transform [75]	WT	NN	BCI III Competition	82.43%
Deep Fusion Feature Learning Network for MI-EEG Classification [76]	WT	CNN	BCI III Competition	86.20%

Table 6
Category wise reported challenges.

Category	Challenges	Papers
Feature Extraction	Time series modeling techniques [TSM]	[36, 70]
	Automatic selection of subject specific characteristics [ASSC]	[28]
	Number of components to be chosen in feature selection [NCC]	[29]
Classification	Robust classifiers [RC]	[33]
	Classification methods considering user in the loop [CM]	[21, 71]
Signal Interpretability	Interpretability of learned algorithms [ILA]	[36]
Hardware	Algorithm device integration [ADI]	[26]
Data collection	Gathering data for individual subject [GD]	[36]
BCI functioning	Long caliberation time [LCI]	[38]
	Signal processing pipeline in multiclass classification [SPP]	[29]
Modality	High dimensionality of EEG signal [HD] Low signal to noise ratio[SNR] Presence of noise [PON]	[36]

processing. Thus, there is a need to test and validate classification algorithms online as they are computationally efficient and can be used in real time. Further, in order to provide a reasonable tradeoff between accuracy and efficiency, robust classifiers have to be developed that can be easily used online and are able to work with non-stationary data efficiently. Furthermore, the authors in Refs. [19,74] suggested a new generation of classification methods considering the user in the loop has to be developed to ensure efficient brain computer interfaces.

7.3. Hardware and BCI functioning

Chih-Yu Chen et al. [26] proposed a novel classification method that has used CSP for feature extraction and LDA for classification to solve the misclassifying problem. The proposed method is efficient and has high accuracy. The author also suggested having algorithm-device integration to make the system more efficient and practicable.

In traditional methods of signal processing, feature extraction and classification was performed separately which associates heavy computational burden. The concept of neural network combines the feature extraction and classification in one pipeline and has been explored for binary classification [24]. However, the use of neural network is successful in binary classification but increases the calibration time in BCI [38]. The author suggested adopting transfer learning and domain adaptation to have calibration free BCIs. Moreover pipelining in multiclass classification is still a challenge [29].

7.4. Data collection and modality

Deep architectures have been successful in computer vision and other fields due to their high learning capacity and being trained on the huge amount of data. In EEG-based BCI researches, gathering subject-specific data and capturing non-stationary nature is a hindrance to classification accuracy of MI tasks [36].

Other challenges could be signal modality [36] and lack of training data [36] that hinders the development of efficient brain computer interfaces.

The above-stated challenges can be explored in different domains, which are machine learning, signal processing, and hardware specifications. Correlation between reported challenges in Table 4 and the prospective research domains have been represented by Fig. 11.

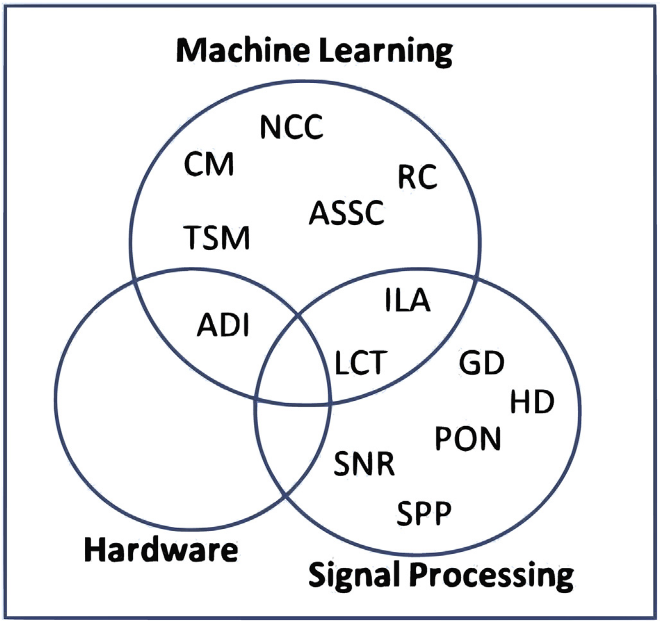

Fig. 11. Challenges coverage across varied domains. The challenges are Time Series Modeling Techniques (TSM), Automatic selection of Subject Specific Characteristics (ASSC), Number of Components (NCC), Classification Methods (CM), Interpretability of Learned Algorithms (ILA), Algorithm-Device Integration (ADI), Gathering Data (GD), Long Calibration Time (LCT), Signal Processing Pipelining (SPP), High Dimensionality of EEG (HD), Signal to Noise Ratio (SNR), Presence of Noise (PON).

8. Conclusion

The paper presented the comprehensive comparison of prominent feature extraction techniques used for EEG based BCI for motor imagery tasks. Currently CSP is the most preferred method of feature extraction. The presented review highlighted the various features like frequency band, spatial filters, and presence of artifacts in the signal on which the performance of CSP is highly dependent.

This paper also discussed the various classification methods currently used for motor imagery BCI. Classification methods are detailed by various categories: linear, non-linear, neural network and deep learning. Support vector machine is the commonly used classifier as it is insensitive to curse of dimensionality. In recent studies, several deep learning architectures were also used as a classification method for motor imagery tasks, among that shallow convolutional neural network is the prominent architecture and has outperformed the traditional methods of classification.

Authors have explored the various challenges of different modules of BCI and these challenges were mapped with the domains of machine learning, signal processing and hardware specifications.

Future work related to MI BCI should focus on developing information extraction techniques that consider the automatic selection of subject relevant temporal information. Additionally, robust classifiers needs to be evolved so as to work with noisy signals and high dimensionality data. There is also a need to develop the new generation of classification methods that should consider the user in the loop to provide feedback from which the user can learn; and help to build an accurate and efficient BCI system.

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