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Current Trends in Brain Computer Interface : a review

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CONTENTS

Abstract

- Brain-Computer Interface (BCI) is a cutting-edge and diverse area of ongoing research that is based on neuroscience, signal processing, biomedical sensors, hardware, etc.

- The BCI domain has yet to be the subject of a thorough examination. As a result, this study provides an in-depth analysis of the BCI issue.

- Finally, each BCI system component is briefly described, including processes, datasets, feature extraction methods, evaluation measurement matrices, present BCI algorithms, and classifiers.

- The study then examines a number of unresolved BCI problems and describes them along with potential solutions.

1. Introduction

- The BCI system utilises signals from the user's brain activity to interact with the computer and provide the desired outcome.
- The three procedures of pre-processing, feature extraction, and classification improve the usability of the associated signal [1].
- Training time and weariness, signal processing and new decoders, shared control to supervisory control in closed-loop, and other issues have plagued BCI paradigm research.
- The human brain's structure, BCI, and its stages, as well as signal extraction methods and algorithms for using the data obtained, have all undergone in-depth reviews.
- This paper presents a concise review of the different feature extraction techniques and classification algorithms that can be applied to brain data.

2. Applications of BCI

- The intended use of a BCI affects the design of the device, and applications based on BCI offer two usability techniques: command and observation.
- Potential medical uses of BCIs have mostly been used in medicine to replace or restore Central Nervous System (CNS) function lost due to disease or injury.
- BCIs are used for biological objectives in effective application fields such as diagnostic applications, therapy, and motor rehabilitation.
- Non-biomedical application of BCI technology has economical promise. Most of these applications are games, emotional computations, or entertaining programmes.

3. Principles of the BCI's operation

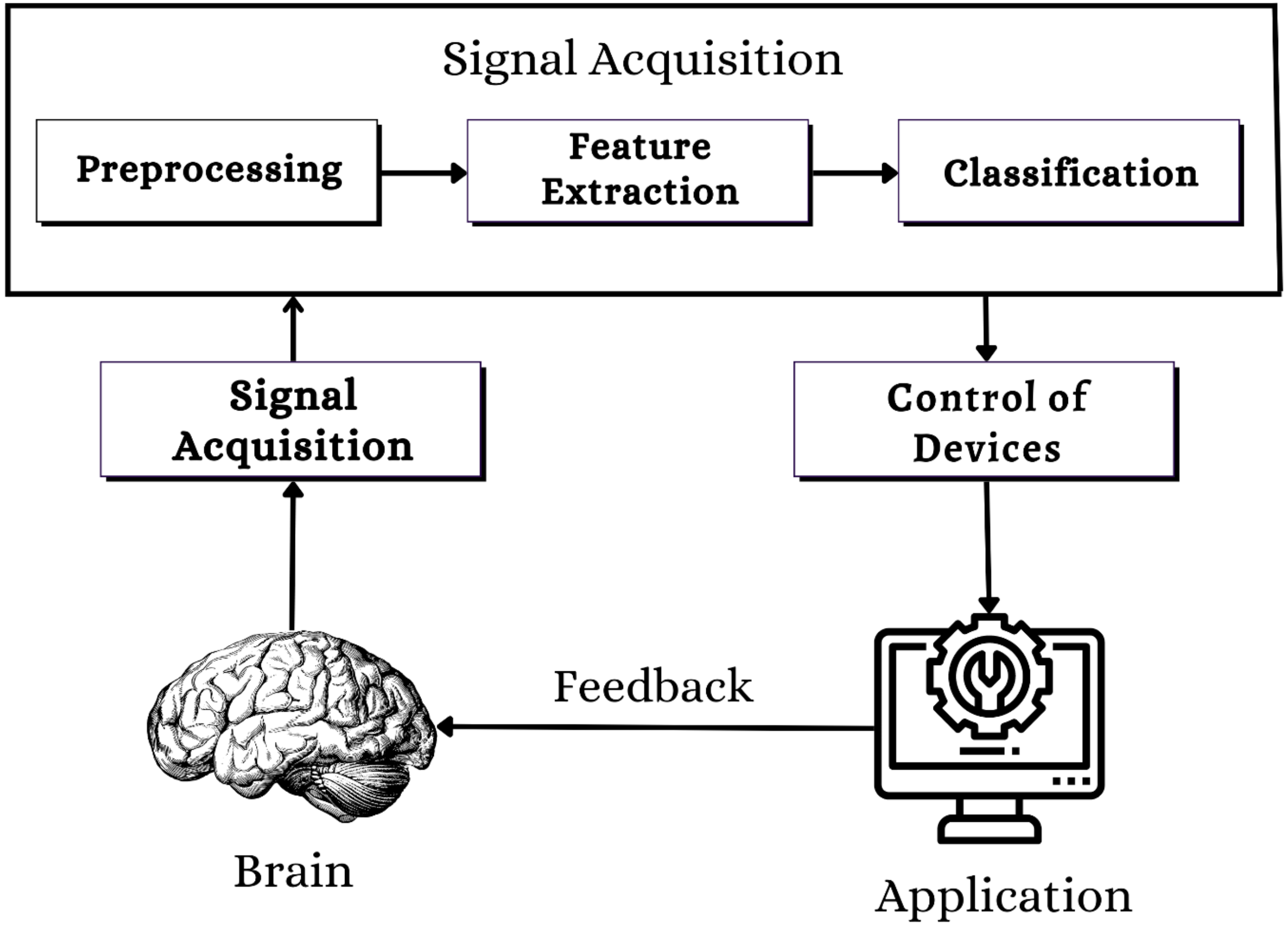

Figure 1. BCI System Architecture

3. Principles of the BCI's operation

- Figure 1, illustrates the processes that take place between receiving signals from the human brain and translating them into a useful command.
- **Signal acquisition**: in BCI, this is the process of collecting brain activity signals and turning them into instructions for a virtual or real-world application.
- **Pre-processing**: when the signals have been captured, pre-processing is required. The signals that the brain produces are often noisy and distorted by artefacts.
- **Feature extraction**: This step includes evaluating the signal and extracting data. It is challenging to get relevant information from the complex brain activity signal by simple analysis. It is crucial to use processing algorithms that enable the extraction of mental attributes like a person's purpose.
- **Classification**: The signal that is free of artefacts is then subjected to classification algorithms.
- **Device control**: The application or feedback device receives a categorization command.

4. Types of BCI

- We may categorize BCI according to several factors, including reliability, invasiveness, and autonomy.

1. **Invasive BCI** - Invasive BCIs, which are placed into the brain, seem to be the most accurate since they can track every neuron's activity.
2. **Partially invasive -** Electrocorticography (ECoG) is a kind of minimally invasive BCI monitoring technique that implants electrodes into the brain's cortical surface to provide data based on electrical activity.
3. **Non-invasive BCI** - The noninvasive technology uses an electrode that looks like a helmet to monitor brain electrical activity outside the skull. EEG, MEG, fMRI, fNIRS, and PET can assess these electrical potentials (PET).

5. Signal processing and signal enhancement

• The signal or data measured or retrieved from datasets are often contaminated with noise.

•The recorded data may deteriorate due to human activity like as heartbeats and eye blinks.

•To provide clean data that can then be processed for feature extraction and classification, these sounds are removed during the pre-processing stage.

• There are several techniques for signal augmentation in the BCI system

1. Independent component analysis
2. Common average analysis
3. Adaptive filters
4. Principal component analysis
5. Surface laplacian

6. Feature Extraction Techniques

- To choose the optimal classifier for a BCI system, one must understand what the features represent, their attributes, and how to apply them.
- Due to its great temporal resolution and low cost, EEG is the most extensively used technology [3].
- A BCI system's EEG signal feature extraction approach is crucial to classifying mental states.
- Time Domain
  - The time-domain features of EEG are simple to fix, but they have the drawback of having non-stationary, time-varying signals.
  - In time-domain techniques, features are often determined using signal amplitude values, which may be altered by interference like noise during EEG recording.

Table 2. An overview of the various feature selection methods

Method	Type	Mean Classification Accuracy	Comments
Particle-Swarm Optimization (PSO)	Metaheuristic	90.4%	Exploration and exploitation together with strong directional search and population-based search.
Artificial Bee-Colony (ABC) Optimization	Metaheuristic	94.48%	Finds the most suited person in each area by searching different parts of the solution space .
Filter Bank Selection	Various	N / A [2]	Used solely for CSP's frequency band selection.
Principal Component Analysis (PCA)	Statistical	76.34%	Assumes that the components with the largest variance contain the most data.
Simulated Annealing	Probabilistic	87.44%	Searches for the global maximum.
Ant Colony Optimization (ACO)	Metaheuristic	84.54%	Uses directional and population-based search techniques that are widely used, but adds search space labelling.
Differential Evolution (DE)	Metaheuristic	95%	With a high capacity for convergence, comparable to GAs.
Genetic Algorithm (GA)	Metaheuristic	59.85%	PSO was proven to be more accurate while being slower.
Firefly Algorithm	Metaheuristic	70.2%	May get caught in local minima; a learning technique was developed to avoid this.

6. Feature Extraction Techniques

Table 3. Various feature extraction, feature selection, and classification methods used in MI EEG-based BCIs

Sl. No.	Feature Extraction Techniques	Feature Selection Techniques	Classification Techniques
1.	Time-Domain Techniques	Principal Component Analysis	Linear Discriminant Analysis
2.	Frequency Domain Techniques	Filter Bank Techniques	Support Vector Machine
3.	Time Frequency Domain Techniques	Evolutionary Algorithms	k-Nearest Neighbor
4.	Common Spatial Pattern Techniques		Recurrent Neural Networks
			Naïve Bayes
			Regression Tress
			Fuzzy Classifiers

6. Feature Extraction Techniques

Table 4: Comparison of MI BCI feature extraction techniques.

Technique	Advantages	Limitations	Analysis method
Fast Fourier Transform	FFT accurately determines signal frequency. Its speed surpasses all others.	FFT is inadequate for the analysis of nonlinear signals. Information about time is not taken into consideration.	Frequency
Autoregressive Model	It offers a decent resolution for frequencies. For short lengths, it has accurate spectral estimations.	The correct choice of model order is essential to the model's validity.	Frequency
Wavelet Transform	Window length and spectral resolution are better balanced with WT. It works better with abrupt signal shifts.	It is essential to choose the right mother wavelet.	Time-Frequency
Common Spatial Pattern	Multichannel signal analysis is appropriate for CSP.	Time-dependent dynamics cannot be handled by CSP.	Dimensional filters

7. Classification Techniques

Table 6: Covers MI BCI classifiers and their strengths and cons.

Technique	Advantages	Limitations
Linear Discriminant Analysis	LDA requires little processing power.	Complex non-linear EEG data are not appropriate for it.
Support Vector Machine	SVM generalises better.	It cannot handle signal dynamics.
Neural networks	A fair trade-off between accuracy and speed is offered by NN.	Weights must be properly selected.
Deep neural networks	It can concurrently train classifier and discrimination features from unprocessed EEG data.	DNN training and testing involves a lot of computation.

7. Classification Techniques

Table 5: Comparison of classifiers using well-known datasets and characteristics.

Ref.	Dataset	Feature	Classifier	Accuracy
[8]	BCI Competition III	WT	SVM	85.54%
[9]	BCI Competition IV-2b	CWT	CNN	Morlet – 78.93%, Bump – 77.25%
[10]	BCI Competition III	WT	NN	82.43%
[10]	BCI Competition III	WT	LDA	MisClassification Rate : 0.1286
[11]	BCI Competition III	WT	CNN	86.20%
[12]	BCI Competition IV-2a	Single Channel CSP	KNN	62.2%
[12]	BCI Competition IV-2a	Single Channel CSP	MLP	63.5%
[12]	BCI Competition IV-2a	Single Channel CSP	LDA	61.8%

Table 7: MI BCI Literature Citation Summary

Ref. No.	Year	Feature Extraction Technique	EEG Features	Class	Motor Imagery	Classification	Dataset	Accuracy
[16]	2013	CSP	Band Power	7	Compound (both hands, left hand+right foot, right hand+left foot), rest state	SVM	Author prepared	70%
[17]	2014	CSP	Spatial features	2	Left and right motor imagery	LDA	Author prepared	91.25%
[13]	2015	FBCSP	Energy based	4	Left hand, right hand, feet and tongue	CNN	BCI competition IV dataset 2A	70.60%
[18]	2016	Fast Fourier transform and wavelet packet decomposition	Frequency domain features	2	Left and right motor imagery	Deep neural network	BCI competition IV dataset 2B	Not provided
[19]	2017	Wavelet decomposition	Sensorimotor rhythms	Multi-class	Rest state, left fist, both fists, right fist, both feet movement	Neural network	Physionet dataset network	93.05%
[20]	2017	STFT	Time frequency representations	2	Left and right hand	CNN	Author prepared	CNN-RELU (86.74%) CNN-SELU-(92.73%)
[13]	2018	FBCSP	Temporal	4	Left, right feet and tongue	CNN	BCI competition IV dataset 2A	74.46%

8. Challenges

- Although though a variety of feature extraction and classification algorithms have been successfully used for EEG-based BCI for motor imagery tasks and have produced high accuracy results, there are several open problems and difficulties that have the focus of researchers from many different fields.
- **Feature Extraction**
  - Despite the fact that Common Spatial Pattern (CSP) and its variations are widely employed in BCI, they do not take into account the signal's temporal structure, which causes a loss of temporal information (information pertaining to time) [95].
- **Classification**
  - Robust classifiers that are effective with non-stationary data must be created in order to give a suitable compromise between accuracy and efficiency.

Table 8: Summary of BCI research papers offering new approaches.

Model	Novelty	Feature Extraction	Architecture	Limitations
P300, ERN, MRCP, SMR	Compact Convolutional neural network for EEG based BCI	Band pass filtering	EEGNet	The methods only work if the feature is familiar.
SSVEP, P300	BCI-based healthcare control system	P300 detector Kernel (FDA+ SSVEP)	Self- paced P300 healthcare system with SSVEP	SSVEP stimulation improves accuracy.
SVM	Fatigue detection system	FFT	Train driver Vigilance detection	NA
WOLA	Dynamic filtering of EEG signals	CSP	Embedded-BCI (EBCI) system	This model does not include muscle or eye blinking.
LSTM, pCNN, RCNN	Online decoding of motor imagery movements using DL models	CSP, log-BP features	Classify Motor Imagery movements	Models have little data.
P300-BCI classification using CNN	Detection of P300 waves	Spatial filters with CNN	NN architecture	Subject variation, identifying important layers
Extended Kalman adaptive LDA	Online training for controlling a simulated robot	LDA classifiers	Online self-paced event detection system	Restricted to two courses, not several classes.
Unified ELM and SB learning	Sparse Bayesian ELM (SBELM)-based algorithm	CSP method	SBELM for Motor Imagery-related EEG classification	Multiband optimization improves accuracy.
Gaussian, polynomial kernel	MKELM-based method for motor imagery EEG classification	CSP	MKELM-based method for BCI	Accuracy and framework expansion are required.

9. Conclusion

- The reviewed material highlighted a number of characteristics, including frequency band, spatial filters, and the presence of artefacts in the signal, which are crucial to CSP performance.
- Support vector machines are the most often used classifiers.
- A number of deep learning architectures were also explored as a classification strategy for motor imaging tasks, with shallow convolutional neural network emerging as the dominant architecture and outperforming more established classification techniques.
- Future research on MI BCI should concentrate on creating information extraction methods that take subject-relevant temporal information into account automatically.
- In order to create an accurate and effective BCI system, it is also necessary to create a new generation of categorization algorithms that include the user in the loop and offer feedback from which the user may learn..

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THANK YOU