Regularized Gaussian Functional Connectivity Network with Post-Hoc Interpretation for Improved EEG-based Motor Imagery-BCI Classification

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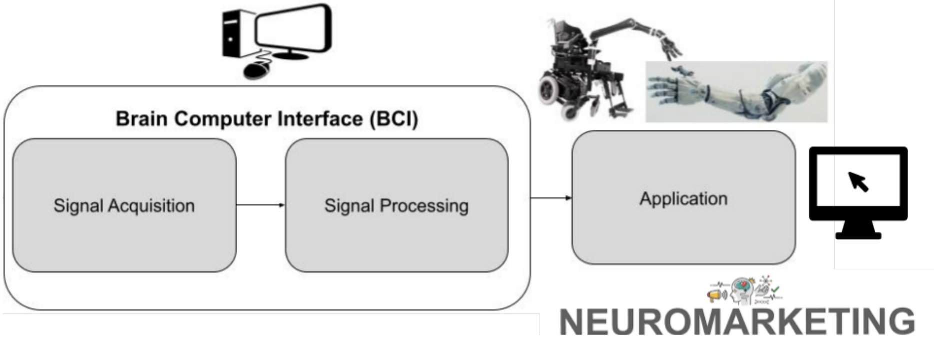
September 14, 2024

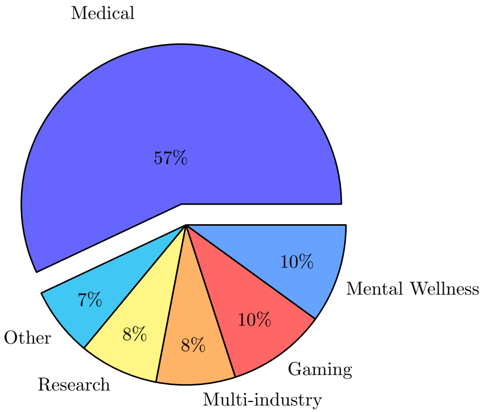
Outline I

Brain computer interface (BCI)

BCI provide people external world communication by translating brain signals [Khan et al., 2020]



Brain computer interface (BCI)

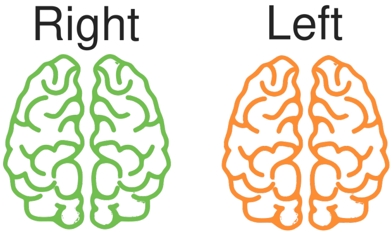


- Over 150 companies specializing in BCI as of 2019.
- BCI market valued at 228 million in 2019, projected to reach 460 million by 2029 [2].

[1] **Image:** Adapted from The World Economic Forum 2024
[2] Global Brain Computer Interface Market Research Report 2023

Motor Imagery (MI)

MI is a widely studied BCI paradigm that allows external motor communication [Cattan et al., 2018].

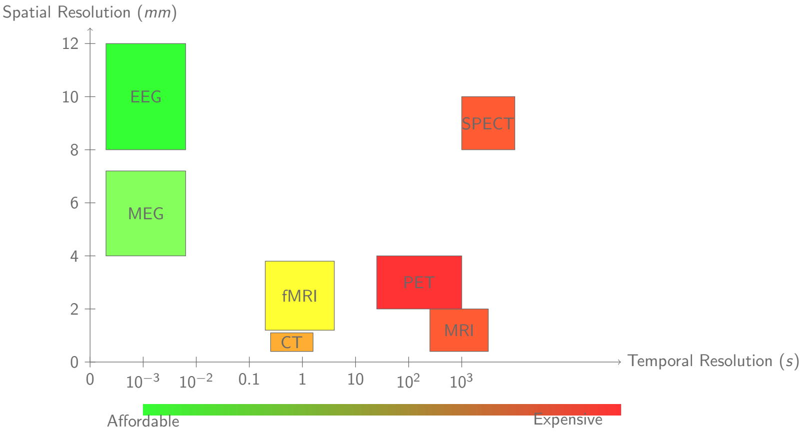


Applications:

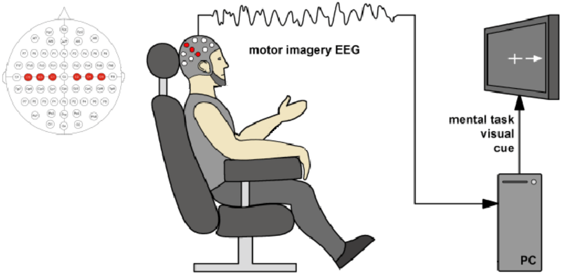
- Recovery of motor functionality [Bonci et al., 2021].
- Motor rehabilitation [Sitaram et al., 2017].
- Virtual reality [Cattan et al., 2018].
- Gaming [Ahn et al., 2014].
- Skill acquisition [Casimo et al., 2017].

Neuroimaging techniques

- MI involves fast-evolving cognitive processes [Vărbu et al., 2022]
- EEG and MEG have remarkable temporal precision [Alsharif et al., 2020]
- EEG is portabile and cost-effective [Janapati et al., 2023, Hosseini et al., 2020]



Experimental setup for MI-based BCIs

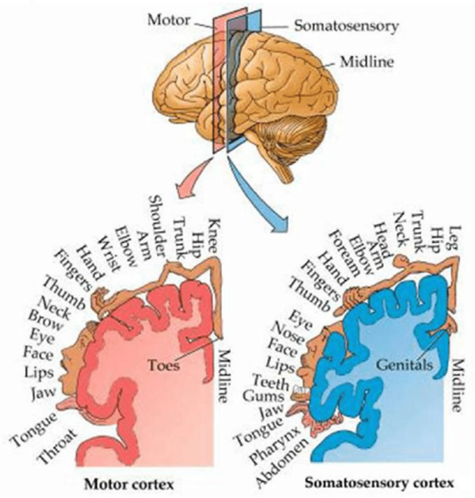


- EEG headsets are equipped with 1 to 256 electrodes [Grigorev et al., 2021].
- Visual cues are often used to guide MI tasks during EEG recordings [Hosseini et al., 2020].

[1] **Image:** Adapted from [Grigorev et al., 2021]

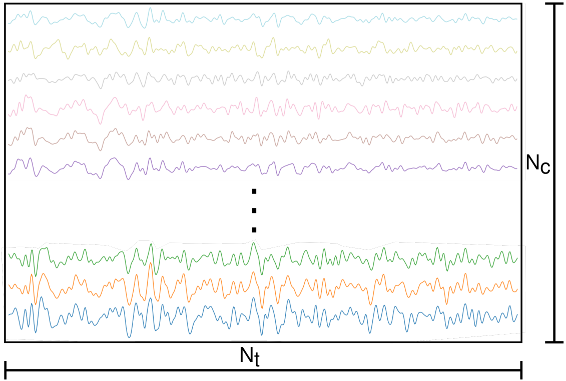
Sensorimotor rhythms (SMRs)

- EEG signals contains multiple electrical variations (rhythms) [Barios et al., 2019].
- Sensorimotor Rhythms (SMRs) occur in the brain's sensorimotor cortex [Altaheri et al., 2023].
- SMRs contain spectral-spatio-temporal patterns of MI tasks [Li et al., 2019].



[1]**Image:** Adapted from [Purves, 2001]

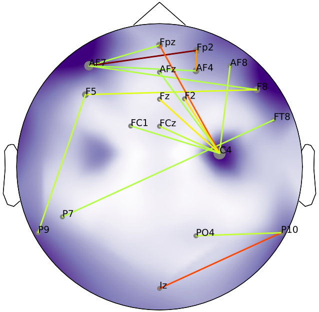
MI-EEG feature extraction



- High number of channels and sampling rate [Chevallier et al., 2024].
- Huge number of data points [Singh et al., 2021].
- Feature extraction strategies are required to reduce dimentionality [Ai et al., 2019].

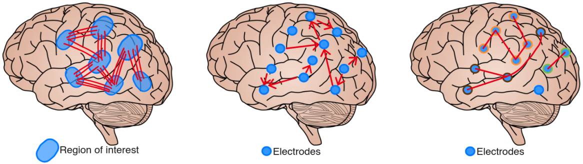
Single channel feature extraction

- Capture rhythms on specific EEG channels [Samuel et al., 2017].
- Time domain: statistical [Hamedi et al., 2014], Hjorth [Yilmaz et al., 2018], etc.
- Spetral doamin: Power spectral density [Oikonomou et al., 2017], Welch's periodigram [Roy et al., 2022], spectral entropy [Sarraf, 2017], etc.



Executing or imagining motor tasks activates multiple brain areas, patterns that single-channel features fail to capture [Chiarion et al., 2023].

Multi channel feature extraction



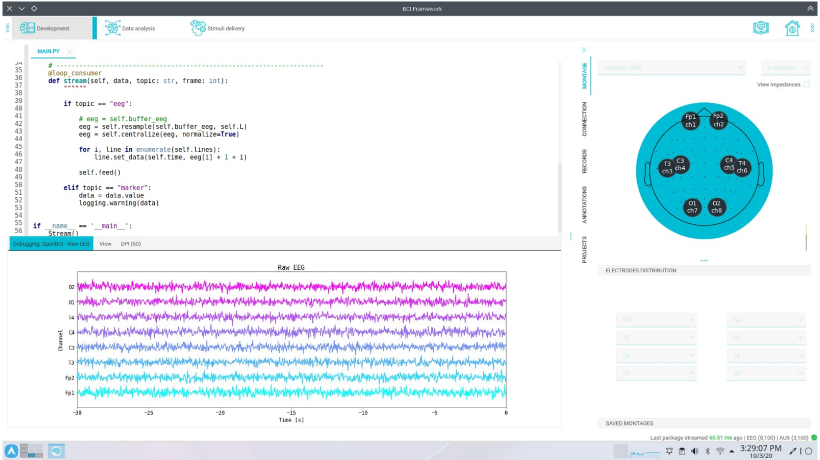
(a) Structural connectivity (b) Effective connectivity (c) Functional connectivity

- Structural connectivity (SC) focuses on physical connections, fails to capture short-living events [Thiebaut de Schotten et al., 2020]
- Effective connectivity (EC) describes direct connections and requires deep cognitive process understanding to select the best causal model [Chiarion et al., 2023].
- Functional connectivity (FC) can describe directed or non-directed connectives usually via statistical correlation [Cao et al., 2022]

FC's simplicity, low computational demands, and lack of rigid assumptions make it ideal for MI-BCI applications [He et al., 2019].

Signal Processing and Recognition Group - SPRG

The SPRG has been working on the design of ML and DL models to improve the performance and explainability of EEG-based MI-BCIs [Collazos-Huertas et al., 2023].



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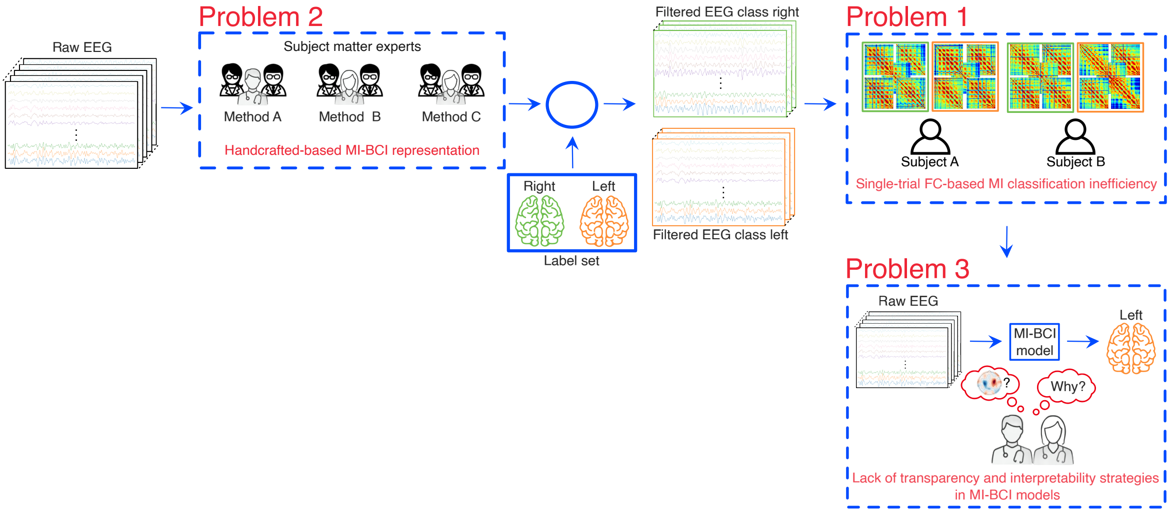
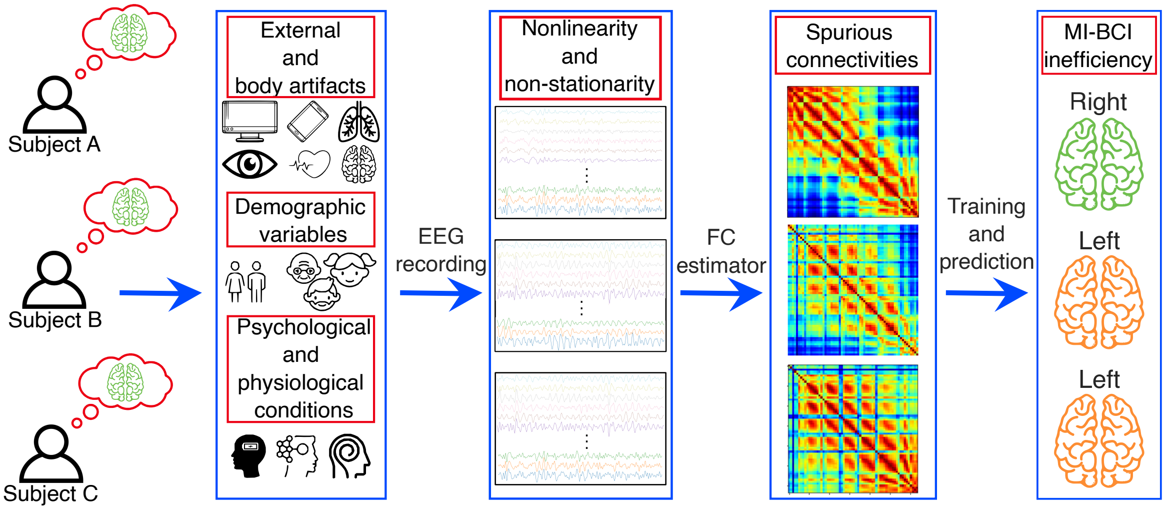
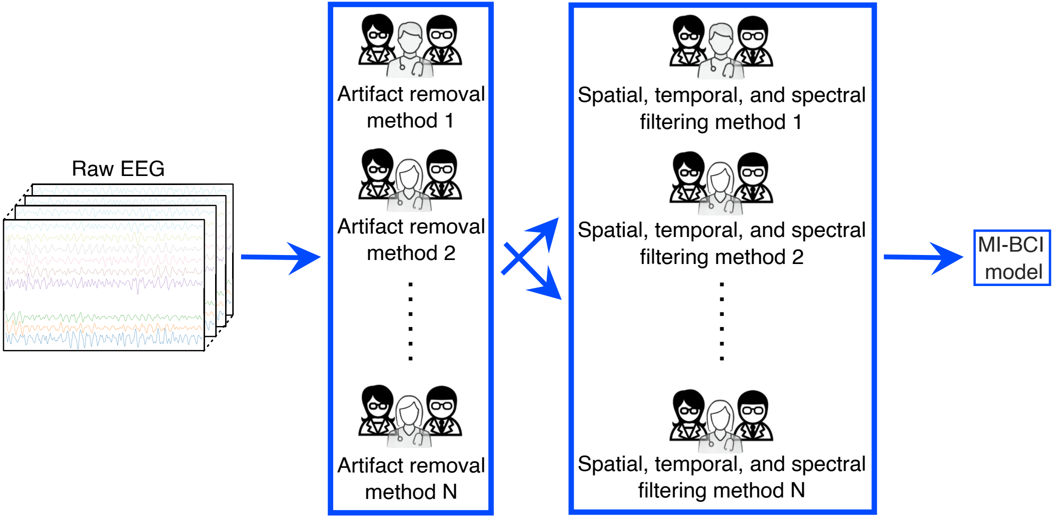
Problem statement



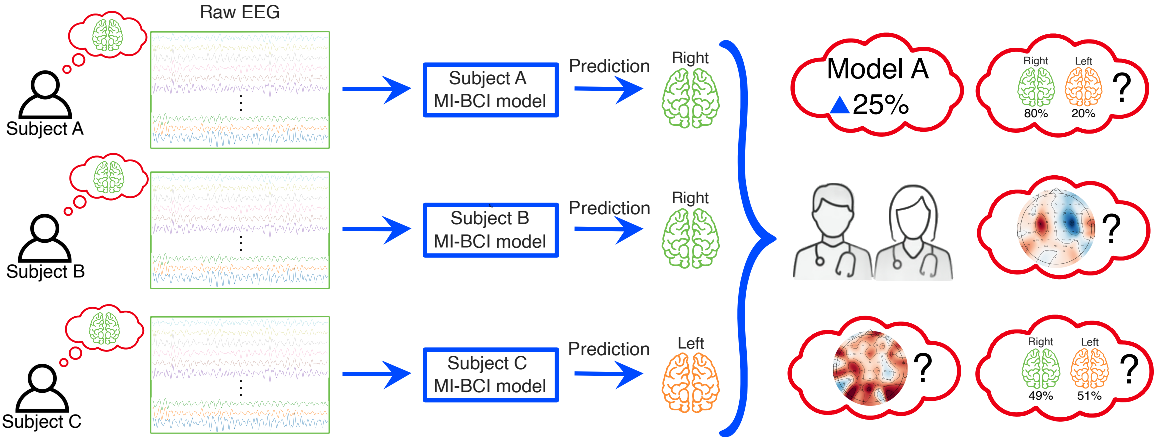
Single-Trial FC MI Classification Inefficiency



Handcrafted-based Subject-Specific EEG-based MI-BCI Representation



Lack of Transparency and Interpretability Strategies in MI-BCI



Research question

How can a single-trail FC be developed to manage non-stationary EEG subject-specific representations, handle spurious connectivities, and encode non-linear spatial, temporal, and spectral discriminative and interpretable MI patterns?

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Functional Connectivity Estimators

	Time Domain	Frequency domain	
Indirect	Corr [Fagerholm et al., 2020]	IPC[Cao et al., 2022a] MSC [Cattai et al., 2021] PC [Gonzalez-Astudillo et al., 2020]	Linear
	MI [Gu et al., 2023] SL [Gonzalez-Astudillo et al., 2021]	PLI [Siviero et al., 2023] PLV [Cattai et al., 2021] WPLI [Gonzalez-Astudillo et al., 2020]	Nonlinear
Directed	Cross-corr [Roy et al., 2022] GC [Rezaei & Shalbaf, 2023]	DTF [Rezaei & Shalbaf, 2023] PDC[Gaxiola-Tirado et al., 2017]	Linear
	TE [Rezaei & Shalbaf, 2023]		Nonlinear

High sensitive Sensitive Less sensitive Robust

Feature Extraction from FC

- FC feature extraction
  - Common spatial patterns
    - Constant regularization [Park et al., 2017]
      $\hat{\mathbf{C}} = \{\mathbf{C} + \alpha \mathbf{I}\}$
    - Lasso - L_1-norm [Zhang et al., 2018a]
      $\arg\max \mathbf{W}\mathbf{C}\mathbf{W}^\top - \sum_c \|\mathbf{w_c}\|_1$
    - Tikhonov L_2-norm [Fauzi et al., 2019]
      $\arg\max \mathbf{W}\mathbf{C}\mathbf{W}^\top - \sum_c \|\mathbf{w_c}\|_2$
    - Elastic-net - L_1, L_2-norm [Gu et al., 2021]
      $\arg\max \mathbf{W}\mathbf{C}\mathbf{W}^\top - \sum_c \|\mathbf{w_c}\|_1 - \sum_c \|\mathbf{w_c}\|_2$
    - Weighted regularization [Deng et al., 2020]
      $\hat{\mathbf{C}} = \{\mathbf{C} + diag(\mathbf{A})\}$
    - $L_{q/p}$ regularization [Cai et al., 2021]
      $\arg\max \mathbf{W}\mathbf{C}\mathbf{W}^\top - \sum_c \|\mathbf{w_c}\|_{p,q}$
    - Easy interpretability [Akuthota et al., 2023]
    - Easy implementation with decent performance [Khademi et al., 2023]
    - Usually $\mathbf{C}$ is calculated as the sample covariance matrix [Guo et al., 2020]
    - Ignores nonlinear interations [Ghanbar et al., 2021]
    - Not design for muti-class scenarios [Alizadeh et al., 2023]
  - Vector representation [Meng et al., 2023, Georgiadis et al., 2018]
    - CSP-like when followed by linear classification [Reuderink et al., 2011]
    - Frequently exhibit poor performance [Xu et al., 2020]
    - Easy integration with deep learning [Zoumpourlis & Patras, 2022]
  - Graph measures [Gu et al., 2023]
    - Intuitive representation [Rodrigues et al., 2022]
    - Oversimplified the cognitives process [Gonzalez-Astudillo et al., 2020]
  - Riemannian geometry [Ding et al., 2023]
    - Take into account $\mathbf{C}$ iner-links [Liu et al., 2024]
    - Hard to find best $\mathbf{C}_{ref}$ [Miah et al., 2020]
  - Topological representation [Altaheri et al., 2023, Collazos-Huertas et al., 2021]
    - Potentially lose information [Altaheri et al., 2023]
    - Performance relies on sufficient channels [Zhao et al., 2019a]
    - Seamless integration with convolutional neural networks [Xu et al., 2020b]

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Input Formulation in Deep Learning

- Deep learning inputs
  - Raw EEG Matrix $[N_c \times N_t]$ [Zhang et al., 2021b]
    - Usually light architecture [Dose et al., 2018]
    - Little or no preprocessing [Amin et al., 2019]
  - Handcraft-based
    - Statistical measures
    - Graph measures
      - Vector $[N_q]$ [Gu et al., 2023]
        - Oversimplified the cognitives process [Gonzalez-Astudillo et al., 2020]
    - Spectral images (E.g., EMD, PSD, FFT, WT, STFT, CWT, FC, CSP)
      - Matrix
        - $[N_c \times N_f]$ [Ma et al., 2020]
        - $[(N_f + N_c) \times N_t]$ [Zhang et al., 2020b]
        - $[(N_t + N_c) \times N_f]$ [Kant et al., 2020]
        - $[(N_t + N_c) \times (N_f + N_c)]$ [Alwasiti et al., 2020]
        - $[N_c \times N_c]$ [Kwon et al., 2021]
      - Tensor
        - $[N_c \times N_f \times N_t]$ [Miao et al., 2020]
        - $[N_c \times N_c \times N_t]$ [Wang et al., 2019]
        - $[N_c \times N_c \times (N_f + N_t)]$ [Collazos-Huertas et al., 2023]
      - Potentially lose information [Altaheri et al., 2023]
    - Topological representation
      - Matrix
        - $[x \times y]$ [Xu et al., 2020b]
      - Tensor
        - $[N_f \times x \times y]$ [Li et al., 2019b]
        - $[N_t \times x \times y]$ [Liu & Yang, 2021]
      - Performance relies on sufficient channels [Zhao et al., 2019a]

Deep Learning Architectures

- Deep learning arquitechtures
  - Discriminative Models
    - MLP [Amin et al., 2019] — Cannot directly extract spatial information [Altaheri et al., 2023]
    - CNN [Zhang et al., 2021c] — Easy to integrate with other architectures [Sharma et al., 2023]; Suitable for automatic spatial, temporal and spectral filtering [Köllőd et al., 2023]
    - RNN
      - LSTM [Kumar et al., 2019]
      - GRU [Luo et al., 2018]
      - Vanish gradient issue [Gao et al., 2022]; Inefficient in isolation [Kostiukevych et al., 2021]
    - GNN [Ju & Guan, 2023] — Complex model architecture [Kulatilleke, 2023]
  - Representative Models
    - DAE [Tabar & Halici, 2016]
    - DRBM [Zhang et al., 2021g]
    - DBN [Zhang et al., 2021f]
      - DBN-RBM [Xu et al., 2020b]
      - DBN-AE [Hassanpour et al., 2019]
    - Smaller datasets can lead to overfitting [Kondratyev et al., 2020]
  - Generative Models
    - VAE [Dai et al., 2019]
    - GAN [Fahimi et al., 2020]
    - Suffers from training instability [Yang et al., 2021b]

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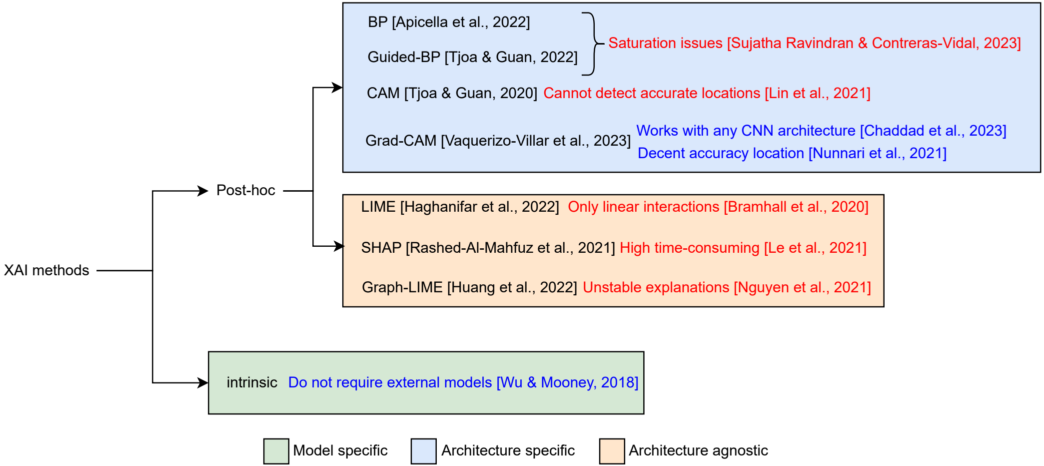
Interpretability Strategies in MI-BCI



Outline I

General Objective

To develop a single-trial indirect functional connectivity framework, accompanied by regularized deep learning approaches, to extract pertinent subject-specific non-linear spatio-temporal-frequency patterns from non-stationary EEG data, improving the MI-BCI system's accuracy and interpretability.

Specific Objectives

1. To develop a single-trial indirect FC for enhanced nonlinear feature extraction, preserving the spatio-temporal-frequency interpretability while favoring the classification performance in MI-BCI and avoiding spurious connectivities.

2. To extend the proposed single-trial FC within a deep learning scheme that handles artifacts and EEG representations, necessitating minimal preprocessing efforts from raw signals.

3. To develop a transparency and interpretability strategy dedicated to MI-BCI classification that emphasizes spatial-temporal-spectral pattern domains, incorporating a qualitative and quantitative relevance analysis assessment.

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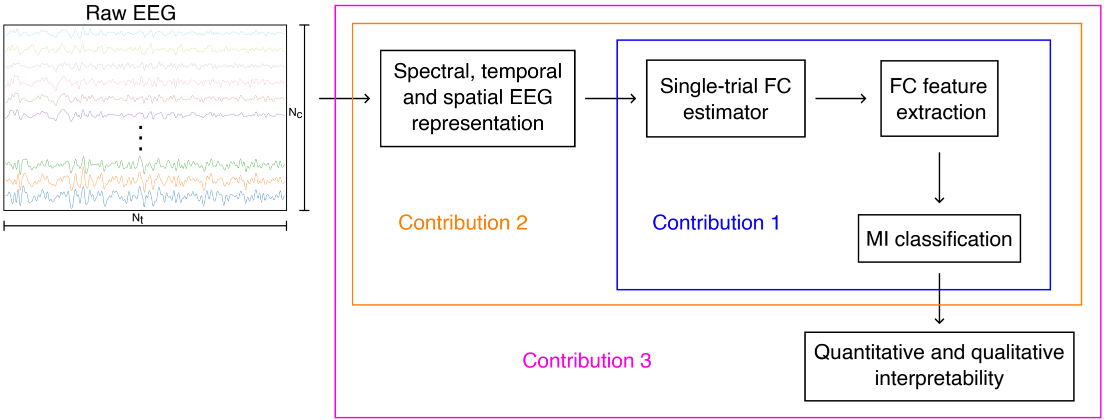
Outline and contributions



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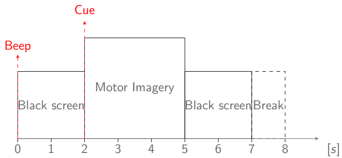
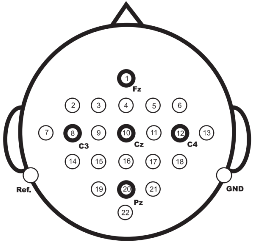
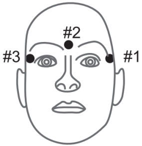
BCI Competition IV Dataset IIa - DBI MI

Acquisition protocol

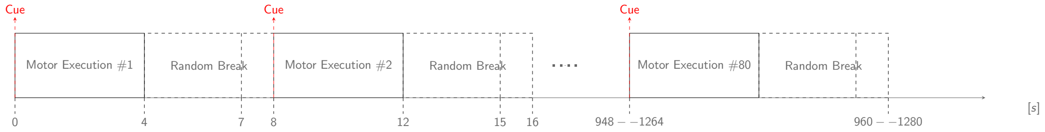


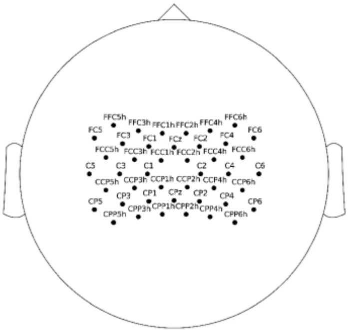
Electrode montage





Gamma Motor Execution Database—DBII ME





MI BCI EEG Giga Science Database - DBIII MI

C

Outline II

7 Proposal and Results
- Single-Trial Kernel-based Functional Connectivity for Enhanced Feature Extraction in EEG-based MI-BCI
- KCS-FCnet: Kernel Cross-Spectral Functional Connectivity Network for Automatic EEG Representation in MI-BCI
- IRKCS-FCnet: Interpretable Regularized Kernel Cross-Spectral Functional Connectivity Network with Qualitative and Quantitative Post-Hoc and Intrinsic Explainability

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Outline II

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Outline II

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