Andrea Turano
Badge Number: 816462
Academic Year 2020 – 2021

Analysis and Processing of EEG Signals for Brain Computer Interface Applications

Supervisor: Francesca Gasparini
Advisor: Aurora Saibene

BRAIN COMPUTER INTERFACES

BCIs can be employed in a large variety of fields[1] including:

BRAIN COMPUTER INTERFACES

BCIs can be employed in a large variety of fields[1] including:

Rehabilitation

BRAIN COMPUTER INTERFACES

BCIs can be employed in a large variety of fields[1] including:

Rehabilitation

Prosthesis control

BRAIN COMPUTER INTERFACES

BCIs can be employed in a large variety of fields[1] including:

Rehabilitation

Prosthesis control

Entertainment

And many others…

BRAIN COMPUTER INTERFACES

BCIs can be employed in a large variety of fields[1] including:

Rehabilitation

Prosthesis control

Entertainment

And many others…

The goal of this work is to implement an EEG processing pipeline in order to distinguish between the motor imagery of different parts of the body.

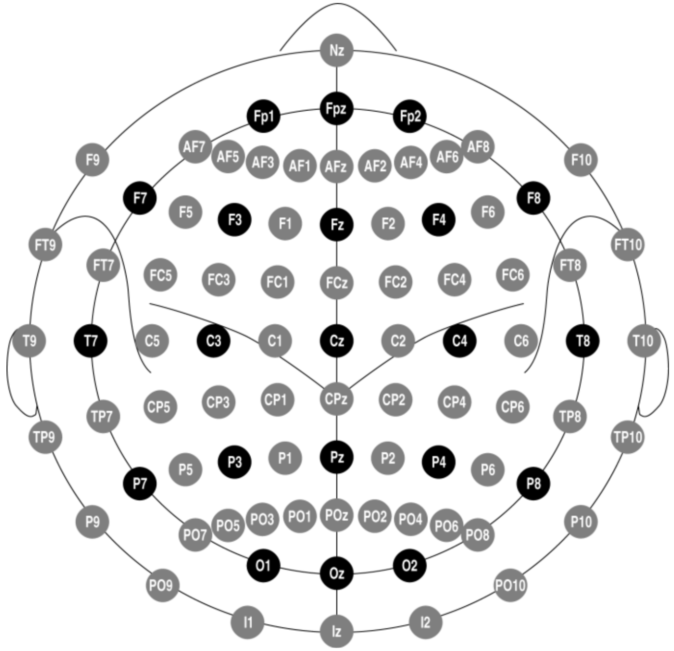
OUTLINE

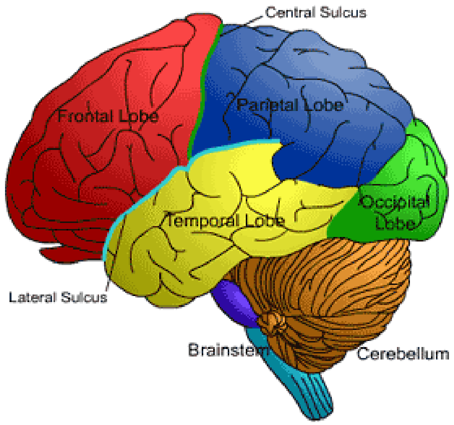
- EEG BASED BCIs
- BCIs & MOTOR IMAGERY
- DATASETS
- PROPOSED PIPELINE
- EXPERIMENTAL RESULTS
- CONCLUSIONS AND FUTURE WORKS

EEG BASED BCIs

Electroencephalogram:

- To record brain activities
- Different standards
- Spatial information (central cortical area)
- Frequency bands [2]: α (7-13 Hz), β (13-30 Hz)

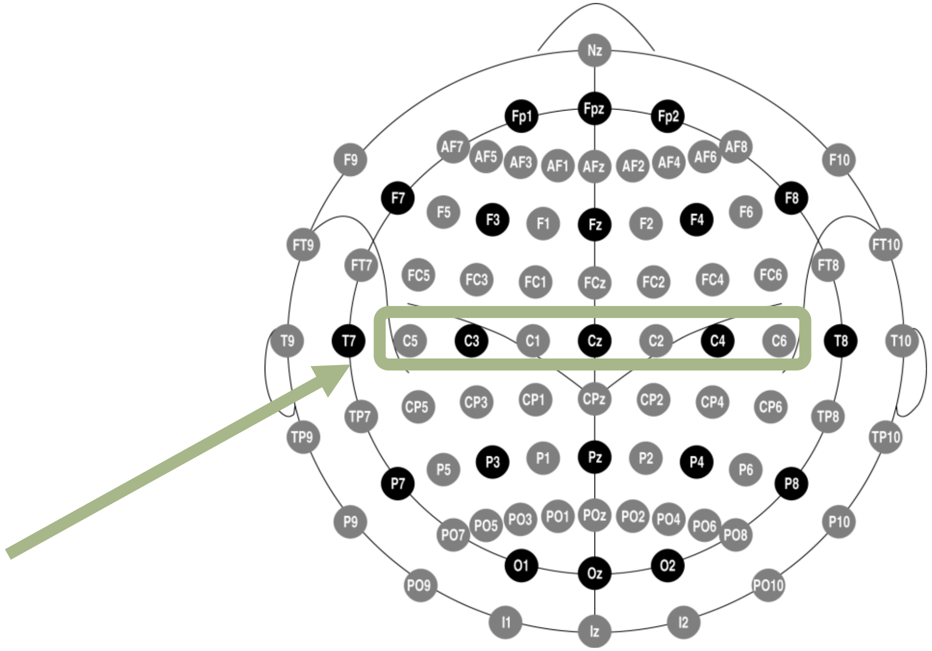


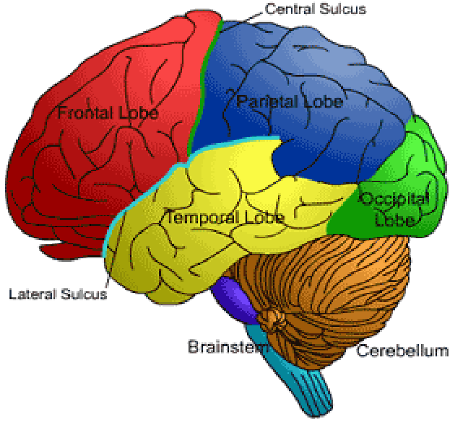


EEG BASED BCIs

Electroencephalogram:

- To record brain activities
- Different standards
- Spatial information (central cortical area)
- Frequency bands [2]: α (7-13 Hz), β (13-30 Hz)



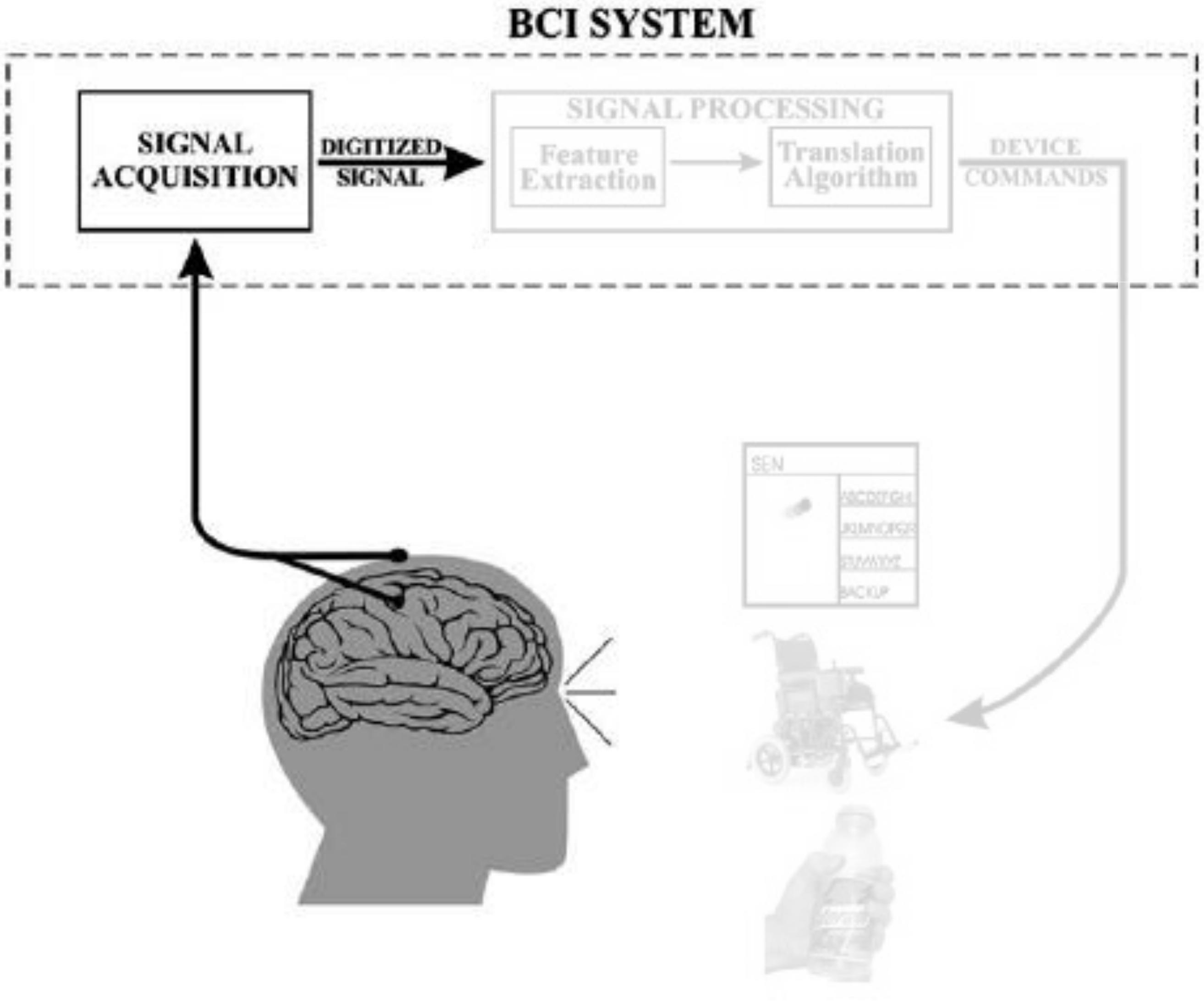


BCIs AND MOTOR IMAGERY

The translation of an EEG signal into a command is based on the concept of Motor Imagery.

A BCI system is composed by three blocks [3]:

- Signal Acquisition Module
- Signal Processing Module
- Application Module

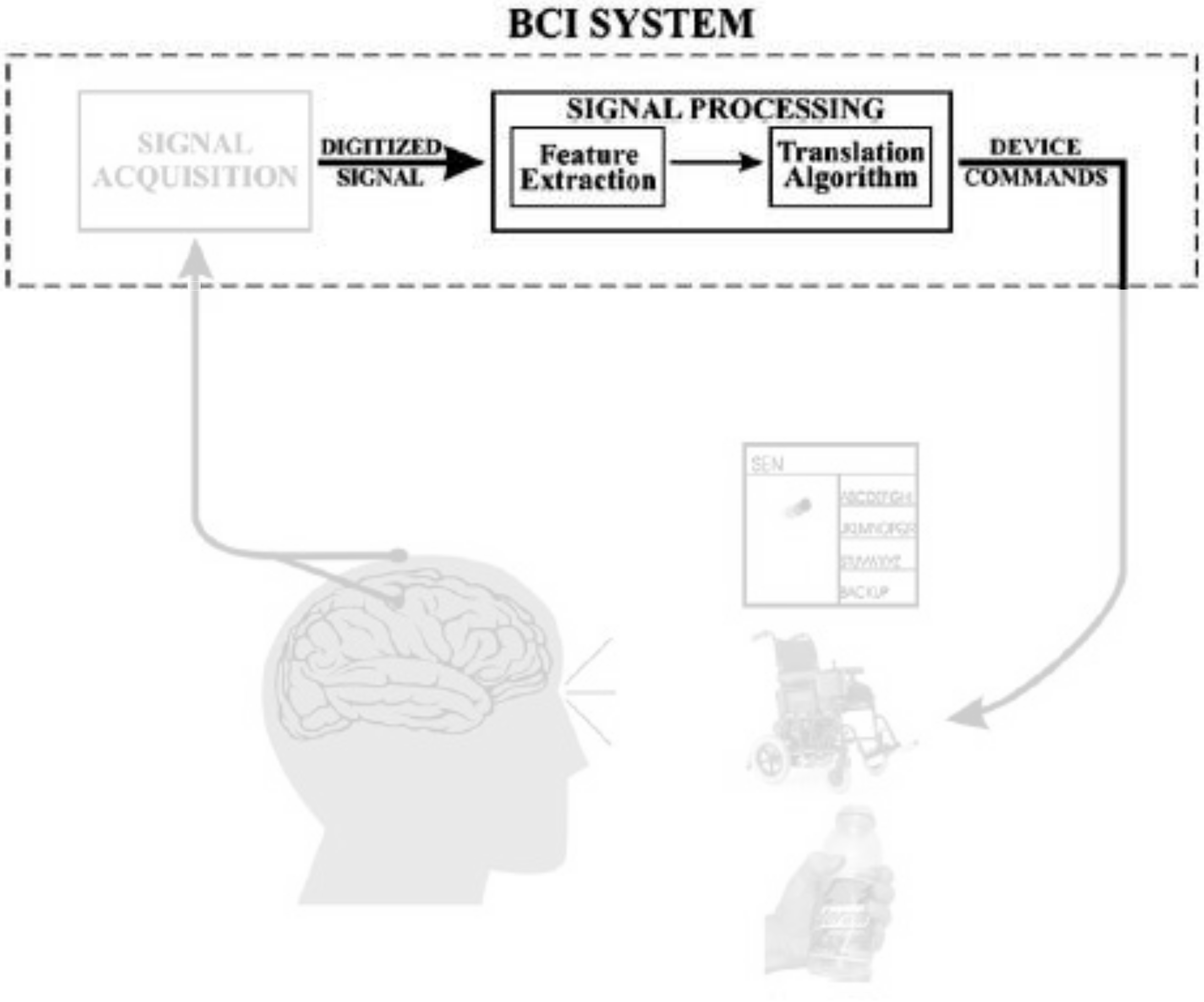


BCIs AND MOTOR IMAGERY

The translation of an EEG signal into a command is based on the concept of Motor Imagery.

A BCI system is composed by three blocks [3]:

- Signal Acquisition Module
- Signal Processing Module
- Application Module

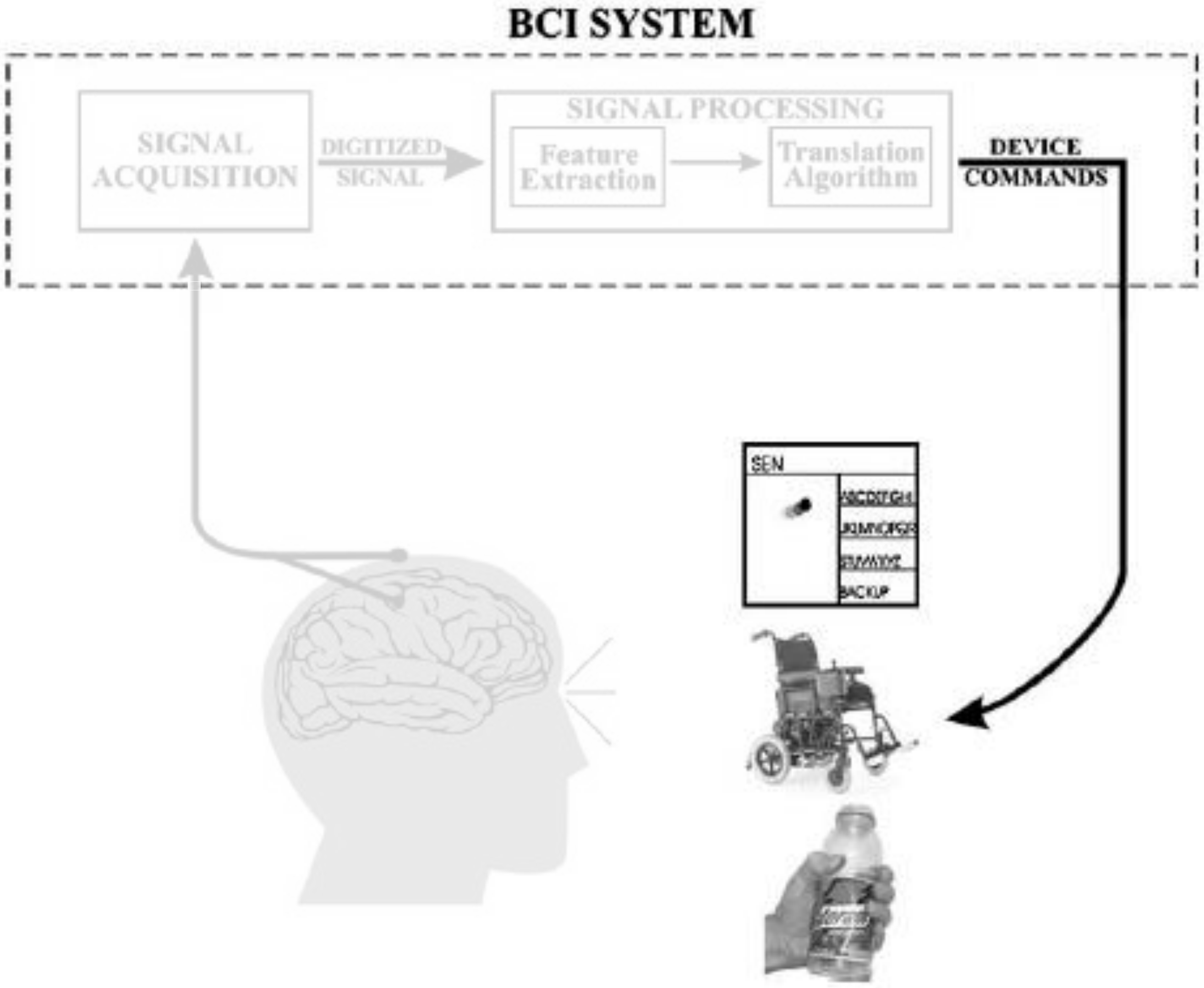


BCIs AND MOTOR IMAGERY

The translation of an EEG signal into a command is based on the concept of Motor Imagery.

A BCI system is composed by three blocks [3]:

- Signal Acquisition Module
- Signal Processing Module
- Application Module

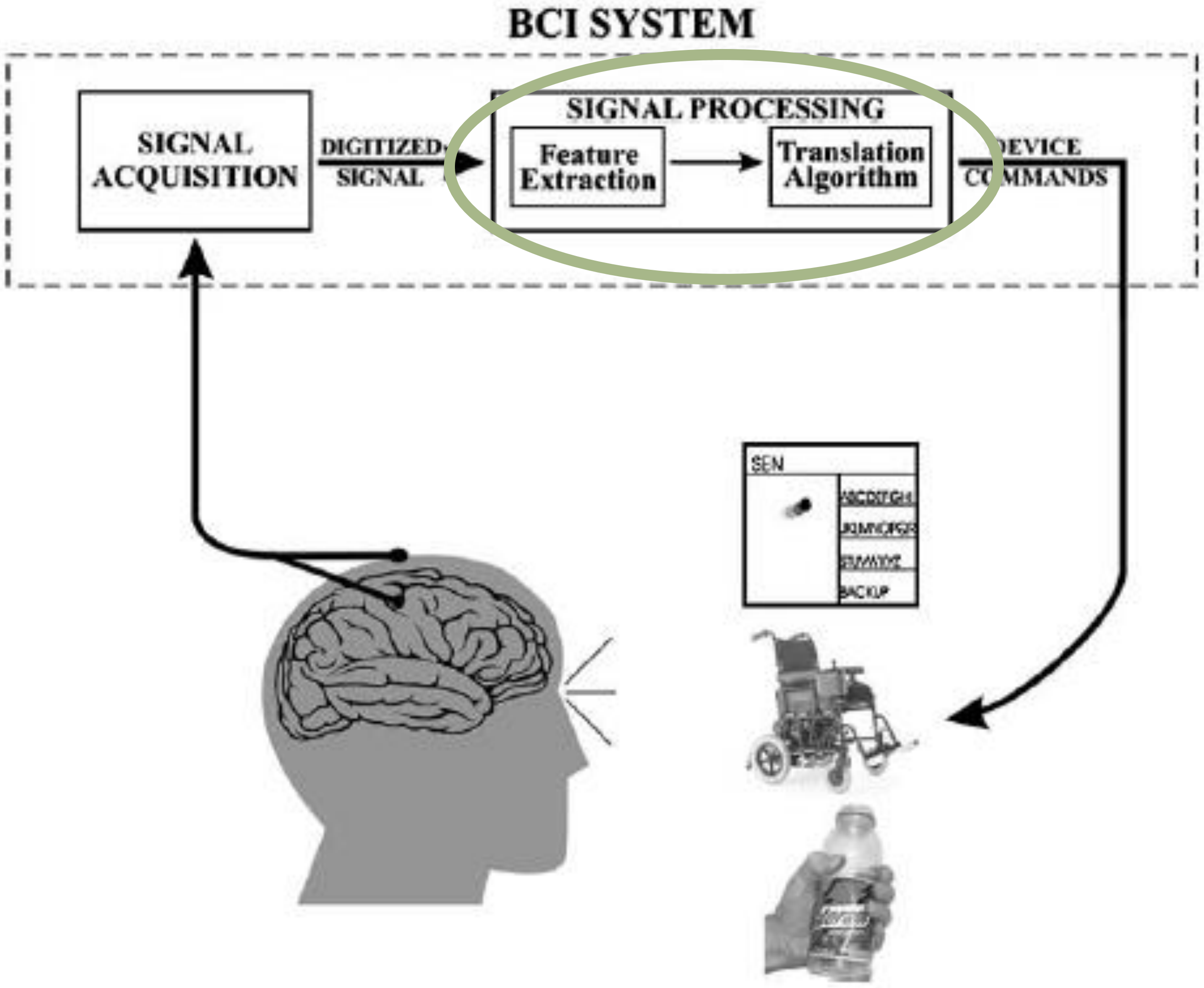


BCIs AND MOTOR IMAGERY

The translation of an EEG signal into a command is based on the concept of Motor Imagery.

A BCI system is composed by three blocks [3]:

- Signal Acquisition Module
- Signal Processing Module
- Application Module

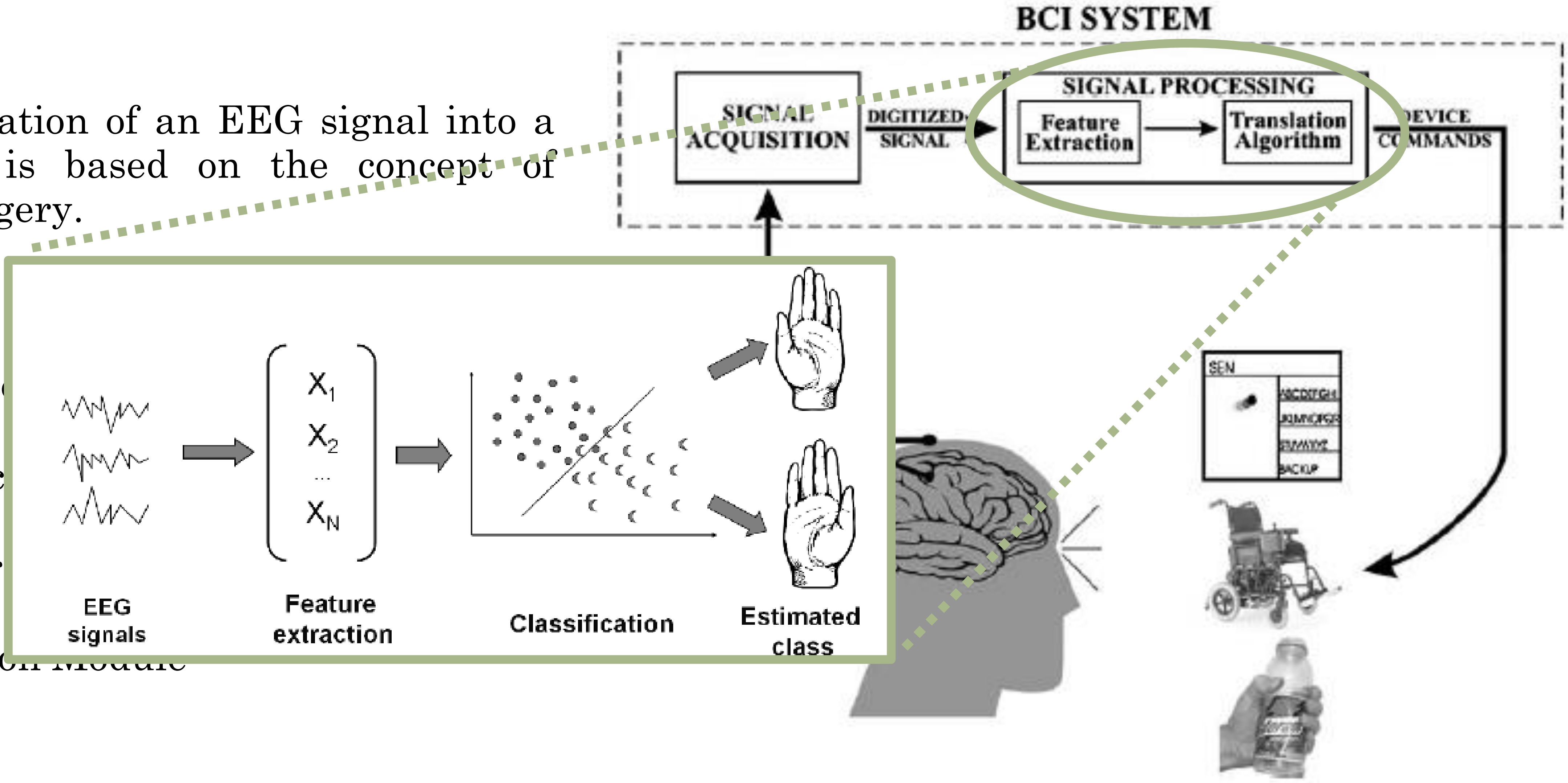


BCIs AND MOTOR IMAGERY

The translation of an EEG signal into a command is based on the concept of Motor Imagery.

A BCI syst

- Signal Ac
- Signal Pr
- Applicati

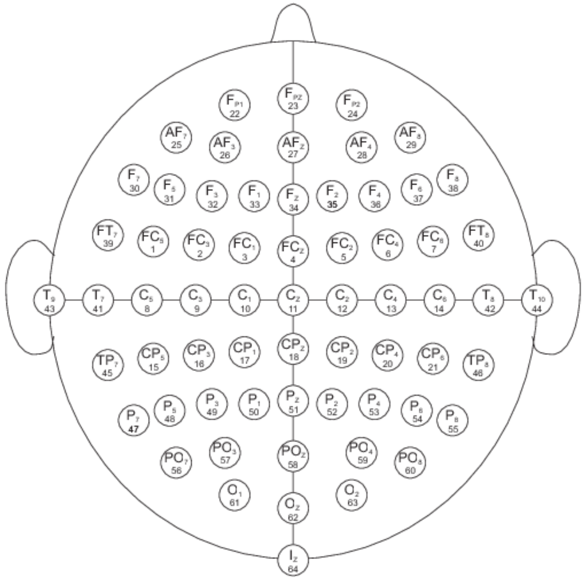


DATASETS

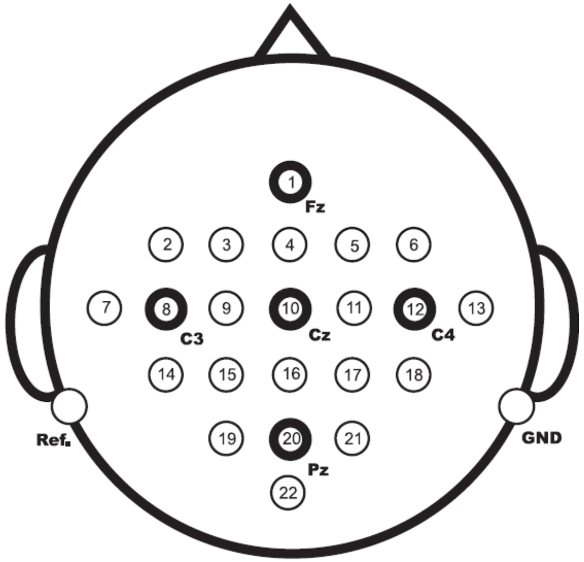
- Physionet MM/MI Dataset [3,4](109 s.): movement execution and imagination of feet and hands.
- BCI Competition IV–2A [5](9 s.): motor imagery of hands, feet and tongue.
- BCI Competition IV–2B [5](9 s.): hands motor imagery.

DATASETS

- **Physionet MM/MI Dataset** [3,4](109 s.): movement execution and imagination of feet and hands.
- **BCI Competition IV–2A** [5](9 s.): motor imagery of hands, feet and tongue.
- BCI Competition IV–2B [5](9 s.): hands motor imagery.



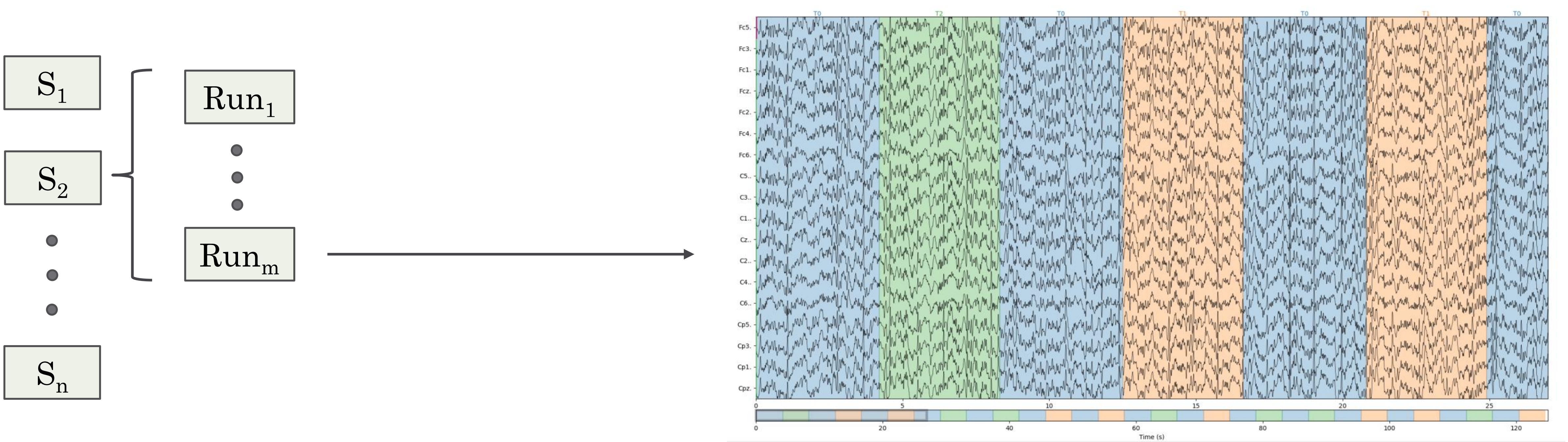
Physionet Dataset



BCI Competition IV-2A Dataset

DATASETS

- **Physionet MM/MI Dataset** [3,4](109 s.): movement execution and imagination of feet and hands.
- **BCI Competition IV–2A** [5](9 s.): motor imagery of hands, feet and tongue.
- BCI Competition IV–2B [5](9 s.): hands motor imagery.



PREPROCESSING

Population based study $\rightarrow$ heterogeneous data

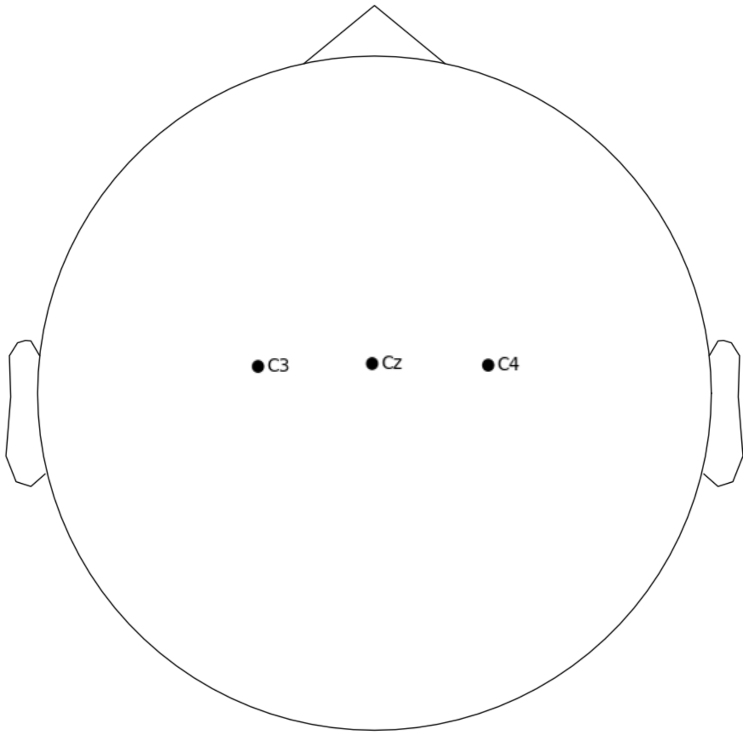
In order to suppress noises and reduce the heterogeneities:

- Band Pass filter: 7 – 30 Hz $\rightarrow$ α and β frequency bands
- Z-score Normalization (run wise) : $X_{new} = \frac{X-\mu}{\sigma}$

CHANNEL SELECTION

Each region of the brain is related to different mental tasks, thus various channel selection methods are explored and compared:

- Motor Channels (C3, C4, Cz).

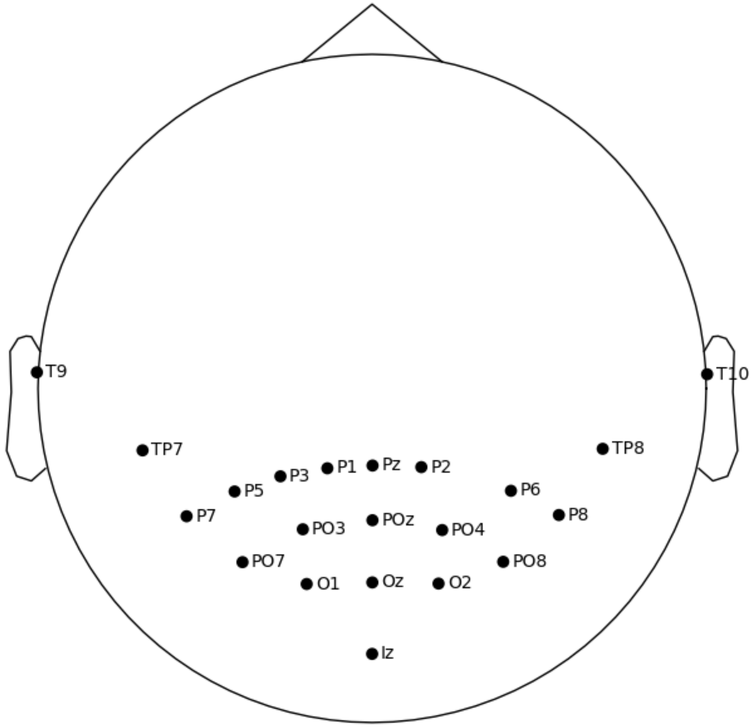


Physionet Dataset montage

CHANNEL SELECTION

Each region of the brain is related to different mental tasks, thus various channel selection methods are explored and compared:

- Motor Channels (C3, C4, Cz).
- Pearson and Spearman correlation indices:
  - I. For each sample the correlation matrix between electrodes is computed.
  - II. The average correlation matrix is extracted trom each trial.
  - III. We consider only those pairs of channels that have a correlation index that is lower than a fixed threshold [6,7].

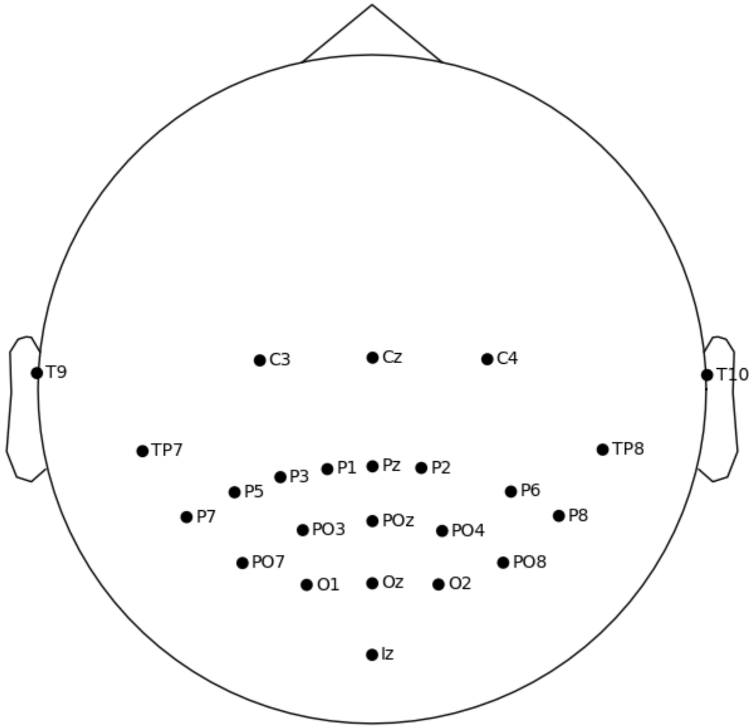


Physionet Dataset montage

CHANNEL SELECTION

Each region of the brain is related to different mental tasks, thus various channel selection methods are explored and compared:

- Motor Channels (C3, C4, Cz).
- Pearson and Spearman correlation indices:
  I. For each sample the correlation matrix between electrodes is computed.
  II. The average correlation matrix is extracted trom each trial.
  III. We consider only those pairs of channels that have a correlation index that is lower than a fixed threshold [6,7].
- Combination of both methods.



Physionet Dataset montage

CHANNEL SELECTION

Each region of the brain is related to different mental tasks, thus various channel selection methods are explored and compared:

- Motor Channels (C3, C4, Cz).

- Pearson and Spearman correlation indices:

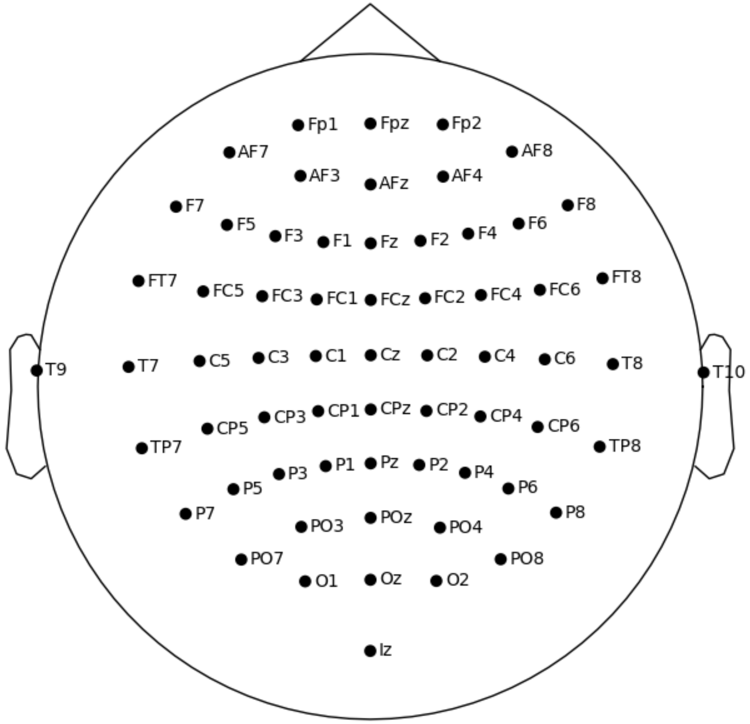
  I. For each sample the correlation matrix between electrodes is computed.

  II. The average correlation matrix is extracted trom each trial.

  III. We consider only those pairs of channels that have a correlation index that is lower than a fixed threshold [6,7].

- Combination of both methods.

- All channels in the montage.

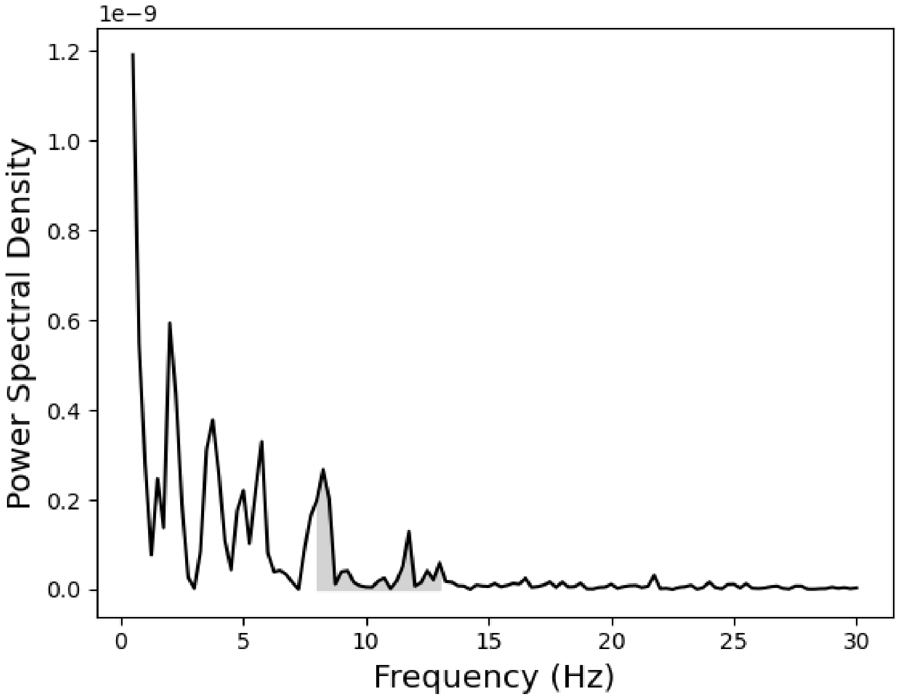


Physionet Dataset montage

FEATURE EXTRACTION

- Selected channels → spatial information.
- Frequency band selection → different mental tasks.

Thus the Power Spectral Density is estimated using the Welch's method [8].



For each selected channel / frequency band:

- Power
- Mean
- Standard Deviation

Then, a min-max standardization is carried out.

CLASSIFICATION METHODS (I)

- Physionet MM/MI Dataset: 105 subjects (+4 removed) → 4725 instances
- BCI Competition IV–2A: 9 subjects → 2592 instances

Three classifiers are trained :

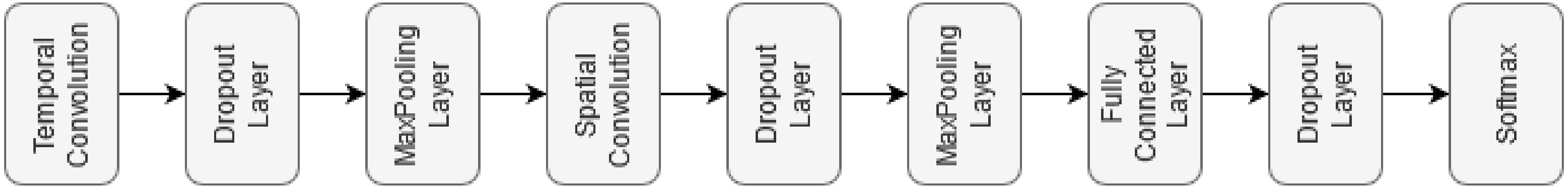
- Split: 70 training (30% of training data as validation set) : 30 test
- Grid seach

SVM	KNN	MLP
▪ $\gamma = \frac{1}{\#features \cdot \sigma}$ ▪ $C = \{0.01, 0.1, 1.0, 10.0\}$ ▪ $Kernel = \{Linear,\ RBF\}$	▪ $K = \{3, 5, 7, 11, 21, 31\}$	▪ 2 Hidden Layers: 64 and 32 neurons (tanh) ▪ Binary Cross entropy ▪ Adam (0.001) ▪ 300 Epochs ▪ Sigmoid

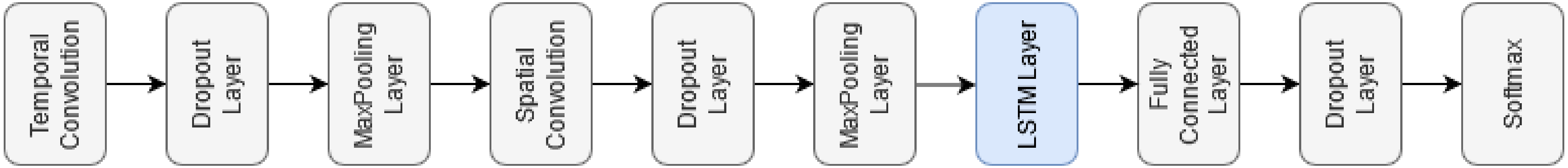
CLASSIFICATION METHODS (II)

In the second part two deep models are trained from scratch using the preprocessed EEG signal from each trial as input.

(I) CNN



(II) CNN+LSTM



EXPERIMENTAL RESULTS – Tasks

Experiments on the *Physionet Dataset*

MM Hands	motor movement of the right and the left hands.
MI Hands	motor imagery of the right and the left hands.
MM Hands / Feet	motor movement of both hands and feet.
MI Hands / Feet	motor imagery of both hands and feet.

Experiments on the *BCI Competition IV-2A Dataset*

R. / L. Hands	motor imagery of the right and the left hands.
L. Hand / Feet	motor imagery of the left hand and both feet.
R. Hand / Feet	motor imagery of the right hand and both feet.
Feet / Tongue	motor imagery of both feet and tongue.

EXPERIMENTAL RESULTS – Physionet Dataset

	TASK			
	MM Hands	**MI Hands**	**MM Hands / Feet**	**MI Hands / Feet**
BEST CHANNEL SEL. METHOD	Spearman + Motor Channels	All	All	Pearson + Motor Channels
BEST MODEL	SVM {Linear, C=10.0}	SVM {Linear, C=1.0}	SVM {Linear, C=10.0}	MLP
ACCURACY	0.55	0.55	0.63	0.57

BEST CHANNEL SEL. METHOD	Motor Channels	Motor Channels	Spearman + Motor Channels	Spearman + Motor Channels
ACCURACY CNN	0.56	0.56	0.57	0.58
ACCURACY CNN+LSTM	**0.61**	**0.61**	**0.69**	**0.61**

EXPERIMENTAL RESULTS – BCI IV-2A Dataset

	TASK (Motor Imagery)			
	R. / L. Hands	**L. Hand / Feet**	**R. Hand / Feet**	**Feet / Tongue**
BEST CHANNEL SEL. METHOD	All	All	All	All
BEST MODEL	SVM {Linear, C=10.0}	SVM {Linear, C=10.0}	SVM {RBF, C=10.0}	SVM {Linear, C=10.0}
ACCURACY	0.67	0.69	0.60	0.70

BEST CHANNEL SEL. METHOD	All	All	All	All
ACCURACY CNN	0.67	0.67	0.64	0.65
ACCURACY CNN+LSTM	**0.74**	**0.76**	**0.72**	**0.78**

DISCUSSION AND CONCLUSIONS

- The proposed channel selection method is not always able to extract a subset of uncorrelated channels. Different experimental settings between datasets:
  - Nature of the stimulus
  - Standard of the headset
- Classify EEG from different subjects is a hard task.
- Classifying an imagined movement is not more difficult than classifying an executed movement.
- The MI of different parts of the body can be more or less complex to classify.
- Deep models outperform traditional classifiers (CNN+LSTM).

FUTURE WORKS

- Record different physiological signals into the university laboratory and implement an integrated sistem in order to analyze them (Electroencephalographic signal, Galvanic Skin Response, Electromiographic Signal, …) .
- Single subject study:
  - Features of different domains (CSP, Hjorth Parameters).
  - Outliers detection.
- Compare different standardization methods and channel selection algorithms.
- Investigate some data augmentation techniques and train different classification models (Gradient Boosting algorithms, Bidirectional / Attention-Based LSTM, Ensemble CNN).

Thanks for the attention

Andrea Turano

Badge Number: 816462

BIBLIOGRAPHY

1. S. N. Abdulkader, et al., "*Brain computer interfacing: Applications and challenges*", Egyptian Informatics Journal, vol. 16, no. 2, pp. 213-230, 2015.

2. F. Lotte, "*Study of electroencephalographic signal processing and classication techniques towards the use of brain-computer interfaces in virtual reality applications*", PhD thesis, INSA de Rennes, 2008.

3. G. Schalk, et al., "*BCI2000: A General-Purpose Brain-Computer Interface (BCI) System*" , IEEE Trans. Biomed. Eng., vol. 51, p. 1034, 07 2004.

4. A. G. et al., "*Physiobank, Physiotoolkit, and Physionet: Components of a new research resource for complex physiologic signals*", Circulation (Online), vol. 101, pp. E215-e220, 2000.

5. M. Tangermann, et al., "*Review of the BCI Competition IV*", Frontiers in neuroscience, vol. 6, p. 55, 2012.

6. B. Ratner, "*The correlation coefficient: Its values range between+ 1/- 1, or do they?*", Journal of targeting, measurement and analysis for marketing, vol. 17, no. 2, pp. 139-142, 2009.

7. M. Mukaka, "*A guide to appropriate use of correlation coefficient in medical research*", Malawi medical journal, vol. 24, no. 3, pp.69-71, 2012.

8. P. Welch, "*The use of fast fourier transform for the estimation of power spectra: a method based on time averaging over short, modied periodograms*", IEEE Transactions on audio and electroacoustics, vol. 15, no. 2, pp. 70-73, 1967.

CLASSIFICATION METHODS – Deep Models Parameters

PARAMETER	VALUE
Activation Function	ReLU
Optimizer	Adam (0.001)
Dropout Rate	0.2
Epochs	300
Loss	Binary Crossentropy
Number of filters (conv. layer)	8
Kernel Shape (temporal conv.)	3
Pool Size	15