A comparison of deep learning architectures for detecting motor execution from EEG data

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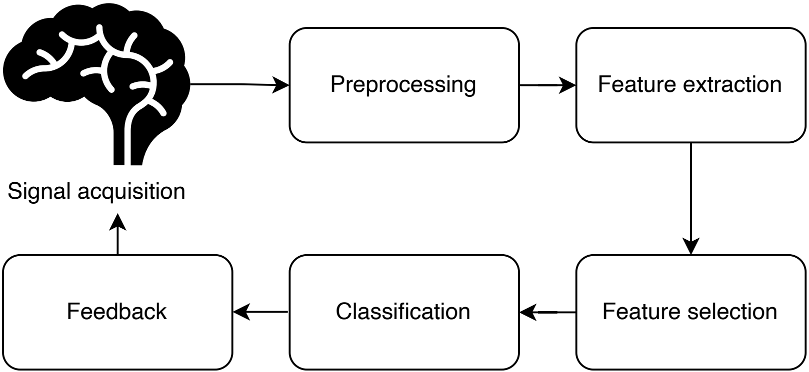
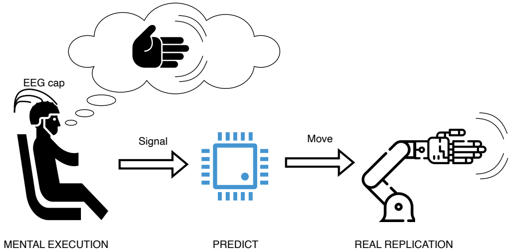
XXX Congresso dell'Associazione Italiana di Psicologia
Sezione Sperimentale, 23 - 25 Settembre 2024 - Noto (SR)

One of the studies of the active brain-computer interface (BCI) focuses on identifying movements from human neurophysiological signals to control external devices such as robotic arms or for safe work together with other instruments. Among many, electroencephalography (EEG) is one of the most common instruments to record brain activity.



Motor BCI

In the BCI field, the problem of Motor Imagery (MI) classification is well known. A person who loses the arm or the ability to move it still has cognitive ability of programming the movement without it actually being executed. For this reason, the study and classification of Motor Execution (ME) is essential to give these people back the possibility of using an external effector without having to change their way of thinking about movement.



REALITY - IMPAIRED PERSON

Previous study published at the 9th this study on Brain-Computer Interfaces (BCI) uses EEG to classify hand movements and resting-state. It introduces a Network Tree with specialised EEGnet patterns, improving accuracy over the three-class classification.

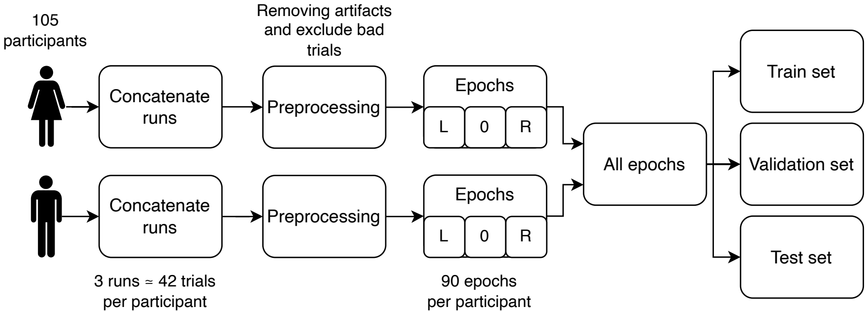
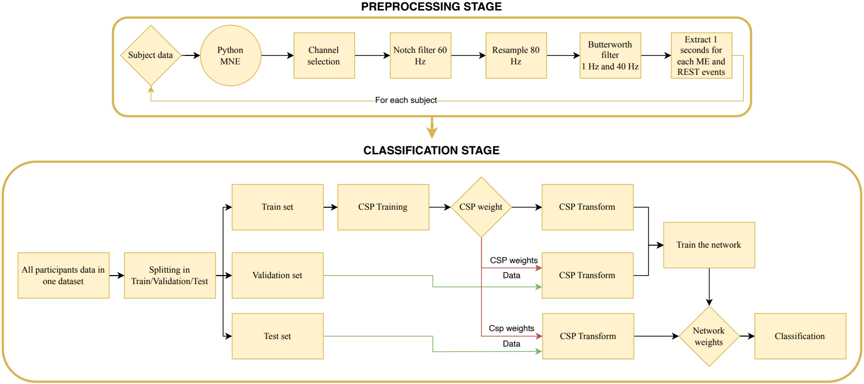


Figure: The split of the original set in train, validation and test set after preprocessing and epochs extraction.

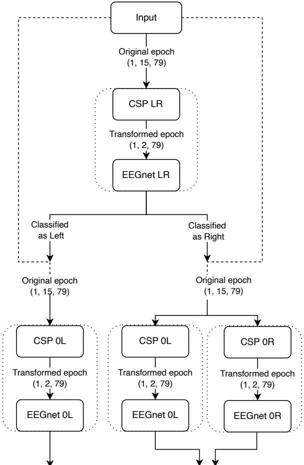
Preprocessing pipeline

The pipeline used to remove artifacts and for the feature extraction.



Network tree

The first classification of the signal is performed by the $EEGnet_{LR}$ and then a classification check is carried out. If L is identified, the input signal is sent to the $EEGnet_{0L}$ for final classification between 0 or L. In case R is classified, the input signal is sent both to the $EEGnet_{0L}$ and $EEGnet_{0R}$. The result of their combined classification returns the result of the final classification between 0 or R. The input undergoes, before being sent to a network, a transformation by the associated CSP.



EEGnet 0L	
REST	LEFT

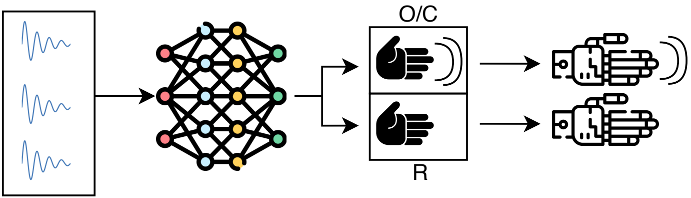
EEGnet 0L	EEGnet 0R	Output
0	Don't care	REST
L	0	REST
L	R	RIGHT

Results

Network	Class	Support	Precision	Recall	F1	Accuracy	Unknown Class	Prediction
EEGnet$_{0LR}$	Rest	574	0.62	0.15	0.24	**0.43**	-	-
	Left	594	0.39	0.96	0.55		-	-
	Right	606	0.72	0.18	0.29		-	-
EEGnet$_{LR}$	Left	600	0.74	0.73	0.74	0.73	Rest	0.46
	Right	582	0.73	0.73	0.73			0.54
EEGnet$_{0L}$	Rest	576	0.66	0.64	0.65	0.67	Right	0.73
	Left	609	0.67	0.69	0.68			0.27
EEGnet$_{0R}$	Rest	568	0.67	0.46	0.55	0.63	Left	0.42
	Right	614	0.61	0.79	0.69			0.58
Network Tree	Rest	591	0.48	0.45	0.46	**0.55**	-	-
	Left	586	0.57	0.61	0.59		-	-
	Right	596	0.58	0.59	0.58		-	-

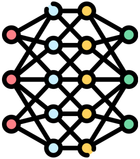
Goal

This study aims to identify the most effective Deep Learning (DL) architecture for ME categorization across several domains, based on the scientific literature for real-time BCI. The study compared three DL architectures for training networks from scratch using preprocessed data from the Physionet and Upper Limb to ensure consistency. This method eliminates bias from feature cleaning, extraction, and selection steps, allowing for more accurate comparisons.

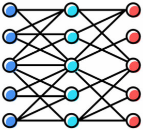


Materials and Methods

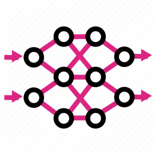
Two datasets and three different architectures were used. The public dataset used are the following: (1) PhysioNet and (2) Upper Limb Graz Dataset for ME and the three DL architectures used are: (1) EEGnetv4, (2) Deep4Net and (3) EEGITnet. These networks were chosen because they were already implemented in the Braindecode library and were suitable for these types of applications and data.



EEGnetV4



EEGITnet



Deep4net

Dataset description

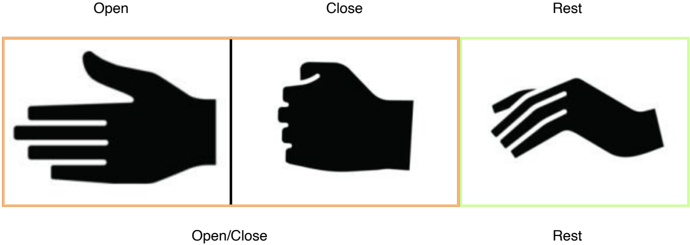
The study used data from 105 individuals from the Physionet dataset, excluding four participants due to inconsistencies, where subjects performed or imagined hand movements for four seconds, with rest periods between, over three sessions. Additionally, it included EEG data from 15 healthy subjects from the Upper Limb Graz dataset, where subjects performed movements or rest for three seconds, across 10 runs with 42 trials per run.

Dataset	*Physionet*					*Upper Limb*				
Parameter	Participants	Classes	Trials	Runs	Time	Participants	Classes	Trials	Runs	Time
Value	105	Open/Close Rest	3	14	4 s	15	Open Close Rest	10	42	3 s

Dataset preparation

This study employed the "open and close left or right fist" and "rest" from the Physionet dataset, as well as "hand close," "hand open," and "rest" from the Upper Limb dataset.

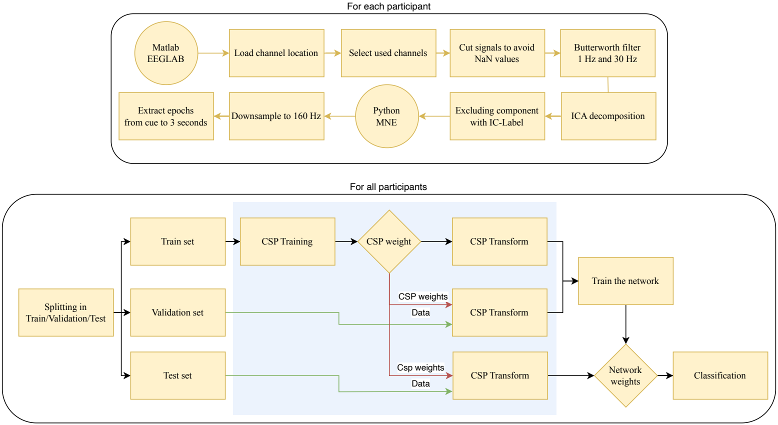
Upper Limb



Physionet

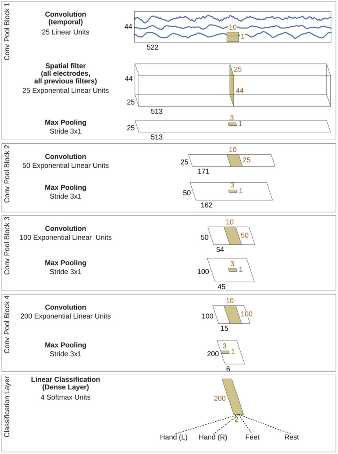
Preprocessing

In the upper part, the pipeline applied to clean the signals is shown performed for each participant. The training and test phases are shown in the lower part after merging all samples in one set. The processes in the blue box are skipped if the CSP transformation is not applied.

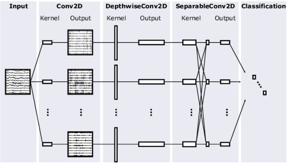


Deep learning models

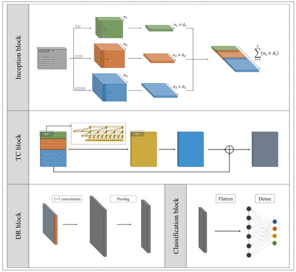
The deep learning models architectures used and the relative hyperparameters set for the training.



Deep4Net



EEGnet



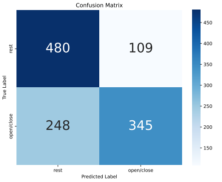
EEGITnet

Results

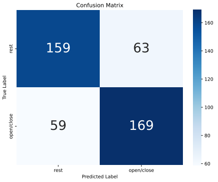
Results achieved using three models trained on two datasets with and without CSP. The best results for both datasets are in bold.

Dataset	Network	Class	Support	Precision	Recall	F1	Accuracy
Physionet	EEGnet	Rest	589	0.66	0.81	0.73	**0.70**
		Open/Close	593	0.76	0.58	0.66	
Physionet	Deep4Net	Rest	595	0.00	0.00	0.00	0.50
		Open/Close	587	0.50	1	0.66	
Physionet	EEGITnet	Rest	551	0.47	0.74	0.57	0.49
		Open/Close	631	0.55	0.28	0.37	
Upper Limb	EEGnet	Rest	237	0.80	0.76	0.78	**0.77**
		Open/Close	213	0.74	0.79	0.77	
Upper Limb	Deep4Net	Rest	221	0.49	1	0.66	0.49
		Open/Close	229	0.00	0.00	0.00	
Upper Limb	EEGITnet	Rest	213	0.47	0.65	0.54	0.48
		Open/Close	237	0.52	0.34	0.41	

Without CSP



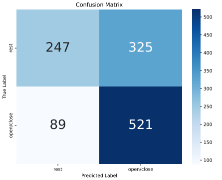
EEGnet Physionet



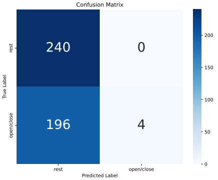
EEGnet Upper Limb

Dataset	Network	Class	Support	Precision	Recall	F1	Accuracy
Physionet	EEGnet	Rest	572	0.74	0.43	0.54	**0.65**
		Open/Close	610	0.62	0.85	0.72	
Physionet	Deep4Net	Rest	590	0.50	0.57	0.53	0.50
		Open/Close	592	0.50	0.44	0.47	
Physionet	EEGITnet	Rest	602	0.54	0.34	0.42	0.49
		Open/Close	580	0.50	0.70	0.59	
Upper Limb	EEGnet	Rest	240	0.55	1	0.71	**0.56**
		Open/Close	210	1.00	0.07	0.12	
Upper Limb	Deep4Net	Rest	224	0.42	0.04	0.08	0.49
		Open/Close	226	0.50	0.94	0.65	
Upper Limb	EEGITnet	Rest	244	0.53	0.25	0.34	0.48
		Open/Close	206	0.46	0.74	0.56	

With CSP



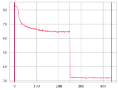
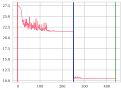
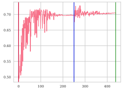
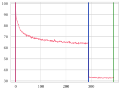
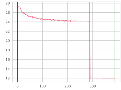
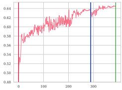
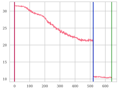
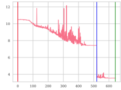
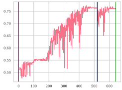
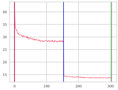
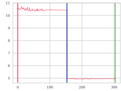
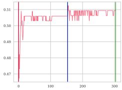
EEGnet Physionet



EEGnet Upper Limb

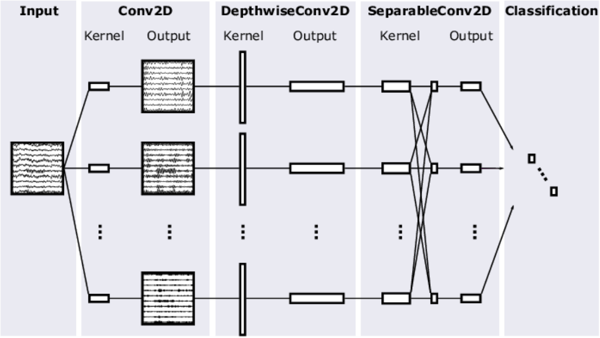
Results

The first two rows illustrate the curve related to the Physionet dataset, whereas the subsequent two rows show the curve for the Upper Limb dataset, without and with CSP.

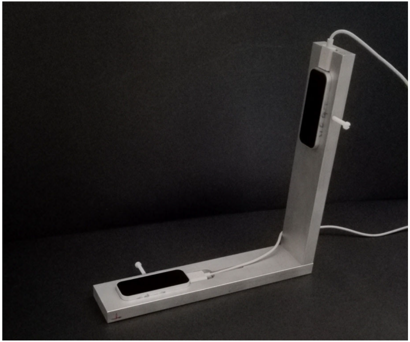
Condition	Training loss	Validation loss	Validation accuracy
EEGnet without CSP on Physionet			
EEGnet with CSP on Physionet			
EEGnet without CSP on Upper Limb			
EEGnet with CSP on Upper Limb			

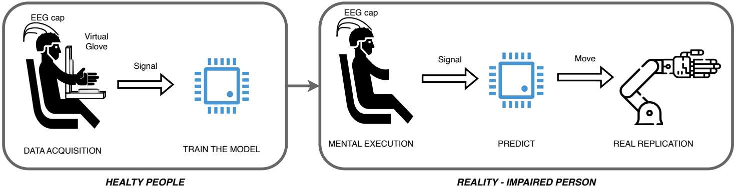
Conclusion

The results show that the best results were achieved using EEGnet without CSP transformation in both dataset, with an accuracy of 0.70 and 0.77 for Physionet and Upper Limb datasets, respectively.

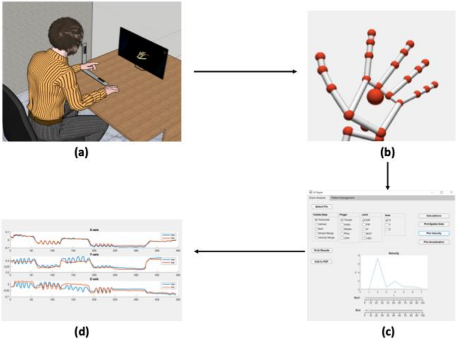


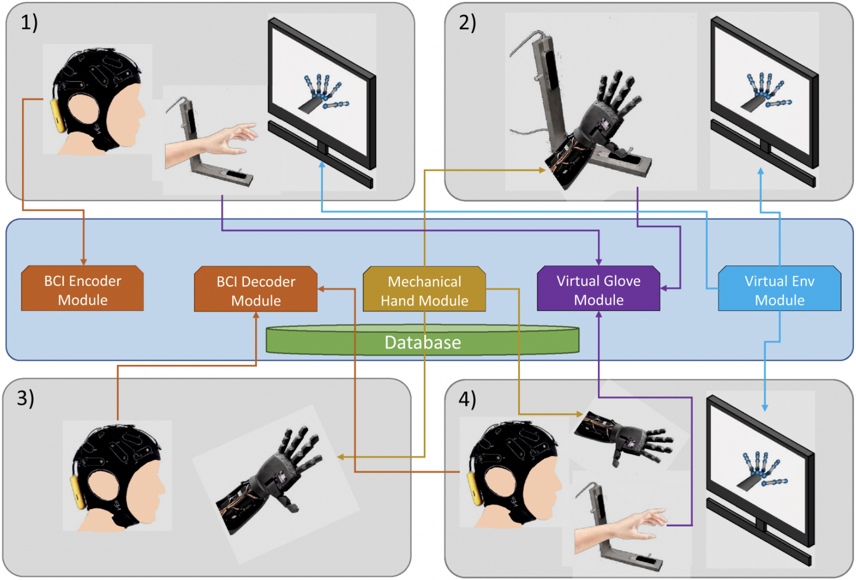
Future directions





Virtual Glove




1)
2)
3)
4)
BCI Encoder Module
BCI Decoder Module
Mechanical Hand Module
Virtual Glove Module
Virtual Env Module
Database

Moving

A Multi-MOdal dataset of EEG signals and VIrtual Glove hand trackING

A multi-modal dataset containing EEG signals and kinematic data associated with three hand movements: open/close, finger tapping, and wrist rotation, as well as a rest period. The dataset, gathered from 11 subjects using a 32-channel dry wireless EEG system, includes synchronized kinematic data from a Virtual Glove (VG) system equipped with two Leap Motion Controllers.

Goal

While this setup allows for quick assembly, it introduces more noise compared to gold standard devices. The study explores the most informative EEG frequency bands for motor task classification and the effects of baseline reduction on gesture recognition. Deep learning methods, such as EEGnetV4, are employed to classify movements using EEG data. The dataset aims to advance BCI research and the development of assistive devices for individuals with impaired hand mobility, contributing to the growing repository of EEG datasets for benchmarking new BCI methods and applications.

EEG data

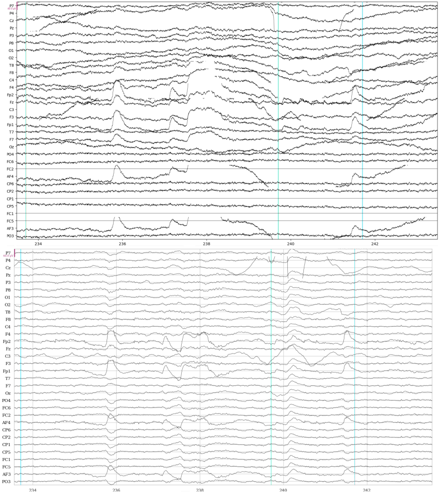


Figure: EEG raw data before (a) and after (b) a cleaning band-pass [1-45Hz] filtering. In (a), the high noise level makes it difficult to visualize high-amplitude brain signals. Vertical lines represent the triggers .

VG data

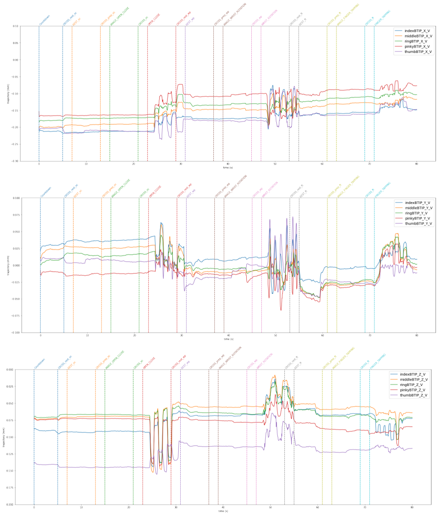
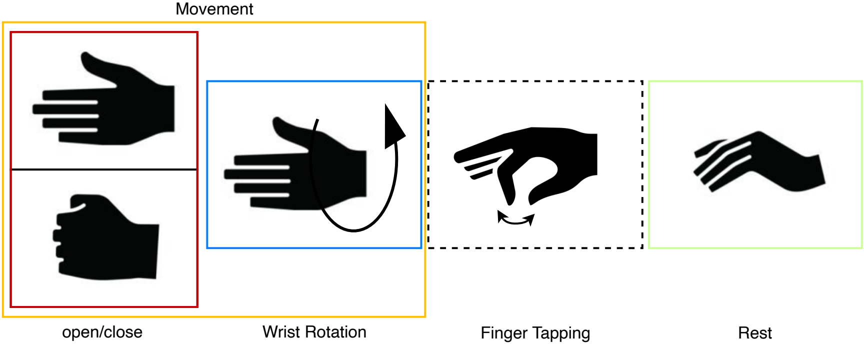
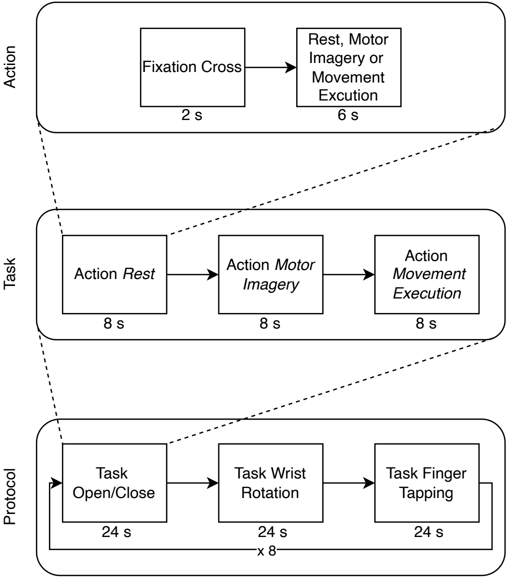


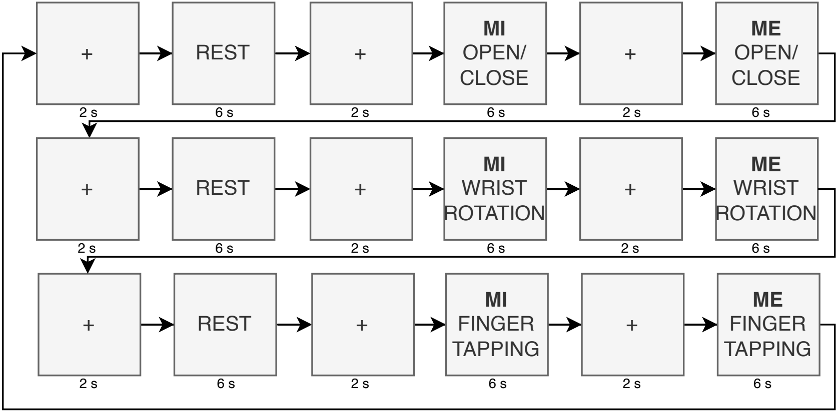
Figure: X (a), y (b), and z (c) components of the fingertip trajectory for the Vertical LMC. All fingertips are reported in a single plot.

Classes



Protocol


Action
Fixation Cross
2 s
Rest, Motor Imagery or Movement Excution
6 s
Task
Action *Rest*
8 s
Action *Motor Imagery*
8 s
Action *Movement Execution*
8 s
Protocol
Task Open/Close
24 s
Task Wrist Rotation
24 s
Task Finger Tapping
24 s
x 8


+
2 s
REST
6 s
+
2 s
MI
OPEN/
CLOSE
6 s
+
2 s
ME
OPEN/
CLOSE
6 s
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MI
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ROTATION
6 s
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2 s
ME
WRIST
ROTATION
6 s
+
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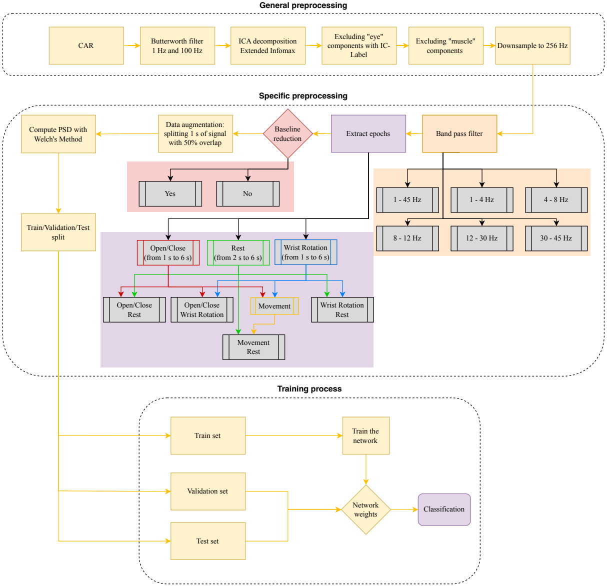
REST
6 s
+
2 s
MI
FINGER
TAPPING
6 s
+
2 s
ME
FINGER
TAPPING
6 s

Pipelines


General preprocessing
CAR
Butterworth filter 1 Hz and 100 Hz
ICA decomposition Extended Infomax
Excluding "eye" components with IC-Label
Excluding "muscle" components
Downsample to 256 Hz
Specific preprocessing
Compute PSD with Welch's Method
Data augmentation: splitting 1 s of signal with 50% overlap
Baseline reduction
Extract epochs
Band pass filter
Yes
No
1 - 45 Hz
1 - 4 Hz
4 - 8 Hz
8 - 12 Hz
12 - 30 Hz
30 - 45 Hz
Train/Validation/Test split
Open/Close (from 1 s to 6 s)
Rest (from 2 s to 6 s)
Wrist Rotation (from 1 s to 6 s)
Open/Close Rest
Open/Close Wrist Rotation
Movement
Wrist Rotation Rest
Movement Rest
Training process
Train set
Train the network
Validation set
Network weights
Classification
Test set

Results

Baseline	Filter	Classes	Precision	Recall	F1 score	Support	Accuracy	Classes	Precision	Recall	F1 score	Support	Accuracy
Yes	1 - 45	rest	0.71	0.51	0.59	346	0.64	rest	0.61	0.56	0.59	177	0.59
		movement	0.60	0.78	0.68	325		open/close	0.57	0.61	0.59	165	
No	1 - 45	rest	0.60	0.62	0.61	341	0.60	rest	0.54	0.73	0.62	165	0.57
		movement	0.60	0.58	0.59	334		open/close	0.64	0.43	0.52	182	
Yes	1 - 4	rest	0.54	0.7	0.61	346	0.54	rest	0.52	0.68	0.59	177	0.51
		movement	0.53	0.37	0.44	325		open/close	0.49	0.33	0.39	165	
No	1 - 4	rest	0.54	0.64	0.59	341	0.55	rest	0.50	0.71	0.58	165	0.52
		movement	0.55	0.45	0.50	334		open/close	0.57	0.35	0.44	182	
Yes	4 - 8	rest	0.60	0.57	0.58	389	0.57	rest	0.64	0.55	0.59	190	0.61
		movement	0.55	0.58	0.57	358		open/close	0.58	0.67	0.62	179	
No	4 - 8	rest	0.58	0.56	0.57	382	0.58	rest	0.51	0.63	0.57	183	0.53
		movement	0.57	0.59	0.58	379		open/close	0.56	0.44	0.49	195	
Yes	8 - 12	rest	0.56	0.51	0.53	403	0.54	rest	0.53	0.68	0.60	191	0.55
		movement	0.52	0.56	0.54	376		open/close	0.59	0.43	0.50	201	
No	8 - 12	rest	0.57	0.48	0.52	414	0.54	rest	0.53	0.51	0.52	191	0.54
		movement	0.51	0.60	0.55	369		open/close	0.55	0.57	0.56	201	
Yes	12 - 30	rest	0.58	0.60	0.59	405	0.57	rest	0.54	0.71	0.61	198	0.55
		movement	0.56	0.55	0.56	383		open/close	0.57	0.39	0.46	198	
No	12 -30	rest	0.58	0.52	0.55	405	0.56	rest	0.52	0.71	0.60	198	0.53
		movement	0.55	0.61	0.57	383		open/close	0.55	0.35	0.43	198	
Yes	30 - 45	rest	0.50	0.32	0.39	405	0.48	rest	0.48	0.55	0.51	198	0.47
		movement	0.48	0.66	0.55	383		open/close	0.47	0.39	0.43	198	
No	30 - 45	rest	0.52	0.44	0.47	405	0.50	rest	0.48	0.62	0.54	198	0.48
		movement	0.49	0.57	0.52	383		open/close	0.47	0.34	0.39	198	

Baseline	Filter	Classes	Precision	Recall	F1 score	Support	Accuracy	Classes	Precision	Recall	F1 score	Support	Accuracy
Yes	1 - 45	rest	0.65	0.49	0.56	172	0.60	open/close	0.52	0.58	0.55	128	0.53
		wrist rotation	0.56	0.71	0.63	157		wrist rotation	0.53	0.48	0.50	128	
No	1 - 45	rest	0.57	0.53	0.55	172	0.54	open/close	0.50	0.43	0.46	128	0.50
		wrist rotation	0.52	0.56	0.54	157		wrist rotation	0.50	0.58	0.54	128	
Yes	1 - 4	rest	0.58	0.63	0.61	172	0.57	open/close	0.56	0.45	0.50	128	0.55
		wrist rotation	0.55	0.50	0.52	157		wrist rotation	0.54	0.65	0.59	128	
No	1 - 4	rest	0.58	0.60	0.59	172	0.56	open/close	0.49	0.46	0.48	128	0.49
		wrist rotation	0.54	0.52	0.53	157		wrist rotation	0.49	0.52	0.51	128	
Yes	4 - 8	rest	0.56	0.64	0.60	183	0.58	open/close	0.56	0.67	0.61	153	0.55
		wrist rotation	0.61	0.53	0.57	195		wrist rotation	0.54	0.43	0.48	141	
No	4 - 8	rest	0.57	0.72	0.63	180	0.61	open/close	0.55	0.38	0.45	159	0.51
		wrist rotation	0.67	0.51	0.58	203		wrist rotation	0.48	0.65	0.55	139	
Yes	8 - 12	rest	0.52	0.51	0.52	194	0.52	open/close	0.53	0.61	0.56	157	0.51
		wrist rotation	0.52	0.53	0.52	193		wrist rotation	0.49	0.41	0.45	144	
No	8 - 12	rest	0.52	0.50	0.51	191	0.53	open/close	0.52	0.24	0.33	164	0.47
		wrist rotation	0.54	0.56	0.55	201		wrist rotation	0.46	0.74	0.56	141	
Yes	12 - 30	rest	0.54	0.55	0.55	191	0.55	open/close	0.57	0.49	0.53	164	0.52
		wrist rotation	0.57	0.56	0.56	201		wrist rotation	0.49	0.56	0.52	141	
No	12 -30	rest	0.53	0.48	0.50	191	0.54	open/close	0.55	0.40	0.46	164	0.50
		wrist rotation	0.55	0.59	0.57	201		wrist rotation	0.47	0.62	0.53	141	
Yes	30 - 45	rest	0.45	0.42	0.43	191	0.47	open/close	0.57	0.45	0.50	164	0.52
		wrist rotation	0.48	0.51	0.50	201		wrist rotation	0.49	0.60	0.54	141	
No	30 - 45	rest	0.46	0.52	0.49	191	0.47	open/close	0.55	0.42	0.48	164	0.50
		wrist rotation	0.48	0.42	0.45	201		wrist rotation	0.47	0.60	0.53	141	

Table: Overview of the results.

k-fold

Results performing 5-fold cross-validation on the best models

k-fold	**rest/mov**	**rest/wrist**	**rest/openclose**
1-fold	0.59	0.63	0.61
2-fold	0.62	0.61	0.60
3-fold	0.62	0.58	0.61
4-fold	0.60	0.59	0.60
5-fold	0.64	0.61	0.61
average±dev.st	*0.61±0.02*	*0.60±0.02*	*0.61±0.01*

Download it!

Explore the dataset

MOVING: a Multi-MOdal dataset of EEG signals and VIrtual Glove hand trackING

Question time

Thanks for listening!

Questions?

References (networks)

The images of the neural network used are taken from:

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