Efficient decoding of code-modulated evoked responses

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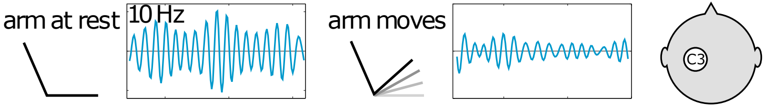
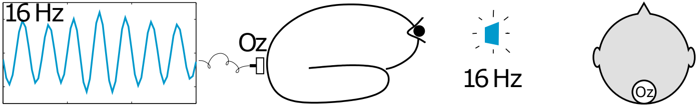
BCI control signals

- **(Spontaneous) oscillations**
  - Not time-locked, internally generated (endogenous)
  - Change in power at a specific frequency, e.g., SMR



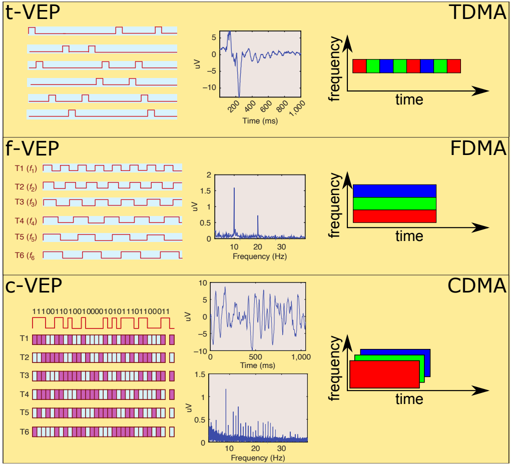
- **Evoked responses**
  - Time-locked to an external event (exogenous)
  - Change in amplitude at a specific latency, e.g., P300



[Blankertz (2014) *BBCI Winter School*]

Evoked responses

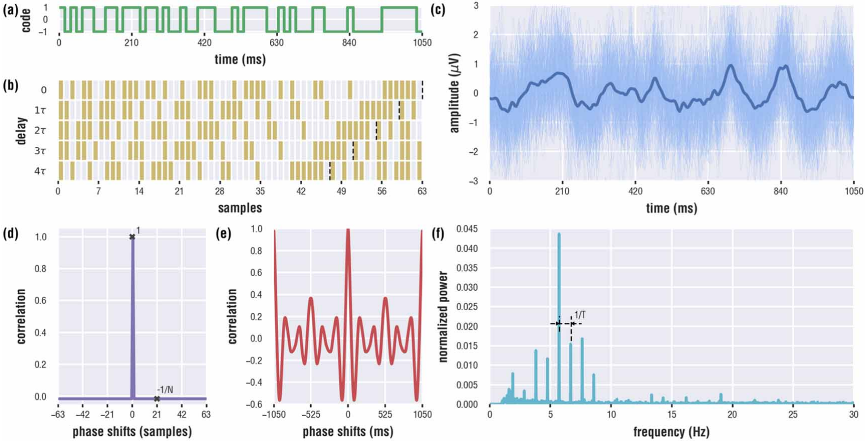
- **Transient responses**
  - Response to a *single* event
  - Protocol: e.g., oddball
  - Examples: P300, ERN, MMN
- **Steady-state responses**
  - Response to *periodic sequence* of events
  - Protocol: frequency-tagging
  - Examples: SSVEP, ASSR, SSSEP
- **Broad-band responses**
  - Response to *pseudo-random sequence* of events
  - Protocol: noise-tagging
  - Examples: c-VEP, c-AEP, c-SEP



[Bin et al. (2009) *IEEE Comput Intell M*] [Gao et al. (2014) *IEEE T Bio-Med Eng*]

Code-modulated visual evoked potential (c-VEP)

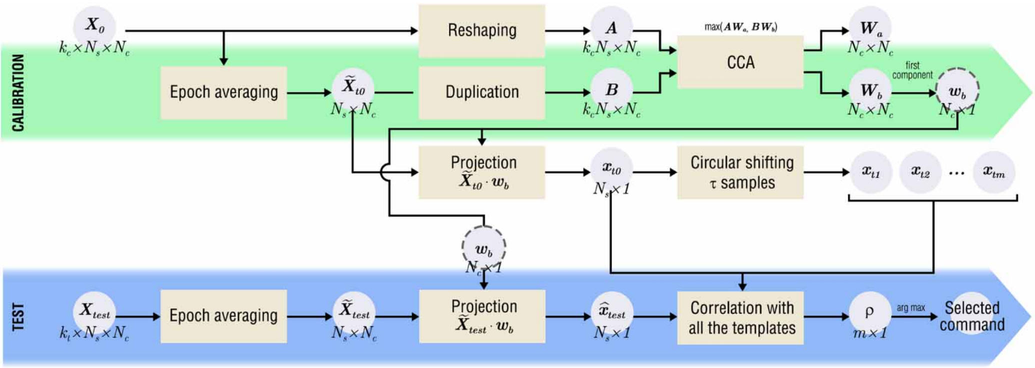
23	24	25	26	27	28	29	30	31	0
31	0	1	2	3	4	5	6	7	8
7	8	9	10	11	12	13	14	15	16
15	16	17	18	19	20	21	22	23	24
23	24	25	26	27	28	29	30	31	0
31	0	1	2	3	4	5	6	7	8



[Spüler et al. (2012) *PLOS ONE*]

[Martinez-Cagigal et al. (2021) *J Neural Eng*]

Reference c-VEP analysis pipeline

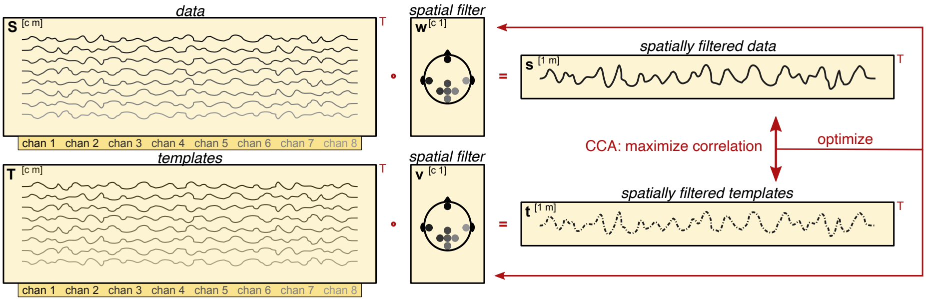


$$\hat{y} = \arg\max_i \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{w}^\top \mathbf{T}_i)$$

[Martinez-Cagigal et al. (2021) *J Neural Eng*]

Canonical correlation analysis (CCA)

1. For each of $i = 1 \dots n$ classes, compute the template $\mathbf{R}_i \in \mathbb{R}^{c \times m}$
2. Stack all epochs/trials: $\mathbf{S} = [\mathbf{X}_0, \dots, \mathbf{X}_k]$
3. Stack all templates: $\mathbf{T} = [\mathbf{R}_{y_0}, \dots, \mathbf{R}_{y_k}]$
4. Apply CCA($\mathbf{S}$, $\mathbf{T}$) to find spatial filters $\mathbf{W} \in \mathbb{R}^{c \times c}$ and $\mathbf{V} \in \mathbb{R}^{c \times c}$



[Hotelling (1936) *Biometrica*] [Spüler et al. (2012) *ESANN*] [Spüler et al. (2013) *IEEE T Neur Sys Reh*]

Downside of the reference analysis pipeline

Requires a large training dataset!

- Depends on averaging epochs/trials to obtain templates
- Even worse when there is no relation between classes (i.e., sequences)

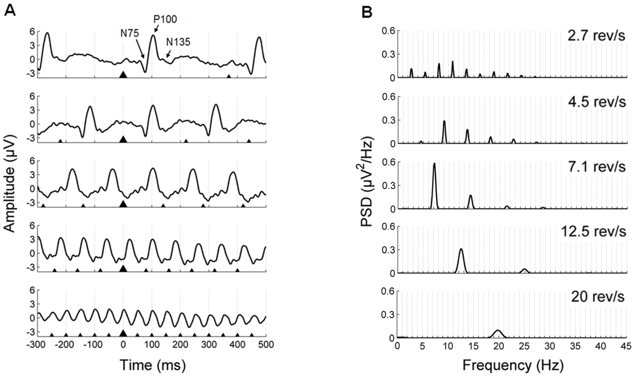
How can one reduce the required amount of data?

- Exploit the repeating structure in the data
- Average events within and across epochs/trials

Linear superposition hypothesis

The response to a sequence of events is the addition of the responses to the individual events.

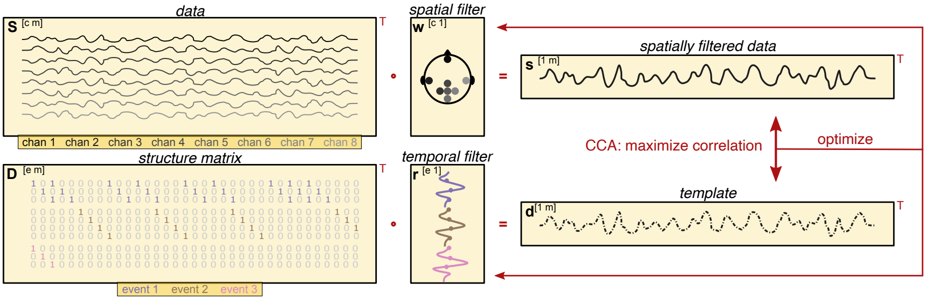
$$x(t) = \sum_i \sum_\tau l_i(t) r_i(t - \tau)$$



[Capilla et al. (2011) *PLOS ONE*]

CCA for spatio-temporal decomposition (reconvolution)

1. Stack all epochs/trials $\mathbf{S} = [\mathbf{X}_0, \ldots, \mathbf{X}_k]$
2. Stack all design matrices $\mathbf{D} = [\mathbf{M}_{y_0}, \ldots, \mathbf{M}_{y_k}]$
3. Apply CCA($\mathbf{S}$, $\mathbf{D}$) to find spatial filters $\mathbf{W} \in \mathbb{R}^{c \times z}$ and temporal filters $\mathbf{R} \in \mathbb{R}^{e \times z}$



[Thielen et al. (2015) *PLOS ONE*] [Thielen et al. (2021) *J Neural Eng*]

From supervised to semi-supervised with reconvolution

Supervised (calibration):

$$\max_{\mathbf{w},\mathbf{r}} \rho(\mathbf{w}^\top \mathbf{S}, \mathbf{r}^\top \mathbf{D}_i)$$

$$\hat{y} = \arg\max_i \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{r}^\top \mathbf{M}_i)$$

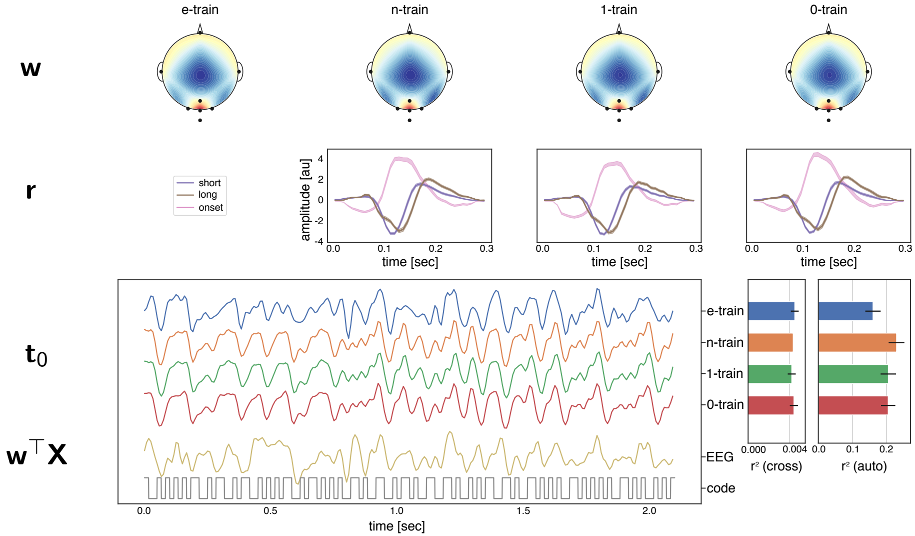
Semi-supervised (calibration-free):

$$\max_{\mathbf{w}_i,\mathbf{r}_i} \rho(\mathbf{w}_i{}^\top \mathbf{X}, \mathbf{r}_i{}^\top \mathbf{M}_i)$$

$$\hat{y} = \arg\max_i \rho(\mathbf{w}_i{}^\top \mathbf{X}, \mathbf{r}_i{}^\top \mathbf{M}_i)$$

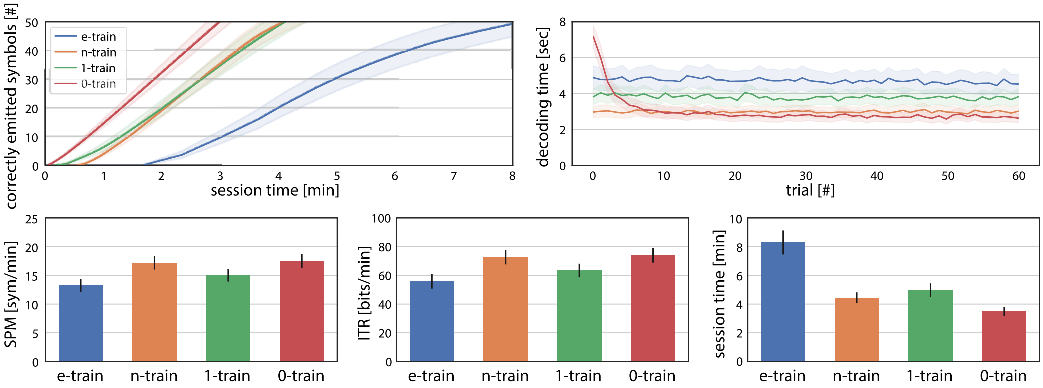
[Thielen et al. (2015) *PLOS ONE*] [Thielen et al. (2021) *J Neural Eng*]

Reconvolution finds a similar model using limited data



[Thielen et al. (2021) *J Neural Eng*]

Reconvolution achieves state-of-the-art performance with limited data



[Thielen et al. (2021) *J Neural Eng*]

Conclusion

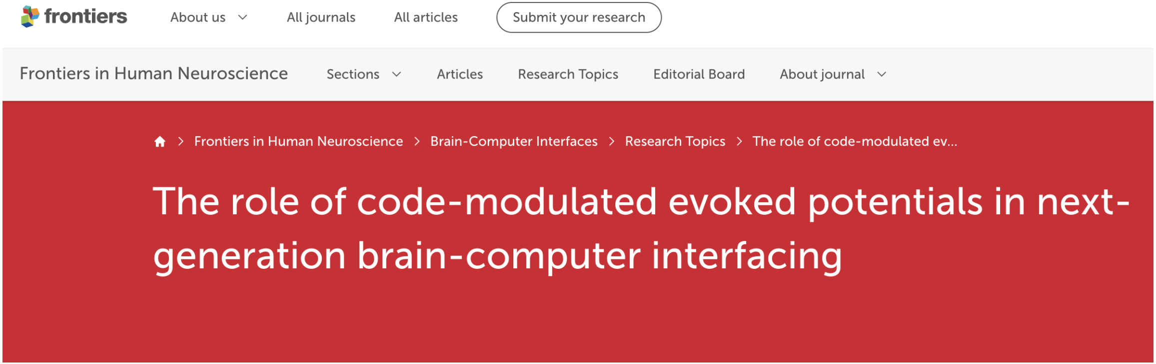
Exploiting **structure in neural data**

- Forward model assuming linear superposition hypothesis
  - Limits number of model parameters
  - Increases number of repetitions per parameter
- Limits as well as eliminates the need for training data
  - Achieves high explained variance and decoding performance
  - Generalizes to unseen data/sequences

Reconvolution CCA (rCCA)

- Tutorial at the end of the workshop
- `https://neurotechlab.socsci.ru.nl/resources/cvep/`
- Python Noise-Tagging (pynt) library compatible with the scikit-learn API
- Matlab Noise-Tagging (mant) library

Frontiers Research Topic accepting contributions



`https://www.frontiersin.org/research-topics/50998/`

`the-role-of-code-modulated-evoked-potentials-in-next-generation-brain-computer-interfacing`

Acknowledgements

Data-Driven Neurotechnology Lab (`https://neurotechlab.socsci.ru.nl/`)

- Michael Tangermann
- Sara Ahmadi

BCI lab

- Peter Desain
- Jason Farquhar
- Pieter Marsman
- Philip van den Broek

Primer on posters:

- 1-F-57: A model-based dynamic stopping method for c-VEP BCI (*Ahmadi*)
- 3-C-22: A comparison of stimulus sequences for c-VEP BCI (*Thielen*)