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EEG-based Brain-Computer Interfaces (BCIs): A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and Their Applications

報告者：張詠翔 黃奕瑋

指導老師：Dr. 紀虹名

Preliminary Introduction

EEG-Based Brain-Computer Interfaces (BCIs): A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and Their Applications

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林進燈

Xiaotong Gu ; Zehong Cao ; Alireza Jolfaei ; Peng Xu ; Dongrui Wu ; Tzyy-Ping Jung ; Chin-Teng Lin All Authors

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Outline

1. Introduction
2. Advances in Sensing Technologies
3. Signal Enhancement and Online Processing
4. BCI-based Healthcare Systems with AI
5. Conclusion

Part 1

Introduction

Introduction

-An Overview of BCI-

- Brain-Computer Interface (BCI) is a **powerful communication tool between users and systems**, which enhances the capability of the human brain in **communicating and interacting** with the environment directly.

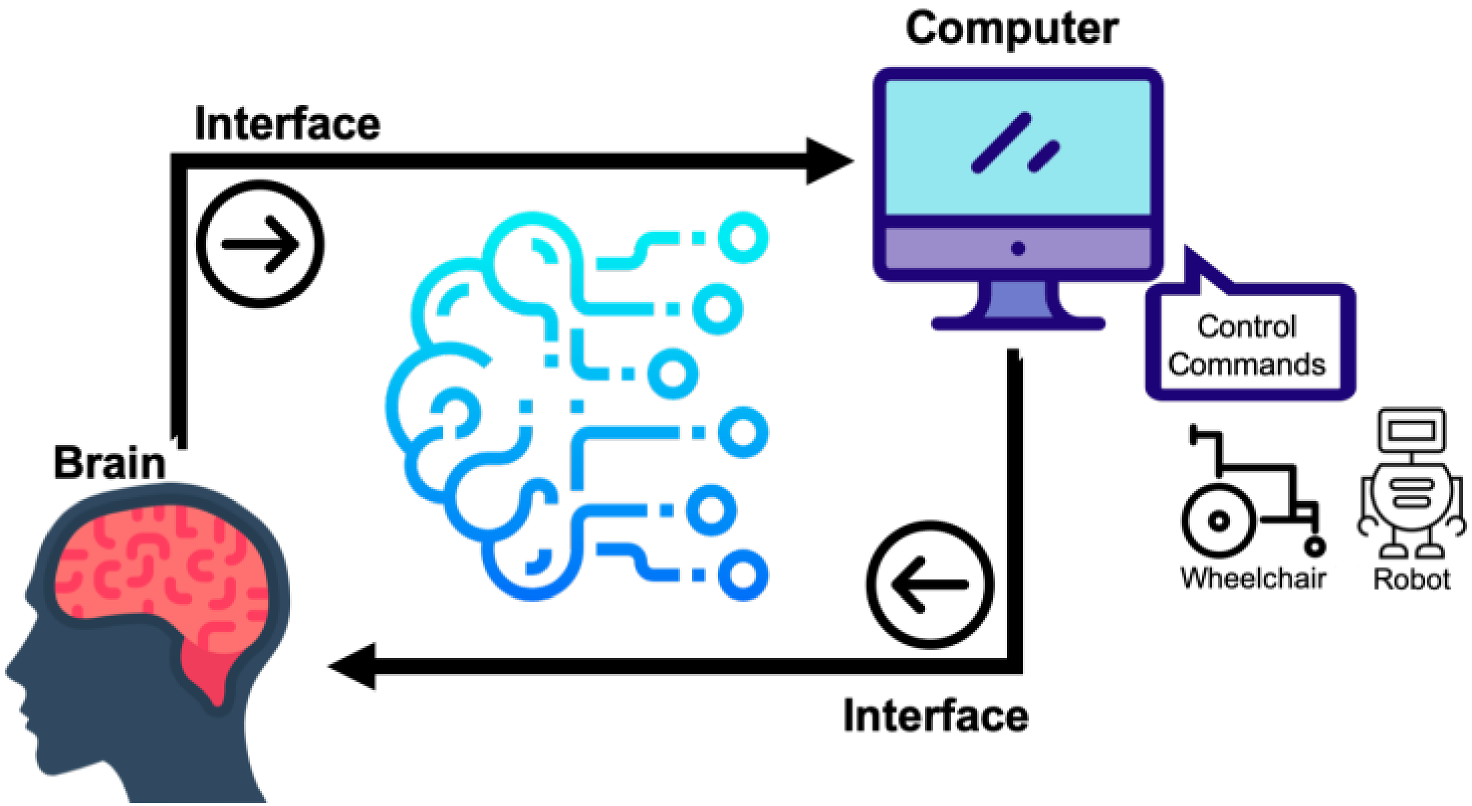


Fig. 1. The framework of brain-computer interface (BCI)

Introduction

-An Overview of BCI-

- The research of BCI was **first released in the 1970s**, addressing an **alternative transmission channel** without depending on the normal peripheral nerve and muscle output paths of the brain.
- Overall, BCIs have contributed to **various fields** of research.

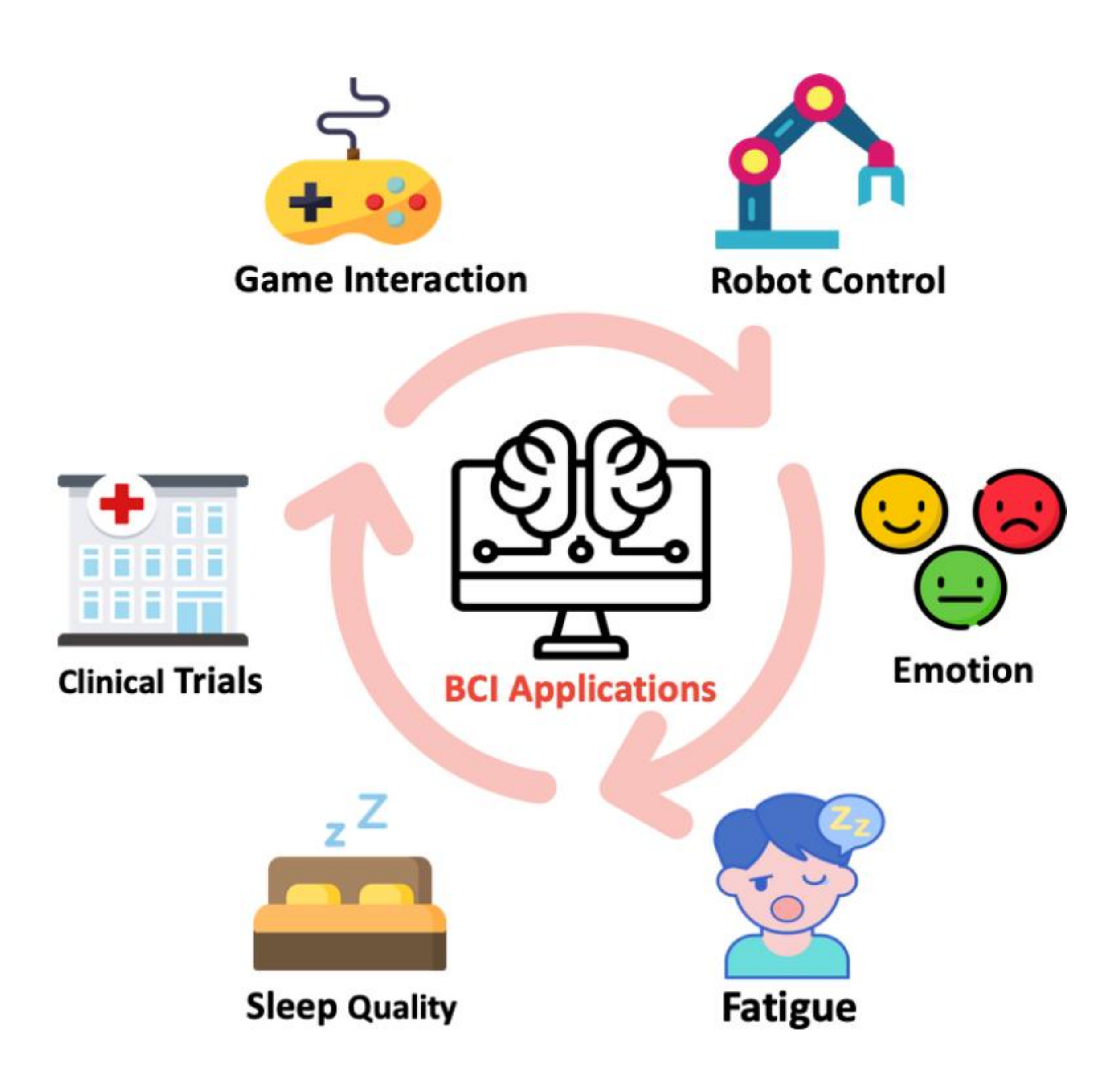


Fig. 2. BCI contributes to various fields of research

Introduction

-Contribution-

- The recent (2015-2019) review articles **lack a comprehensive survey** in recent EEG sensing technologies, signal enhancement for specific BCI applications, in addition to healthcare systems.

- In our survey, we aim to **address the above limitations** and include the recently released BCI studies in 2019.

Advances in Sensing Technologies

Part 2

Advances in Sensing Technologies

-An overview of EEG sensors/devices-

Wet sensor technology

- For non-invasive EEG measurements, wet electrode caps are normally attached to users' scalp with gels as the interface between sensors and the scalp.

- The application of the gel interface is to decrease the skin-electrode contact interface impedance, which could be uncomfortable and inconvenient for users and can be too time-consuming and laborious for everyday use.

- However, without the conductive gel, the electrode-skin impedance cannot be measured, and the quality of measured EEG signals could be compromised.

Advances in Sensing Technologies

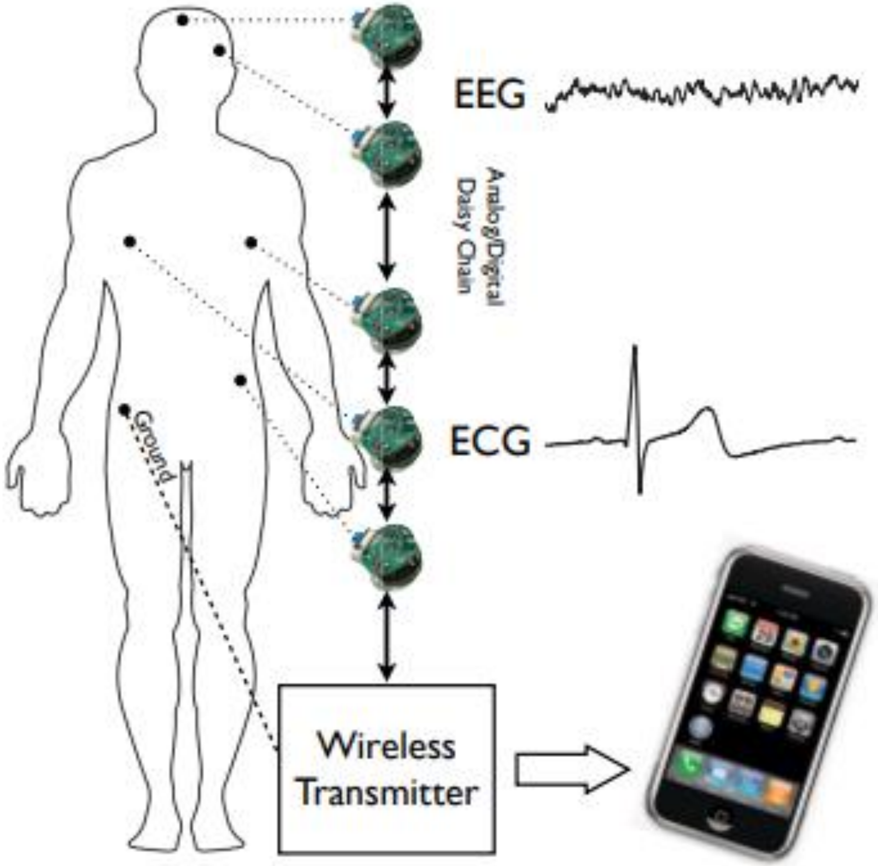
-An overview of EEG sensors/devices-

Dry sensor technology

- The major advantages for dry sensors, compared with wet counterparts, is that it substantially enhances system usability, and the headset is very easy to wear and remove, which even allows skilled users to wear it by themselves in a short time.

- Chi et al. [1] developed a new integrated sensor controlling the sensitive input node to attain prominent input impedance, with a complete shield of the input node from the active transistor, bond-pads, to the specially built chip package.

Fig. 3. Block diagram of wireless BSN



[1] Chi et al., "Wireless Non-contact EEG/ECG Electrodes for Body Sensor Networks," 2010 International Conference on Body Sensor Networks, 2010, pp. 297-301, doi: 10.1109/BSN.2010.52.

Advances in Sensing Technologies

-Commercialized EEG devices-

- Fig. 4. lists 21 products of 17 brands with eight attributes providing a basic overview of EEG headsets.

Brand	Product	Wearable	Sensors type	Channels No.	Locations	Sampling rate	Transmission	Weight
NeuroSky	MindWave	Yes	Dry	1	F	500 Hz	Bluetooth	90g
Emotiv	EPOC(+)	Yes	Dry	5-14	F, C, T, P, O	500 Hz	Bluetooth	125g
Muse	Muse 2	Yes	Dry	4-7	F, T		Bluetooth	
OpenBCI	EEG Electrode Cap Kit	Yes	Wet	8- 21	F, C, T, P, O		Cable	
Wearable Sensing	DSI 24; NeuSenW	Yes	Wet; Dry	7-21	F, C, T, P, O	300/600 Hz	Bluetooth	600g
ANT Neuro	eego mylab / eego sports	Yes	Dry	32 - 256	F, C, T, P, O	Up to 16 kHz	Wi-Fi	500g
Neuroelectrics	STARSTIM; ENOBIO	Yes	Dry	8-32	F, C, T, P, O	125-500 Hz	Wi-Fi; USB	
G.tec	g.NAUTILUS series	Yes	Dry	8-64	F, C, T, P, O	500 Hz	Wireless	140g
Advanced Brain Monitoring	B-Alert	Yes	Dry	10-24	F, C, T, P, O	256Hz	Bluetooth	110g
Cognionics	Quick	Yes	Dry	8-30; (64-128)	F, C, T, P, O	250/500/1k/2k Hz	Bluetooth	610g
mBrainTrain	Smarting	Yes	Wet	24	F, C, T, P, O	250-500 Hz	Bluetooth	60g
Brain Products	LiveAmp	Yes	Dry	8-64	F, C, T, P, O	250/500/1k Hz	Wireless	30g
Brain Products	AntiCHapmp	Yes	Dry	32-160	F, C, T, P, O	10k Hz	Wireless	1.1kg
BioSemi	ActiveTwo	No	Wet (Gel)	280	F, C, T, P, O	2k/4k/8k/16k Hz	Cable	1.1kg
EGI	GES 400	No	dry	32-256	F, C, T, P, O	8k Hz	Cable	
Compumedics Neuroscan	Quick-Cap + Grael 4k	No	Wet	32-256	F, C, T, P, O		Cable	
Mitsar	Smart BCI EEG Headset	Yes	Wet	24-32	F, C, T, P, O	2k Hz	Bluetooth	50g
Mindo	Mindo series	Yes	Dry	4-64	F, C, T, P, O		Wireless	

Abbreviation: Frontal (F), Central (C), Temporal (T), Partial (P), and Occipital (O)

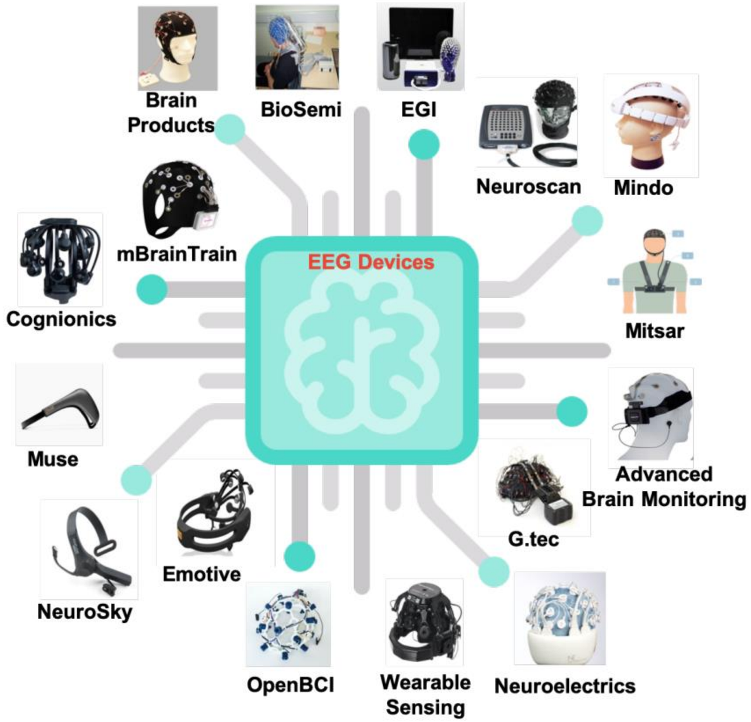


Fig. 4. Commercialized EEG devices for BCI applications

Part 3

Signal Enhancement and Online Processing

Signal Enhancement and Online Processing

-Artefact handling-

Based on a broad category of unsupervised learning algorithms for signal enhancement, **Blind Source Separation** (BSS) estimates original sources and parameters of a mixing system and **removes the artefact signals**, such as **eye blinks and movement**, and the **muscle artefacts**.

Fig. 5. Comparison of the advantages and disadvantages of various artifact removal techniques [2]

	No additional sensors required	No *a priori* user input required	Automatic artifact removal	Can operate on-line	Can operate on single channels	Can operate in the non-linear domain
Adaptive filter	×	×	✓	✓	✓	✓
Wiener filter	✓	×	✓	×	✓	✓
Kalman filter	✓	×	✓	✓	✓	✓
Particle filter	✓	×	✓	✓	✓	✓
Independent Component Analysis	✓	✓	×	✓	×	✓
Canonical Correlation Analysis	✓	✓	×	×	×	✓
Single Channel ICA	✓	✓	×	×	✓	✓
Dynamical Embedding ICA	✓	✓	×	×	✓	✓
Dynamical Embedding SSA	✓	✓	✓	×	✓	×
Morphological Component Analysis	✓	×	✓	×	✓	×
Wavelet ICA	✓	✓	×	×	✓	✓
Empirical Mode Decomposition ICA	✓	✓	×	×	✓	✓

[2] Sweeney et al., "Artifact Removal in Physiological Signals—Practices and Possibilities," in IEEE Transactions on Information Technology in Biomedicine, vol. 16, no. 3, pp. 488-500, 2012, doi: 10.1109/TITB.2012.2188536.

Signal Enhancement and Online Processing

-Eye blinks and movements-

Eye blinks and movements are common artefacts in EEG data.

- **Artefact subspace reconstruction** (ASR) is used for removing large-amplitude or transient artefacts, but it has limitations for single-channel EEG recordings.
- ICA-based mechanisms can complement ASR for cleaning EEG signals and effectively remove eye artefacts.

Signal Enhancement and Online Processing

-Muscle artefacts-

Muscle artefacts in EEG data can result from muscle contractions and stretches near the recording sites.

- Various techniques, including **EEMD-CCA**, **BSS-CCA**, and **IVA**, are used to remove muscle artefacts.

- The combination of methods, such as **BSS-CCA** followed by **spectral-slope rejection** and **IVA**, can be effective in removing muscle artefacts.

EEMD-CCA: Combination of the ensembled empirical mode decomposition (EEMD) and Canonical Correlation Analysis (CCA).
BSS-CCA: Combination of the BSS and CCA.
IVA: Independent vector analysis.

Part 4

BCI-based Healthcare Systems with AI

BCI-based Healthcare Systems with AI

-Machine Learning-

Machine learning tasks are generally classified into several models, such as supervised learning and unsupervised learning.

- Performing machine learning requires to create a model for training purpose.
- In EEG-based BCI applications, various types of models have been used and developed for machine learning.

BCI-based Healthcare Systems with AI

-Machine Learning-

In the last ten years, the leading families of models used in BCIs include **linear classifiers**, **neural networks**, **non-linear Bayesian classifiers**, **nearest neighbour classifiers** and **classifier combinations**.

- The **linear classifiers**, such as Linear Discriminant Analysis (LDA), Regularized LDA, and Support Vector Machine (SVM), classify discriminant EEG patterns using linear decision boundaries between feature vectors for each class.

- In terms of **neural networks**, they assemble layered human neurons to approximate any nonlinear decision boundaries, where the most common type in BCI applications is the Multilayer Perceptron (MLP) that typically uses only one or two hidden layers.

BCI-based Healthcare Systems with AI

-Machine Learning-

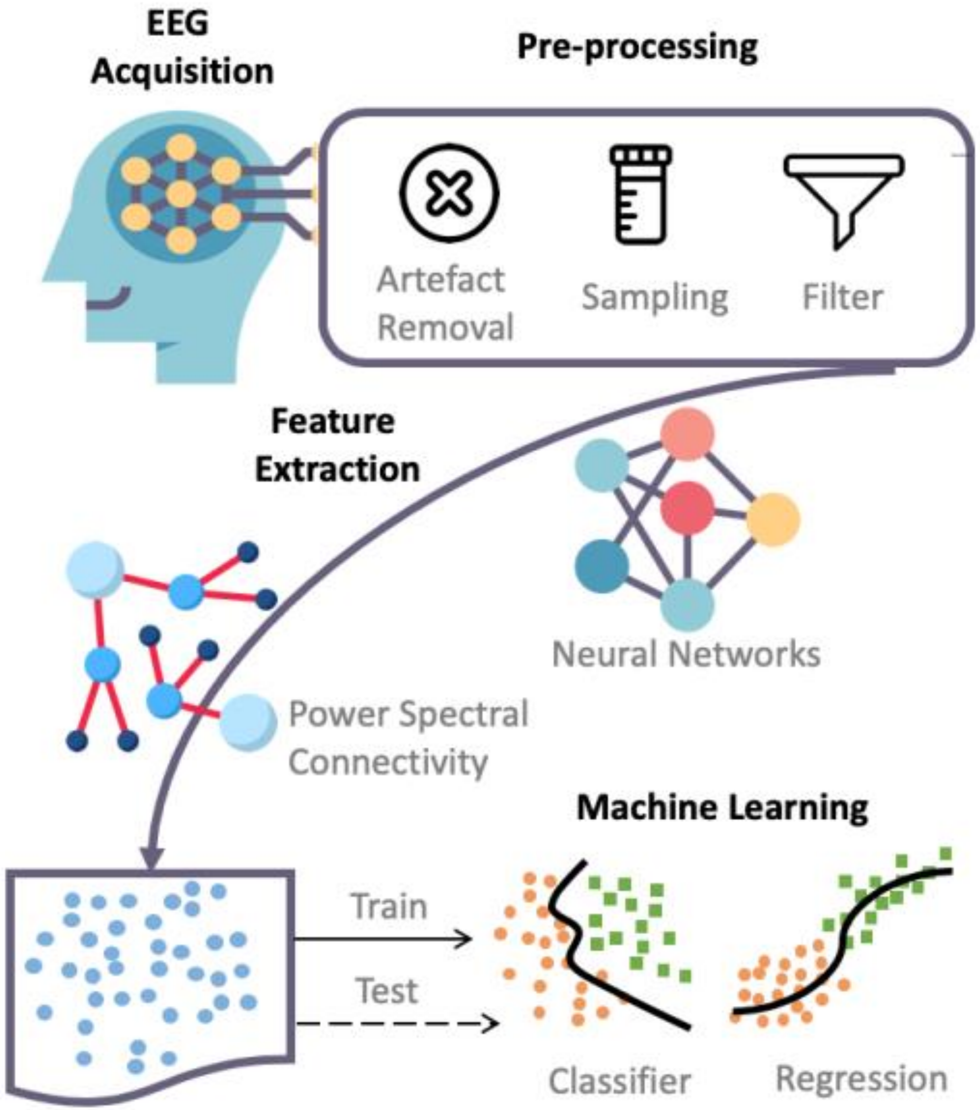
- Considering the physical distances of EEG patterns, the nearest neighbour classifier, such as the **k nearest neighbour** (kNN) algorithm, proposes to assign a class to the EEG patterns based on its nearest neighbour.

- Finally, **classifier combinations** are combining the outputs of multiple above classifiers or training them in a way that maximizes their complementarity.

BCI-based Healthcare Systems with AI

-Machine Learning-

- Additionally, to apply **machine learning algorithms** to **the EEG data**, we need to pre-process EEG signals and extract features from the raw data, such as frequency band power features and connectivity features between two channels.



BCI-based Healthcare Systems with AI

-Deep Learning(CNN)-

Deep learning is a specific family of machine learning algorithms in which features, and the classifier are **jointly learned** directly from data.

- The representative architectures of deep learning include **Convolutional Neural Networks** (CNN**), Generative Adversarial Network** (GAN), **Recurrent Neural Networks** (RNN), and **broad Deep Neural networks** (DNN).

- For BCI applications, **deep learning** has been applied broadly compared with **machine learning** technology mainly because currently most machine learning research concentrates on static data which is not the optimal method for accurately categorizing the quickly changing brain signals.

BCI-based Healthcare Systems with AI

-Deep Learning(CNN)-

- The nature of **CNNs** with stacked layers is to reduce input data to easily-identifiable formations with minimal loss, and distinctive spatial dependencies of the EEG patterns could be captured by applying **CNN**.

- In addition to this, the recent five BCI applications employing CNNs in **fatigue**, **stress**, **sleep**, **motor imagery** (MI), and **emotional studies**, are reviewed below.

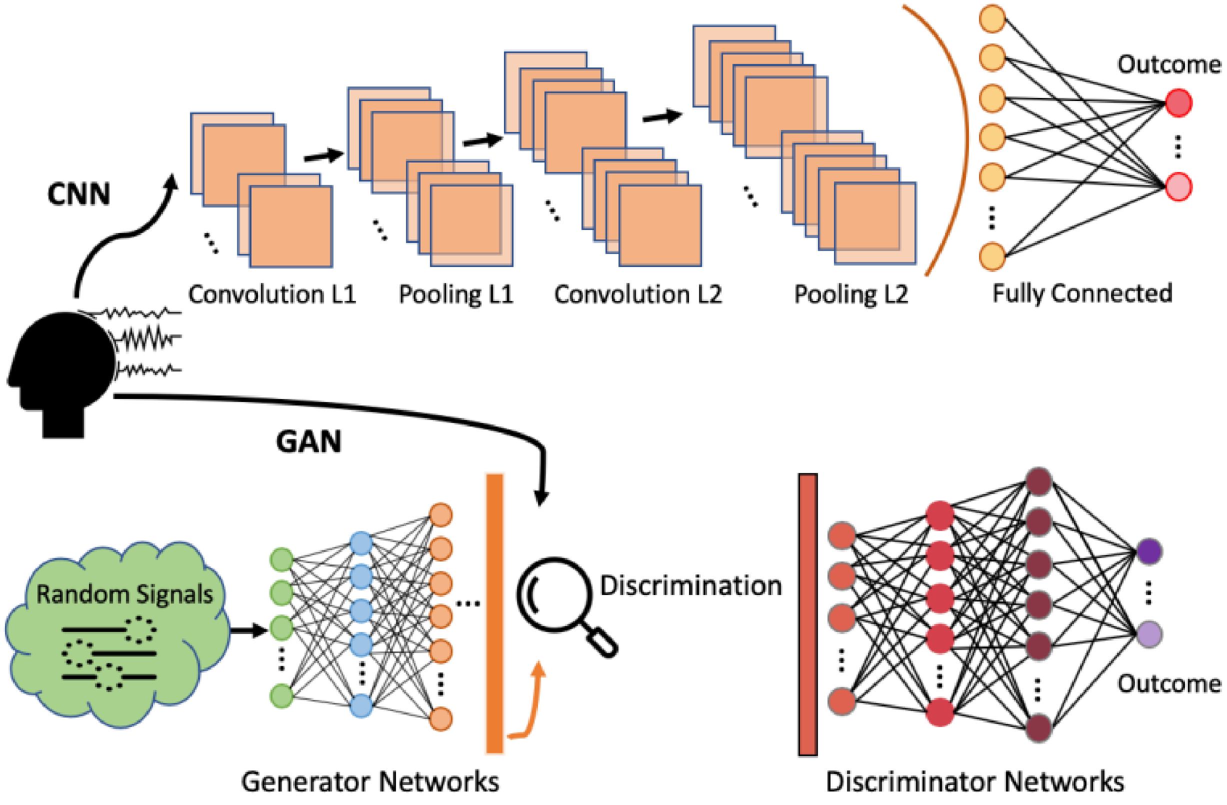


Fig. 7. CNN and GAN for BCI applications

BCI-based Healthcare Systems with AI

-Deep Learning(GAN)-

- In classification tasks, a substantial amount of real-world data is required for training machine learning and deep learning modules, and in some cases, there are limitations of acquiring enough amount of real data or simply the investment of time and human resources could be too overwhelming.

- Proposed in 2014 and becoming more active in recent years, **GAN** is mainly used data augmentation to address the question of how to generate artificial natural looking samples to mimic real-world data via implying generative models, so that unrevealed training data sample number could be increased.

- To the best of our knowledge, in contrast with **CNN, GAN** was comparatively less studied in BCIs. One major reason is that the feasibility of using **GAN** for generating time sequence data is yet to be fully evaluated.

BCI-based Healthcare Systems with AI

-Deep Learning(RNN)-

- Over the past several years, the research of the **RNN** framework in EEG-based BCIs has increased substantially with many studies showing that the results of **RNN-based methods** outperform a benchmark or other traditional algorithms or the **RNN combined with other deep neural networks** such as **CNN** to optimize performance.

- The **RNN framework** has also been applied to **other EEG-based tasks**, such as **identifying individuals**, **hand motion identification**, **sleep staging**, and **emotion recognition**.

BCI-based Healthcare Systems with AI

-Deep Learning(RNN)-

- Other novel framework proposals based on **RNN**, such as the **spatial-temporal RNN** (STRNN) for feature learning integration from both temporal and spatial information of the signals, are also being explored in recent years.

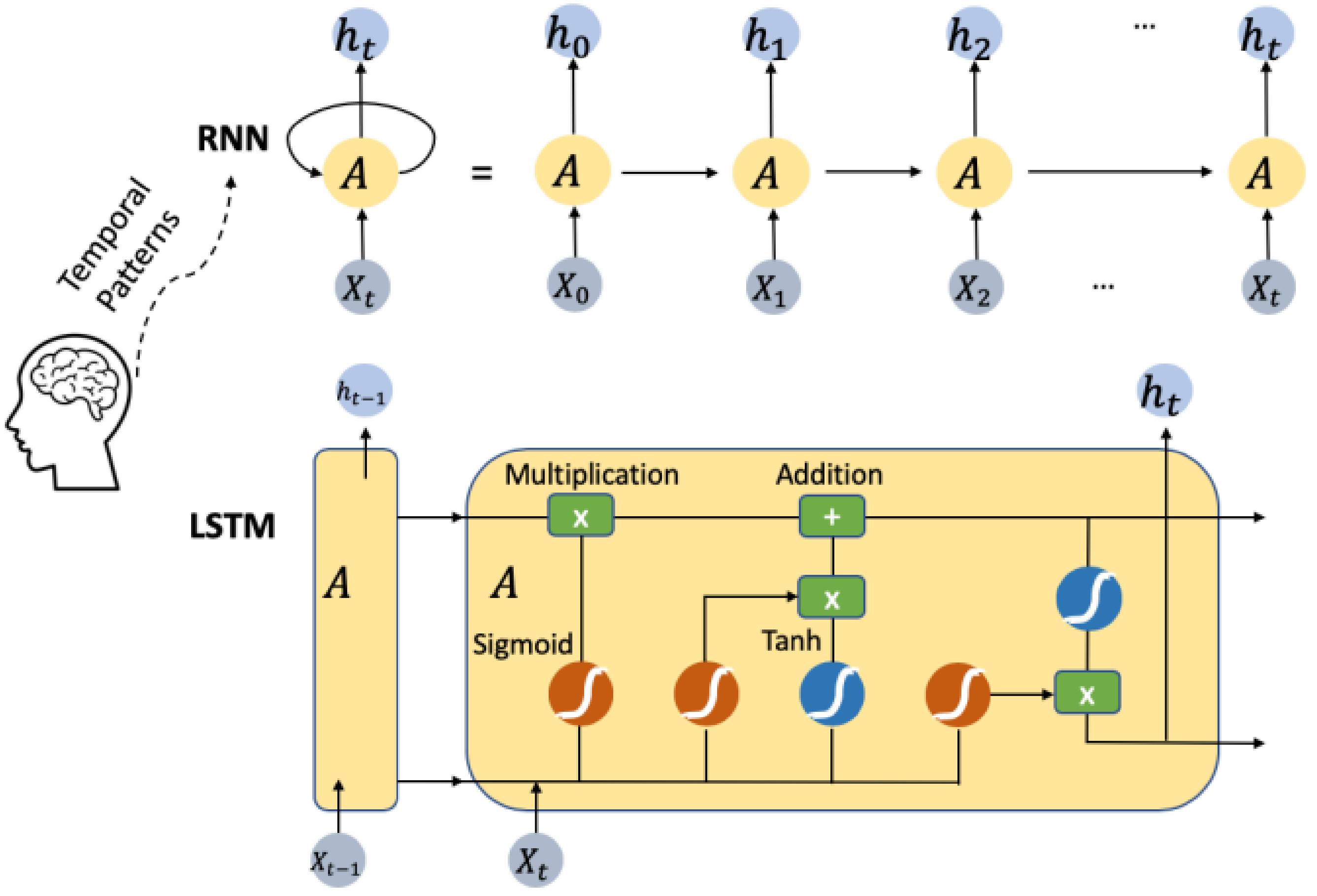
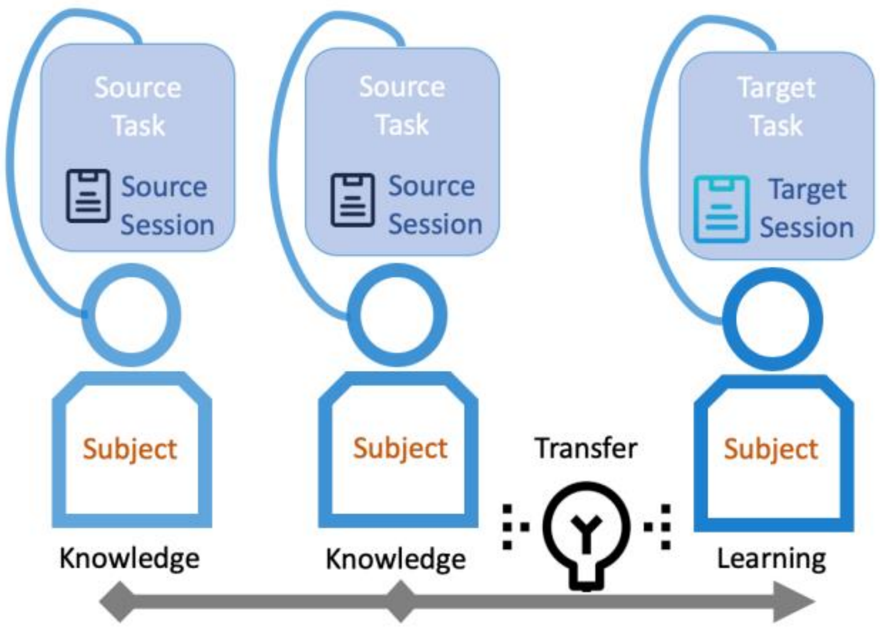


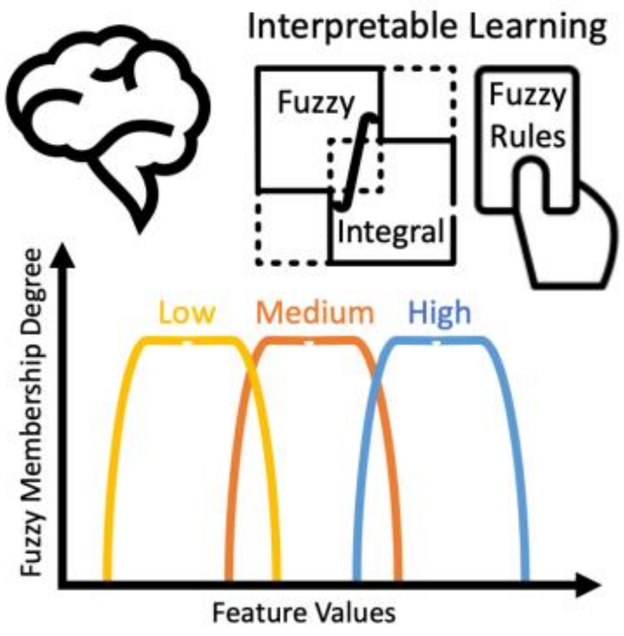
Fig. 8. Illustration of RNN and LSTM

BCI-based Healthcare Systems with AI

-Theory-



Transfer Learning In BCI



Fuzzy sets, fuzzy rules, and fuzzy integrals for interpretability

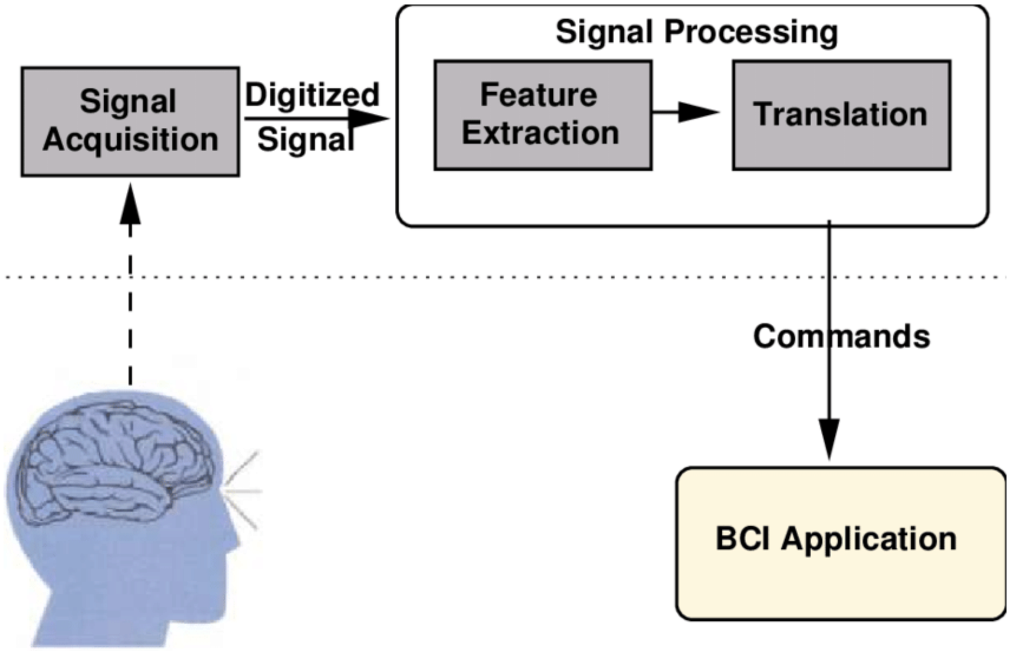
Part 5 Conclusion

Conclusion

-An overview of EEG sensors/devices-

It would be encouraging to pursue experiments with adaptive EEGbased BCI training.

- Integrating BCI with other technical or physiological signals, which is hybrid BCI system, would be a future focus of research for improving classification accuracy and general outcomes.



Conclusion

- Previous researches have been inducing one popular protocol used in exogenous BCIs, with visual stimulus from AR glasses such as smart glasses used in, and capturing the response by measuring EEG signals to perform tasks.

- The scientific community is also investigating enhanced conjunction of technology and interface for HCI that is the combination of Augmented Reality (AR) and EEG-based BCI.

- With the accessibility of AR and commercialised noninvasive BCI devices, using AR and EEG devices, augmentation becomes feasible and also effective in outcomes.

Conclusion

Finally, recent research has shown that：

- ➢ deep learning (and even traditional machine learning) models in EEG-based BCIs are vulnerable to adversarial attacks, and there is an urgent need to develop strategies to defend such attacks.

Thanks