Department of Computer Sciences, Systems and Communication

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Academic Year 2019-2020

Deep learning strategies for motor imagery electroencephalographic signals – from raw to time frequency representation

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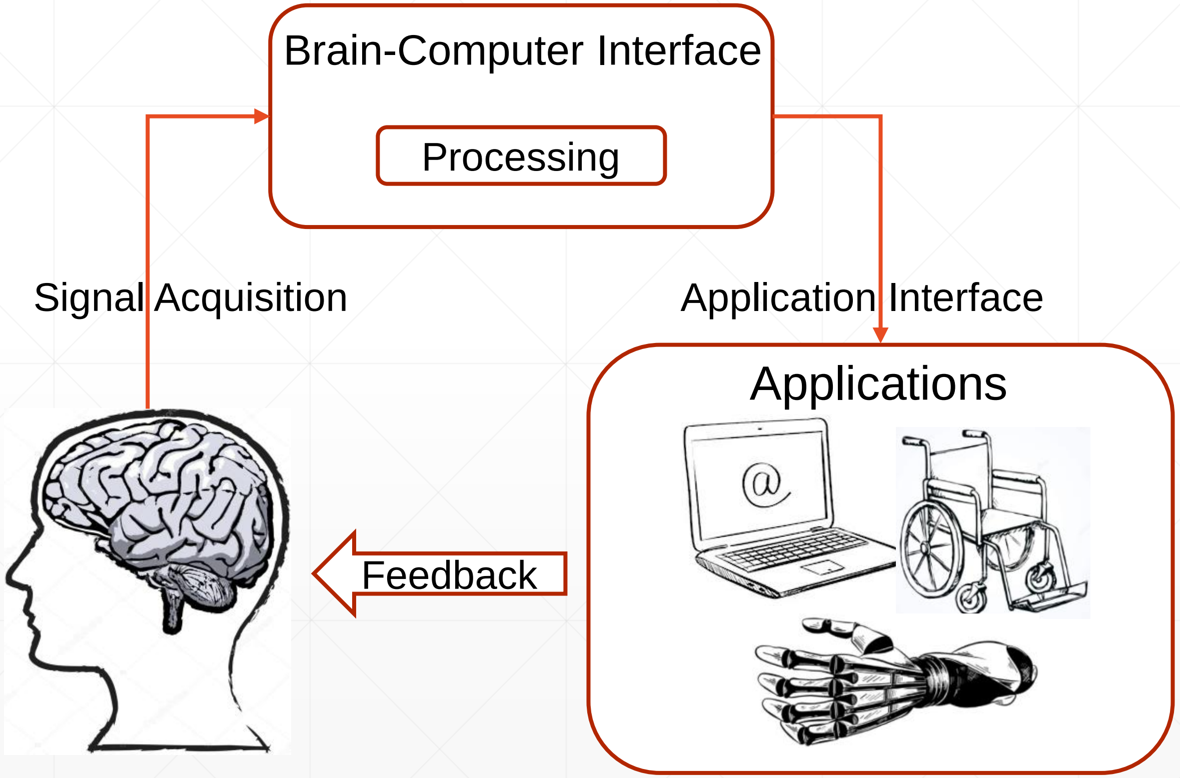
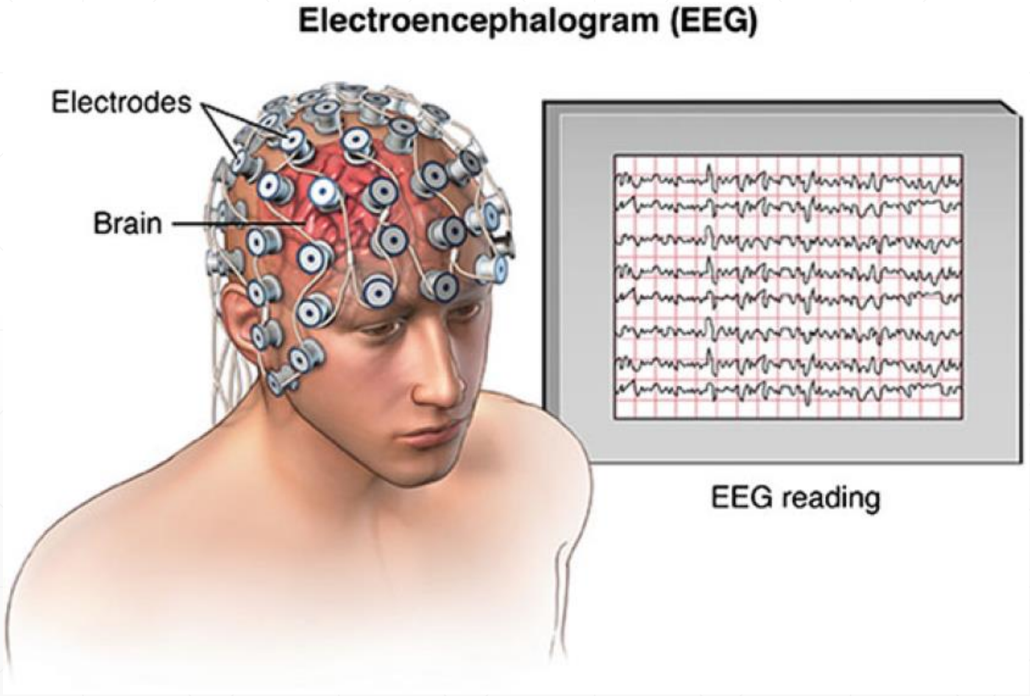
Advisor: Doctor Aurora Saibene

Thesis objective

- To understand if EEG-based real movement can be replaced with EEG-based imaginary movement in order to use Motor Imagery tasks in Brain-Computer Interface systems.

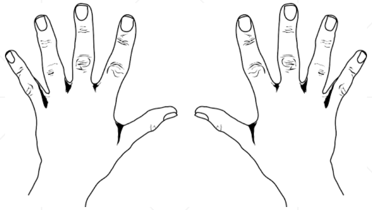




Thesis objective

The brain activations obtained with real movement are very similar to those obtained with imaginary movement

No distinction at classification level



- The project was based on two benchmark Deep Learning models [Schirrmeister et al. (2017)].
  1. Repeatability experiments with the reference dataset
  2. Reproducibility experiments on another dataset
  3. Test of the best model on real and imaginary movements
     A. Input variation from raw to time-frequency representation
     B. Architecture variation

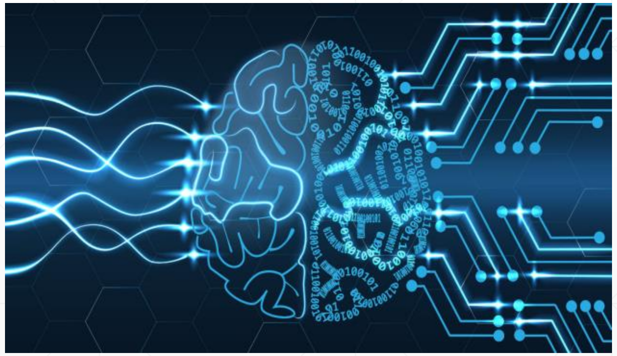
Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., et al. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping, 38(11), 5391–5420.

Current challanges in EEG processing

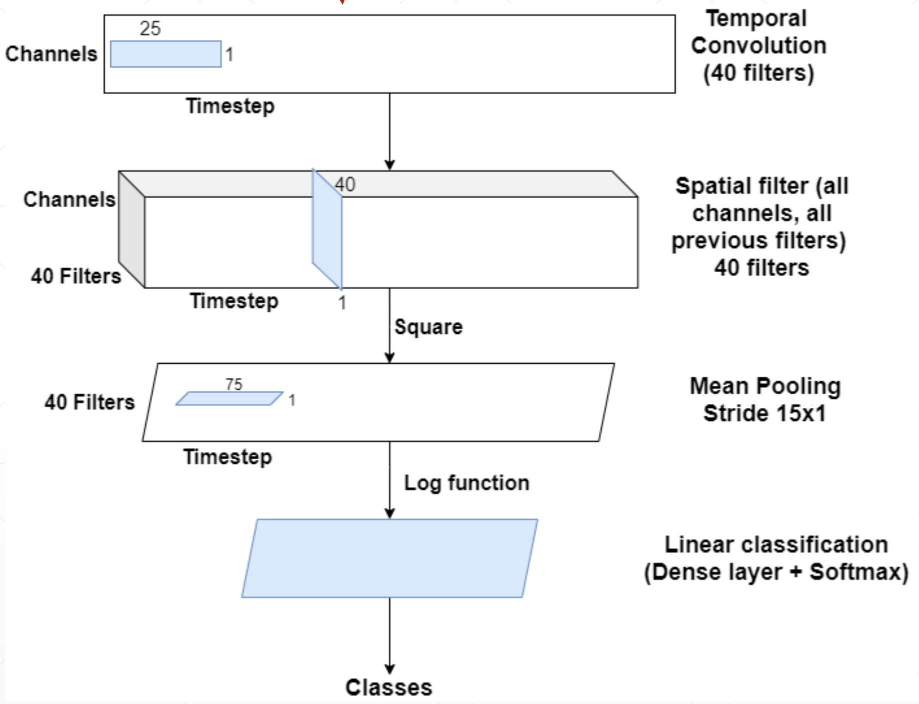
- Low Signal-to-Noise Ratio (SNR)
- EEG is a non-stationary signal
- High intra and inter-subject variability

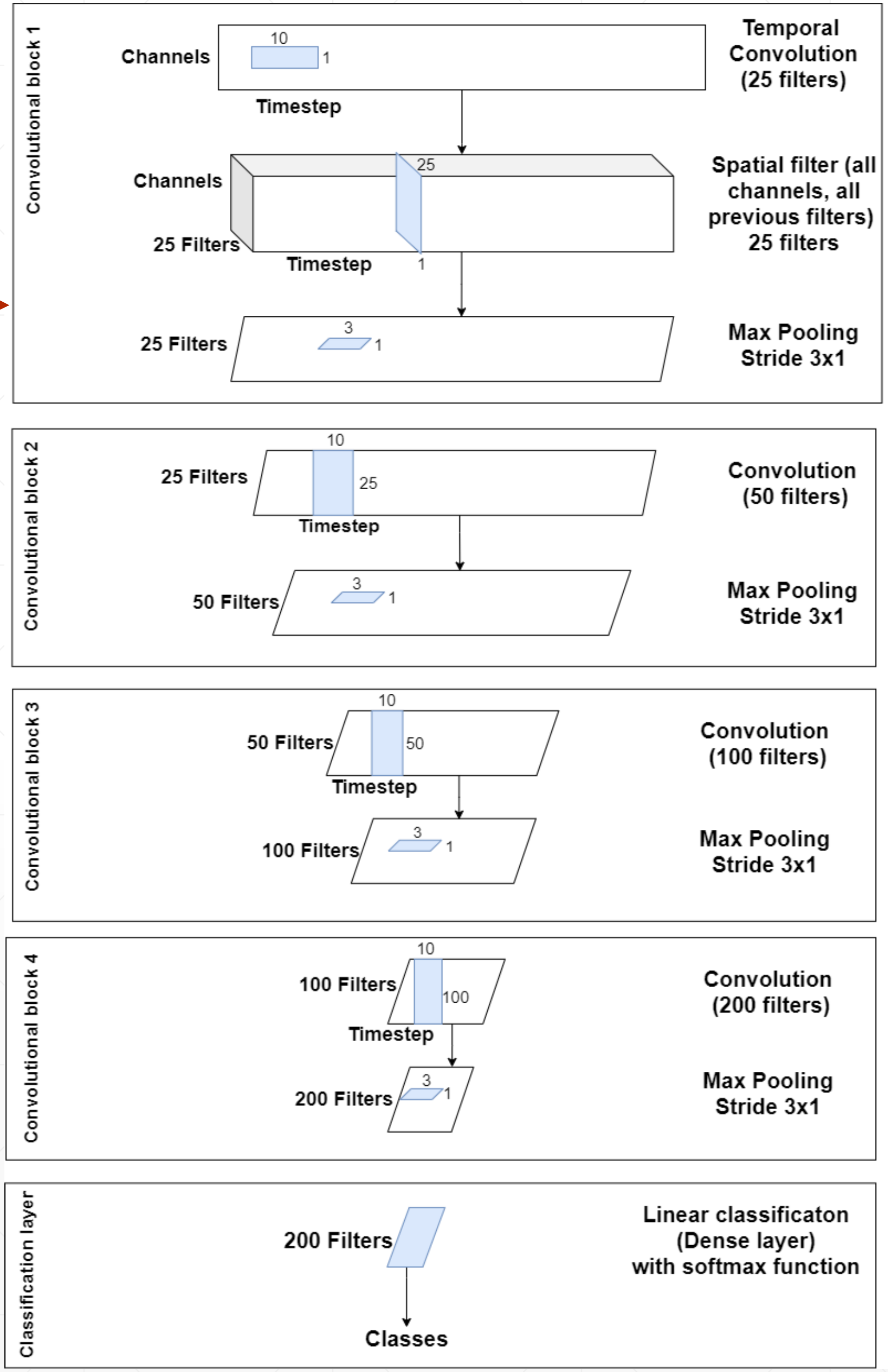
Improving EEG processing with Deep Learning:

- Automatic feature extraction without a domain expert
- More expressive features than hand-crafted ones
- Extraction of both high-level features and latent dependencies



Shallow and Deep ConvNet





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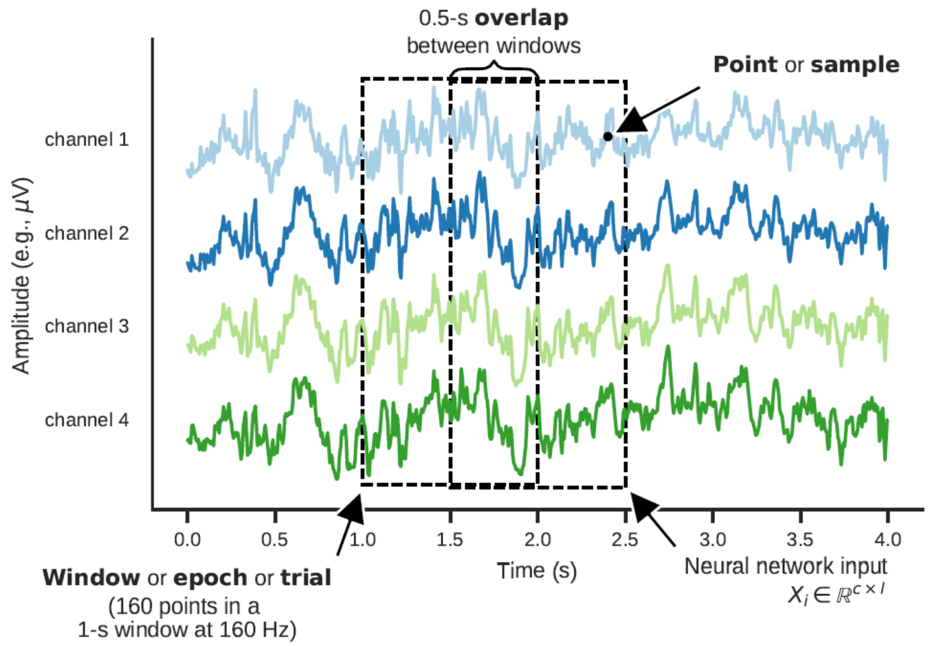
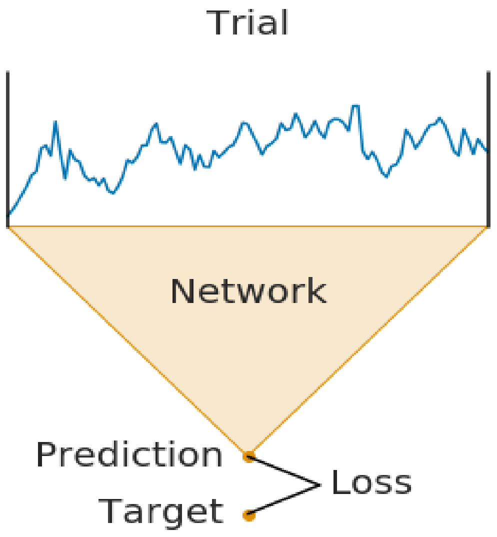
Trialwise and cropped training

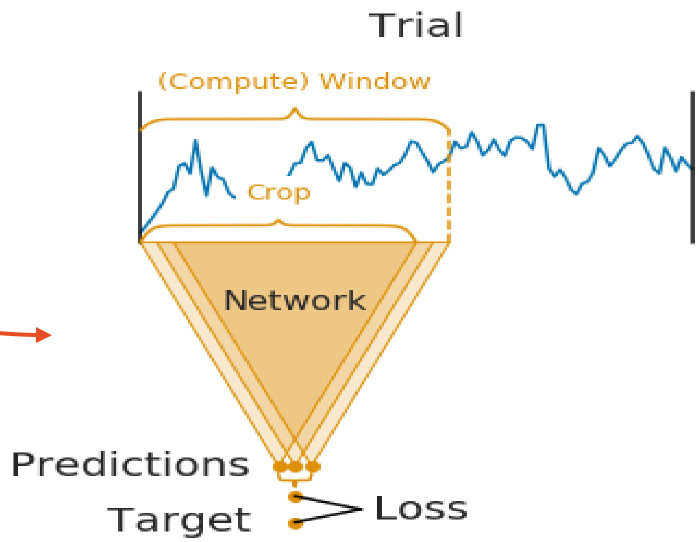


Time series input

Trialwise training



Cropped training



Dataset

Name	# subject	classes	real	imaginary
BCI IV 2a [1]	9	Left/right hand, feet, tongue	✗	✓
BCI IV 2b [2]	9	Left/right hand	✗	✓
PhysioNet [3]	30	Left/right hand	✓	✓

A. Repeatability experiments. Best architecture: Shallow ConvNet

B. Reproducibility experiments. Best training mode: cropped training

C. Core experiments:
- → raw signal with Shallow ConvNet (cropped training)
- → time-frequency images with Shallow ConvNet (trialwise training)
- → time-frequency images with Shallow ConvNet variation (trialwise training)

Core experiments

- Dataset: PhysioNet.
  Classes: real and imaginary movement of left hand and right hand
- Model: Shallow ConvNet with cropped training
- Number of subjects: 30 (45 trials for each type of movement)

Test number	Classes description	# classes
1	Left/right-hand real movement	2
2	Left/right-hand Imaginary movement	2
3	Left/right-hand real and imaginary movement	4
4	Left/right-hand (no distinction between real and imaginary)	2

Core experiments – result with raw signal

- Dataset: PhysioNet.
  Classes: real and imaginary movement of left hand and right hand
- Model: Shallow ConvNet with cropped training
- Number of subjects: 30 (45 trials for each type of movement)

	2 classes	2 classes	4 classes	2 classes
	Left/right Real (test 1)	**Left/right Imaginary (test 2)**	**Left/right Real and imaginary (test 3)**	**Left and right hand (test 4)**
mean	67,9%	66,8%	60%	73%

Core experiments – input variation

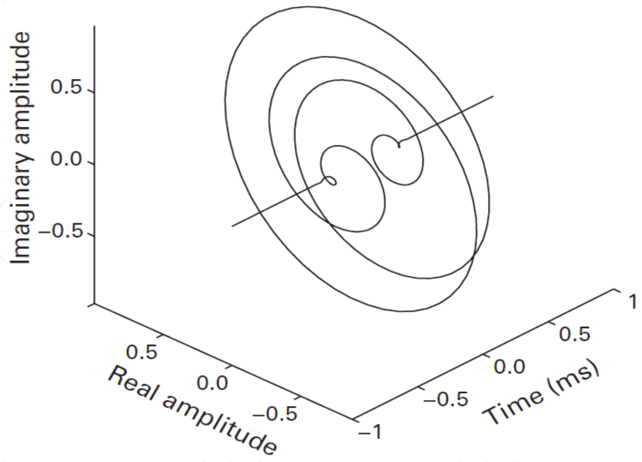
- Generation of time-frequency images for each window extracted from the EEG signal

Complex sine wave= $e^{i\,2\,\pi\,f\,t}$

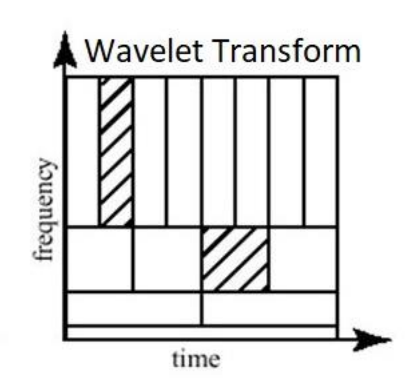
$s = \frac{n}{2\,\pi\,f}$ Time-frequency trade-off

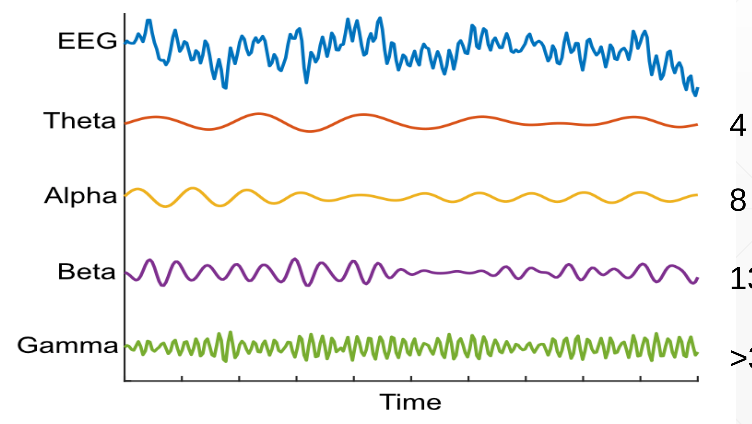
Gaussian $= e^{-t^2/2s^2}$

Complex Morlet wavelet $=$ *Complex sine wave* $\cdot$ *Gaussian*



- Wavelet advantage: allow a multi-scale analysis





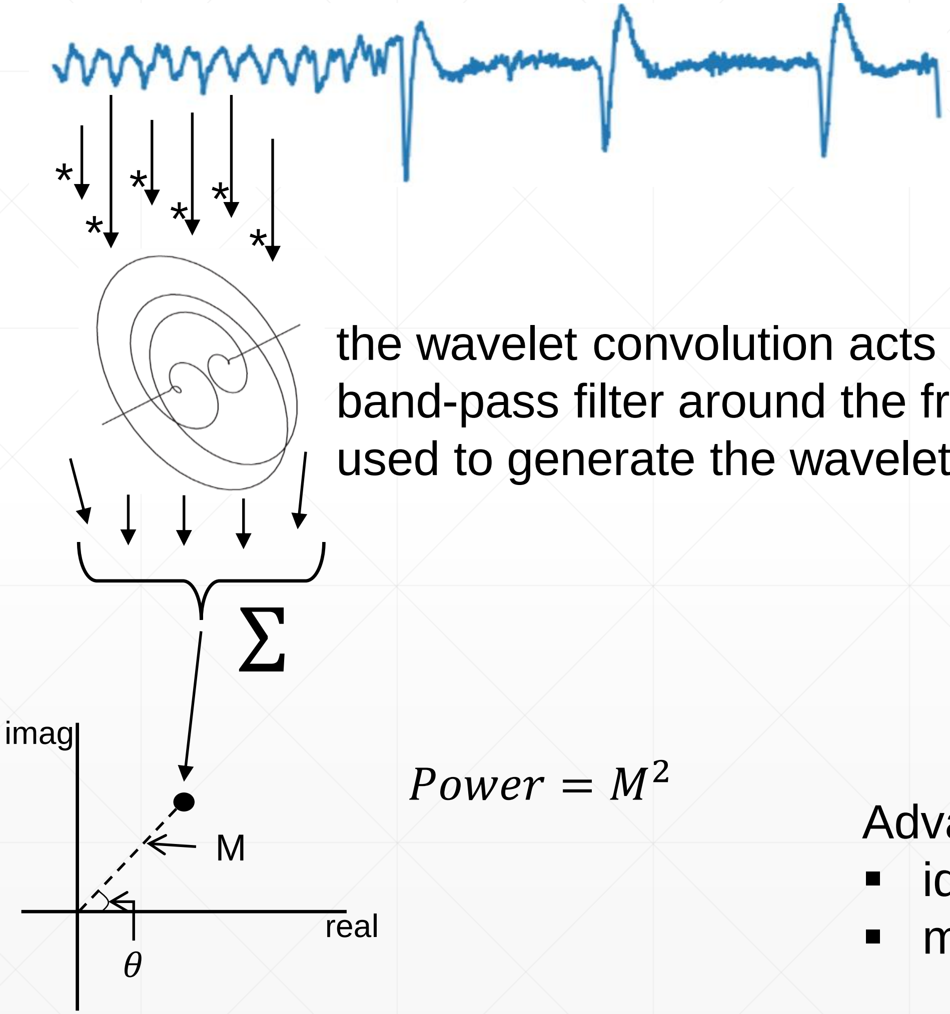
4 – 8 Hz

8 – 13 Hz

13 – 30 Hz

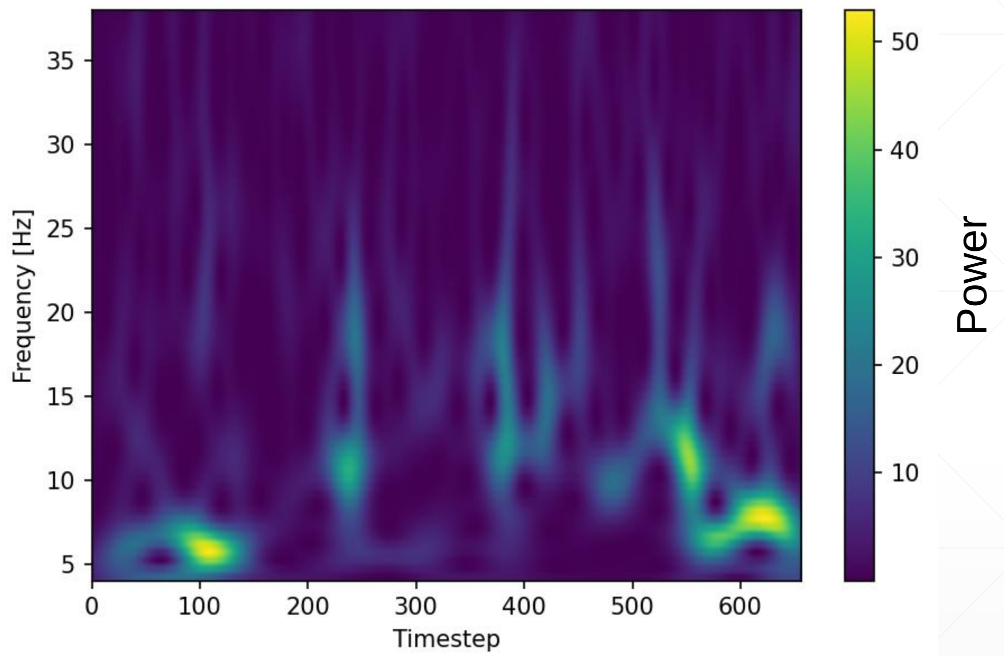
>30 Hz

Core experiments – input variation



the wavelet convolution acts as a band-pass filter around the frequency used to generate the wavelet

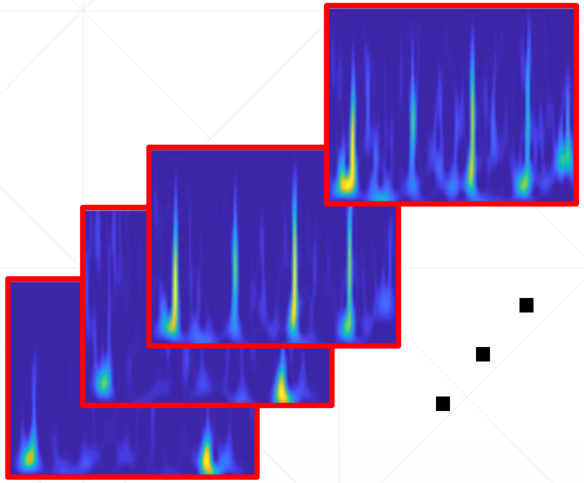
$$Power = M^2$$



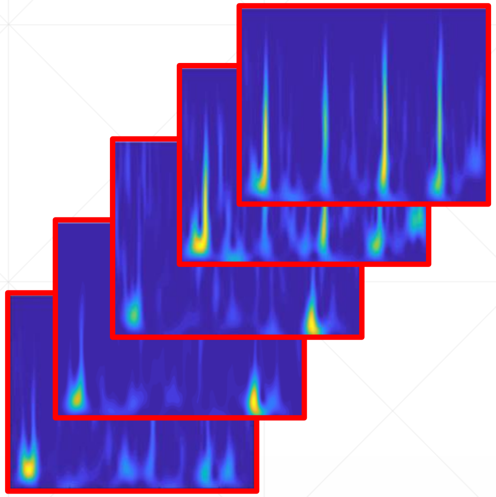
Advantages of time-frequency representation:

- identifies different frequency patterns over time
- mitigates the problem of small dataset size

Core experiments – input variation

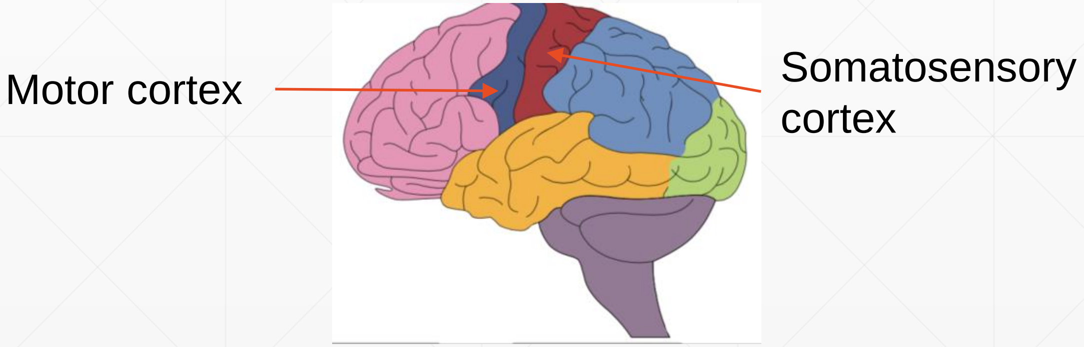


64 time-frequency images
of all channels



5 time-frequency images

Trialwise training with pseudo-3D convolution



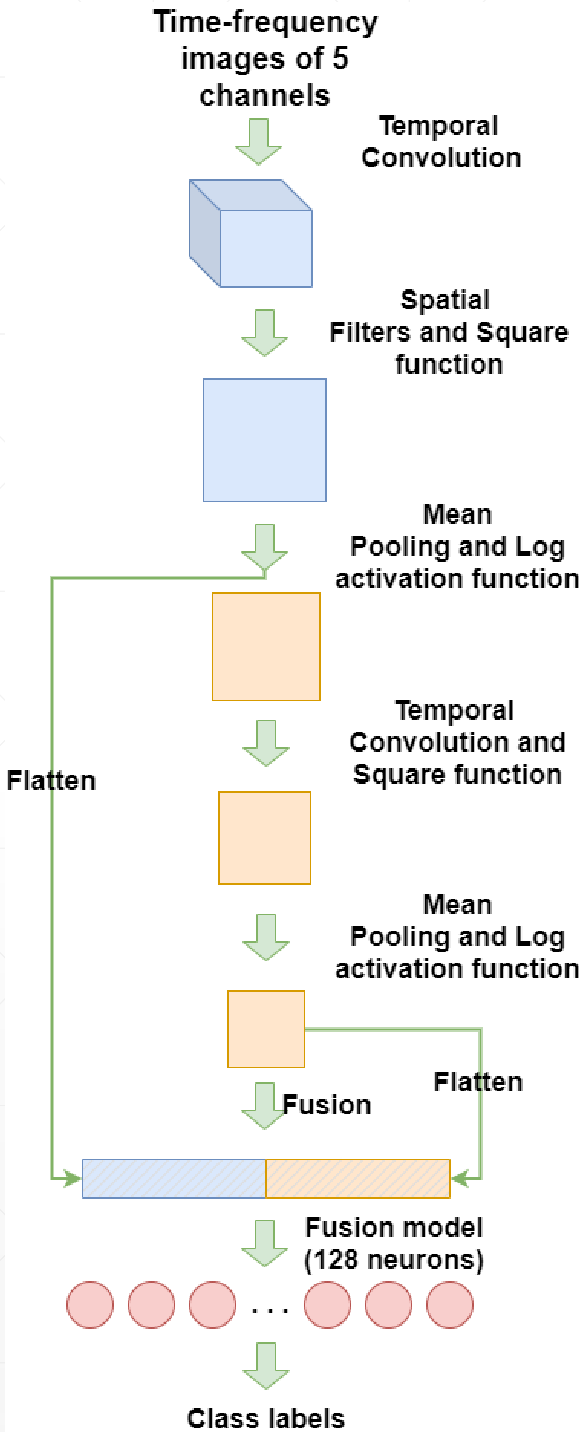
Core experiments – result with time-frequency images

- Dataset: PhysioNet.
  Classes: real and imaginary movement of left hand and right hand
- Model: Shallow ConvNet with trialwise training
- Number of subjects: 30 (45 trials for each type of movement)

	2 classes	2 classes	4 classes	2 classes
	Left/right Real (test 1)	**Left/right Imaginary (test 2)**	**Left/right Real and imaginary (test 3)**	**Left and right hand (test 4)**
Mean raw	67,9%	66,8%	60%	73%
Mean 5 tf images	71%	67%	42%	76%

Core experiments – Multi layer feature fusion

- Verify if good relevant features can be extracted from the various layers to be used later for classification
- Shallow ConvNet variation:
  1. classification layer removal
  2. addition of a second convolutional block
  3. merging the features at the end of the first and second convolutional blocks
  4. classification with a fusion model



Core experiments – result with feature fusion

- Dataset: PhysioNet.
  Classes: real and imaginary movement of left hand and right hand
- Model: Shallow ConvNet with trialwise training
- Number of subjects: 30 (45 trials for each type of movement)

	2 classes	2 classes	4 classes	2 classes
	Left/right Real (test 1)	**Left/right Imaginary (test 2)**	**Left/right Real and imaginary (test 3)**	**Left and right hand (test 4)**
Mean raw	67,9%	66,8%	60%	73%
Mean 5 tf images	71%	67%	42%	76%
Mean feature fusion	66%	64%	38%	72%

Conclusions

- The left/right hand real movement is hardly discernible from the respective imaginary movement
- Time-frequency images identified significant feature from change in EEG rhythms
- Real movement seems to be easier to discriminate than the imaginary one

Future works

- Pre-train the Shallow ConvNet variation and then perform a fine-tuning to train only the fusion model or the deeper layers
- Use a group-based approach
- Divide the tensor of time-frequency images into multiple frames and use a Long Short-Term Memory to extract temporal dependencies between frames

Dataset bibliography

- [1] Clemens Brunner, Robert Leeb, Gernot Muller-Putz, Alois Schlogl, and G Pfurtscheller. Bci competition 2008-graz data set a. Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology, 16:1-6, 2008. URL: http://www.bbci.de/competition/iv/desc_2a.pdf.
- [2] R Leeb, C Brunner, G Muller-Putz, A Schlogl, and G Pfurtscheller. Bci competition 2008-graz data set b. Graz University of Technology, Austria, pages 1-6, 2008. URL: http://www.bbci.de/competition/iv/desc_2b.pdf.
- [3] Eeg motor movement/imagery dataset. URL: https://physionet.org/content/eegmmidb/1.0.0/.