CALIBRATION-FREE c-VEP BCI

Confidence-weighted cumulative rCCA with post hoc re-analysis: Unsupervised adaptive learning for calibration-free c-VEP BCI

Jordy Thielen

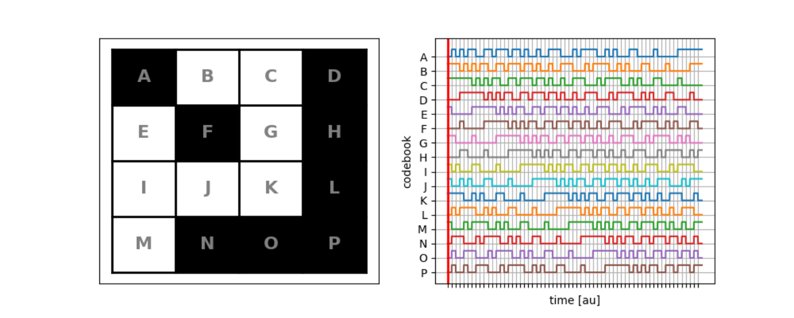
jordy.thielen@donders.ru.nl

Machine Learning & Neural Computing — Donders Institute — Radboud University, Nijmegen, Netherlands

Graz Brain–Computer Interface Conference 2026

BCI based on the code-modulated visual evoked potential (c-VEP)

c-VEP: the EEG response to visual stimulation with *pseudo-random* stimulation.



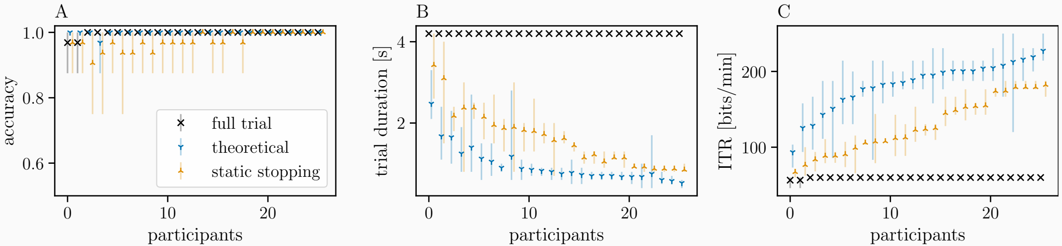
Today, world's fastest non-invasive BCI for **communication and control**
Also core method in **sensory diagnostics**, e.g., audiometry

Martinez-Cagigal et al. (2021) *J Neural Eng* doi: 10.1088/1741-2552/ac38cf

Guyonnet-Hencke et al. (2025) *Int J Audiol* doi: 10.1080/14992027.2025.2478523 — https://www.mindaffect.nl

No BCI inefficiency in VEP-based BCI?

"BCI control fails for approximately 15–30% of users"



A c-VEP BCI works for **all users**, but they obtain varying degrees of speed

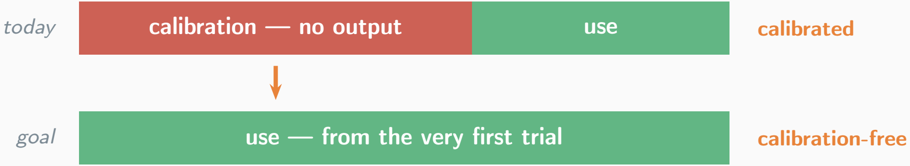
Blankertz et al. (2010) *NeuroImage* doi: 10.1016/j.neuroimage.2010.03.022

Thielen (2025) *Biomed Phys Eng Express* doi: 10.1088/2057-1976/ade316

Volosyak et al. (2020) *Biomed Phys Eng Express* doi: 10.1088/2057-1976/ab87e6

The problem: long calibration

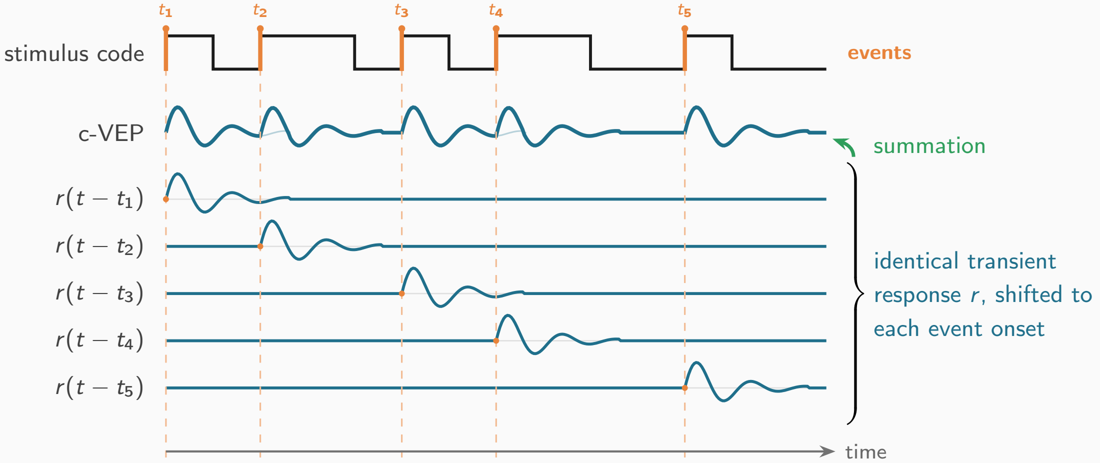
Before spelling a single letter, every user sits through a tedious calibration session.



Calibration hinders real-world, plug-and-play use. Can we remove it entirely?

Tangermann et al. (2021) J Neural Eng doi: 10.1088/1741-2552/addf80

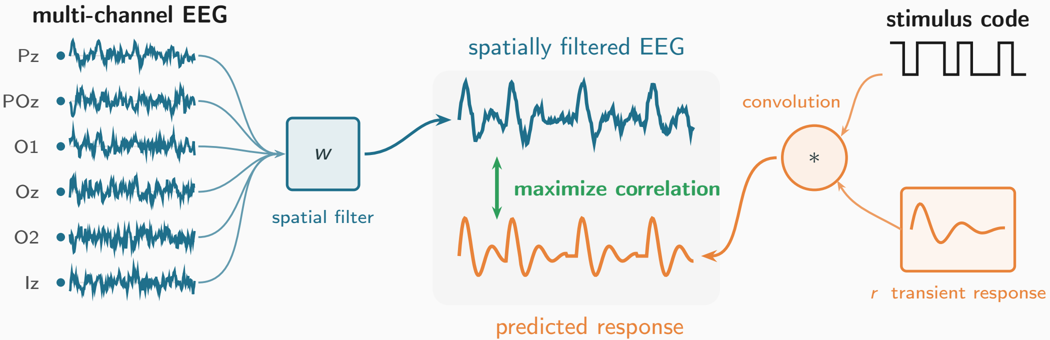
Step 1 — Reconvolution: c-VEP as a linear superposition of flash responses



Capilla et al. (2011) *PLOS One* doi: 10.1371/journal.pone.0014543

Thielen et al. (2015) *PLOS One* doi: 10.1371/journal.pone.0133797

Step 2 — Jointly learn a transient response and spatial filter



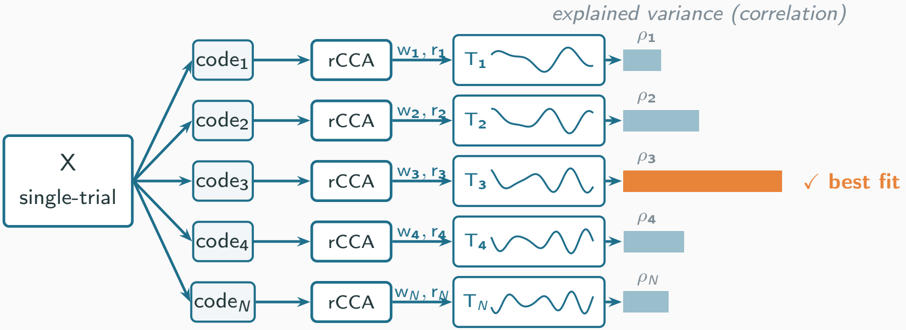
This yields **reconvolution canonical correlation analysis (rCCA)**.

Thielen et al. (2021) ***J Neural Eng*** **doi: 10.1088/1741-2552/abecef**

pyntbci.classifiers.rCCA `https://pypi.org/project/pyntbci/`

Step 3 – Unsupervised classification

No labels? Try *every* candidate code and select the model that best explains the data.



This yields ***unsupervised* reconvolution canonical correlation analysis (rCCA)**.

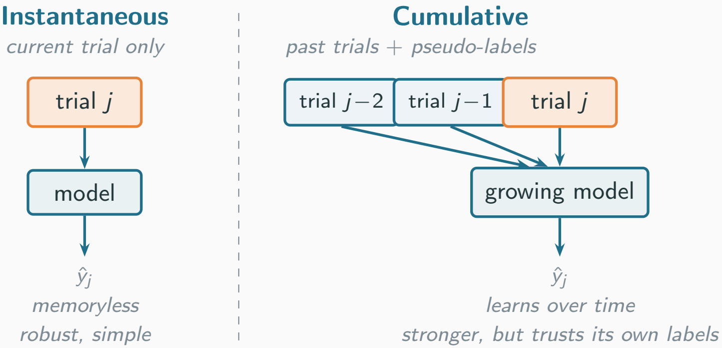
Thielen et al. (2021) *J Neural Eng* doi: 10.1088/1741-2552/abecef

pyntbci.classifiers.UnsupervisedRCCA `https://pypi.org/project/pyntbci/`

Step 4 – Learning from the past

Rather than decoding every trial from scratch, learn from the past.

Use the predicted labels as **pseudo-labels**.



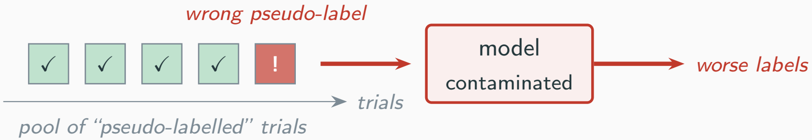
Thielen et al. (2021) *J Neural Eng* doi: 10.1088/1741-2552/abecef

Thielen et al. (2024) *GBCIC* doi: 10.3217/978-3-99161-014-4-057

Thielen & Tangermann (2025) *IEEE SMC* doi: 10.1109/SMC58881.2025.11342596

The problem of learning using pseudo-labels

Learning from your own predictions assumes those predictions are correct.

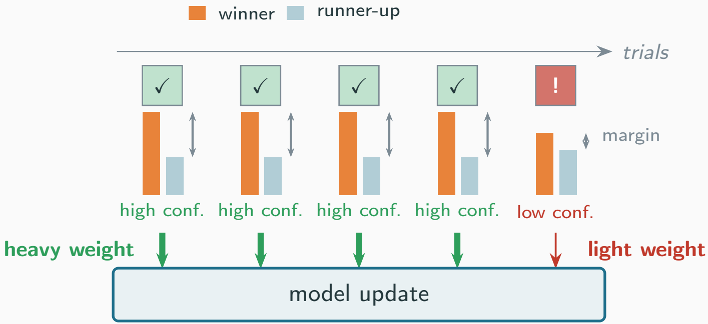


Wrongly predicted labels can snowball. Two remedies:

- Confidence-weighted updates
- Post hoc re-analysis

Idea 1 — Confidence weighting

Let each trial influence the model in proportion to how confident the decoder was.



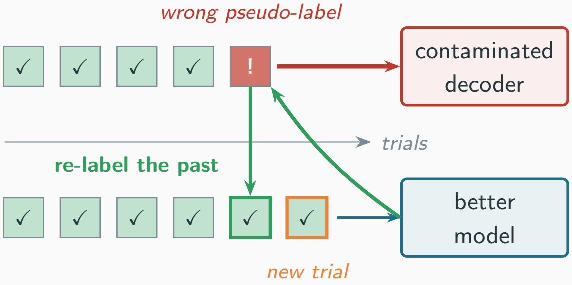
Confidence as normalised correlation margin: $c = \dfrac{\rho_w - \rho_r}{\sigma}$ (winner vs. runner-up).

Sosulski & Tangermann (2021) *arXiv* doi: 10.48550/arXiv.2306.11830

Thielen (2026) *GBCIC*

Idea 2 — Post hoc re-analysis

A later, better model reconsiders all previous trials and relabels them.



Fixing earlier mistakes makes every *later* update rest on cleaner labels.

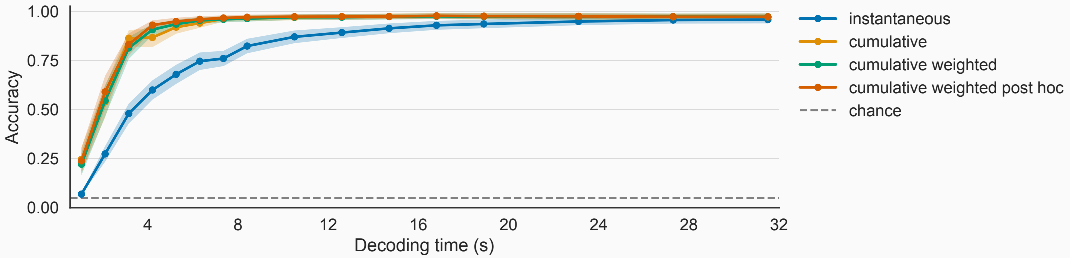
Kindermans et al. (2014) *PLOS One* doi: 10.1371/journal.pone.0102504

Hübner et al. (2017) *PLOS One* doi: 10.1371/journal.pone.0175856

Thielen (2026) *GBCIC*

Preliminary results: Decoding curve

Instantaneous << Cumulative <= Weighted <= Weighted post hoc



Open-access c-VEP dataset (**Thielen et al. (2021)** ***J Neural Eng*** **doi: 10.1088/1741-2552/abecef**)

30 participants | 8 water-based electrodes | 4 × 5 speller | 20 modulated Gold codes | hundred 31.5-second trials

Summary: Calibration-free adaptive BCI

Calibration-free
instantaneous
cumulative

No training session: Try every hypothesis, learn across trials.

Confidence
weighting

Downweigh trials of low confidence.

Post hoc
re-analysis

Correct earlier mistakes with later model.

Unsupervised adaptive learning for calibration-free BCI

→ For **c-VEP** and **ERP** (Thielen & Tangermann (2025) *IEEE SMC* doi: 10.1109/SMC58881.2025.11342596)

→ Evaluation on a multitude of **datasets**, e.g., MOABB

→ Combination with **dynamic stopping** (Thielen et al. (2021) *J Neural Eng* doi: 10.1088/1741-2552/abecef)

→ Pending **online** evaluation, e.g., with Dareplane (Dold et al. (2025) doi: 10.1088/1741-2552/adbb20)