A continuous control paradigm for Motor Brain-Computer Interfaces

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Motivation

- Standard Motor Imagery BCIs rely on **highly controlled, artificial paradigms**.
- These lack **goal-directed behavior**, timing, and realistic interaction.
- These evaluations **neglect transferability** as a part of evaluation.
- **We propose:** a continuous, goal-driven BCI paradigm with realistic control demands.
- Simultaneous **EEG + EMG** provides precise ground truth (onset, duration, intensity).
- A two-part paradigm allows us to test **transfer from calibration to control**.
- Using **EMG to steer** the car allows for **offline analysis** without depending on an a-priori model.

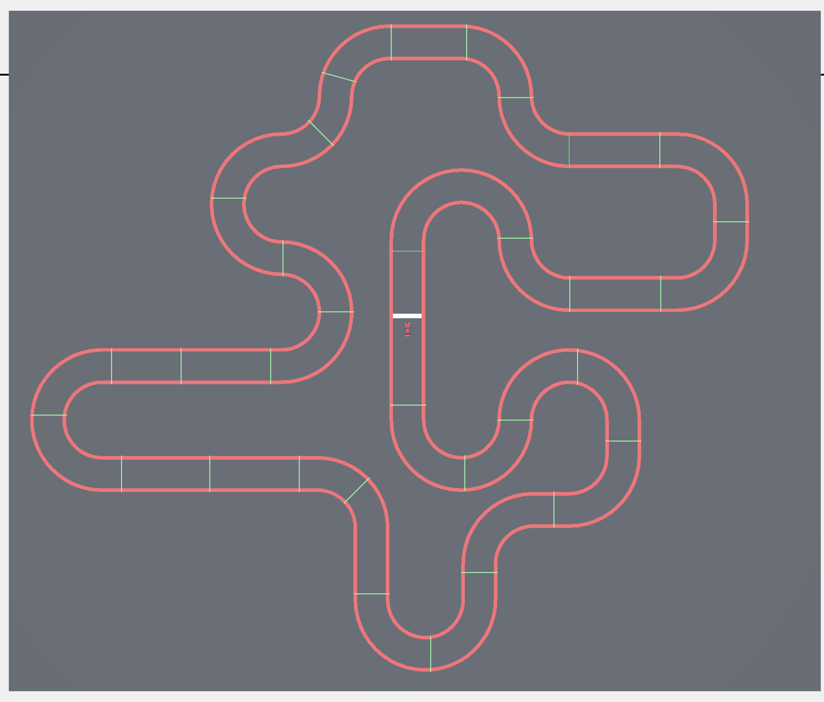
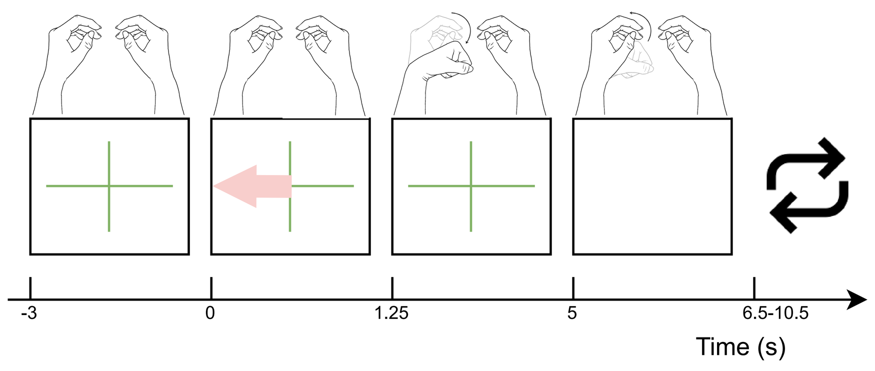
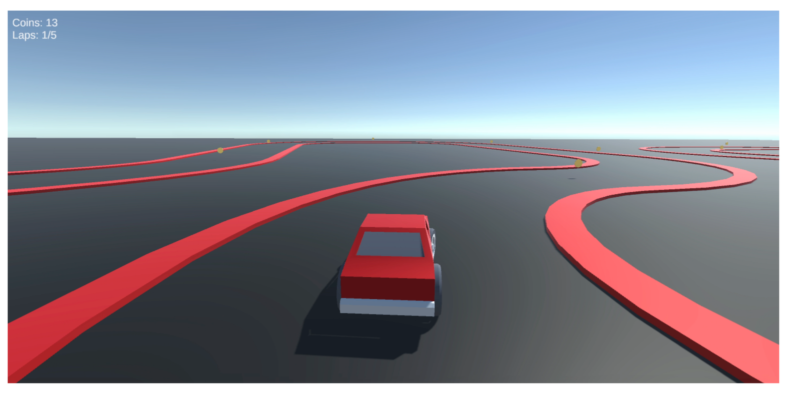


Figure 1. **Target:** to steer a car around this track with EEG.

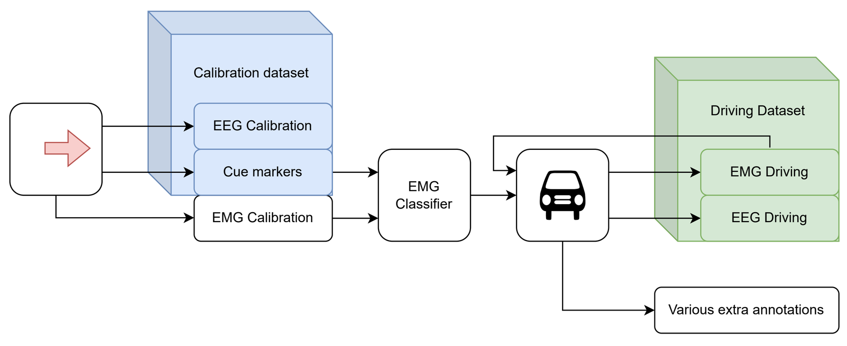
Experimental Paradigm



Step 1. Calibration with time-locked motor imagery.



Step 2. Continuous driving task with EMG recordings.

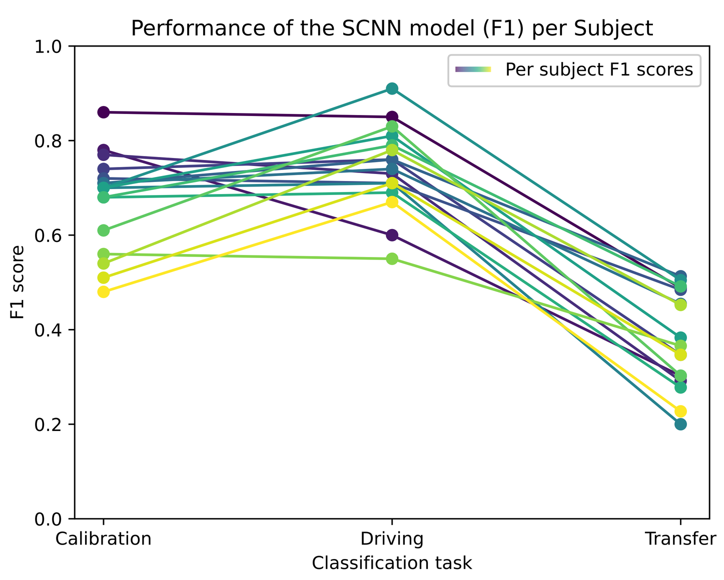


Step 3. EEG + EMG acquisition and offline decoding pipeline.

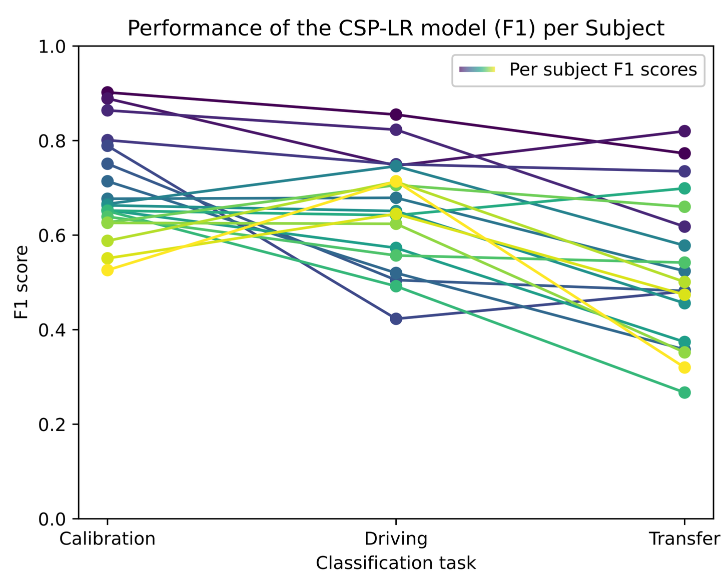
Key Takeaways

- **Context matters:** calibration does not reflect real usage.
- **Deep Learning overfits** to experimental conditions.
- **Simpler models** can generalize better.
- Continuous decoding raises challenges.

Transfer: Calibration → Real Control



(a) ShallowConvNet
High performance in isolation, but poor transfer.



(b) CSP + LR
Lower peak accuracy, but robust transfer.

Figure 2. Model performance across calibration, driving, and transfer. **Deep models overfit context**, while simpler methods generalize better.

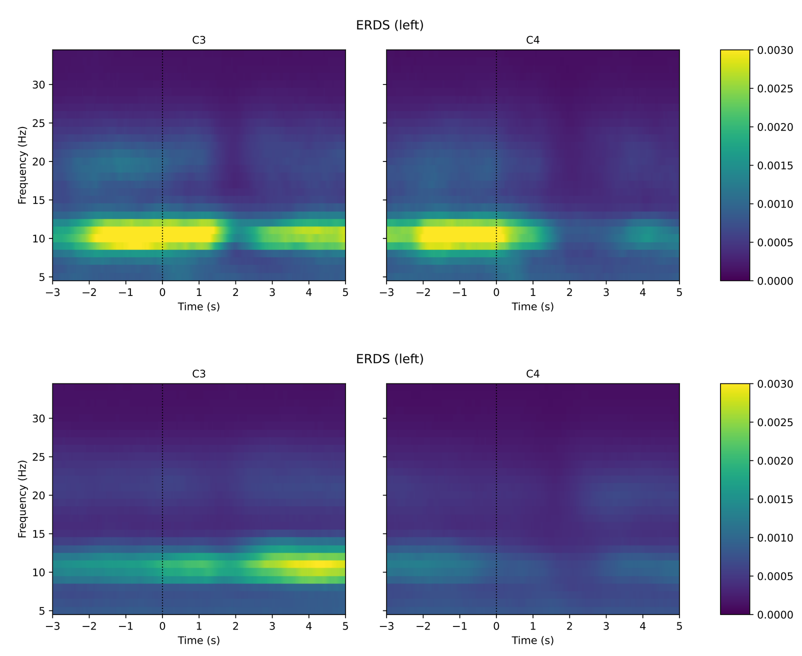


Figure 3. **Sensorimotor rhythms shift** between calibration and driving, explaining transfer failure. Traditional **Machine Learning is robust** to this, but Deep Learning overfits.

Open Questions

- Will foundation Deep Learning models transfer better?
- What is the neurophysiology in continuous movement?
- How can we best predict continuous movement? Predict change, or current state? Synchronous or asynchronous?

References

IP de Jong, LL van den Wittenboer, et al. (2024). Transferring BCI models from calibration to control: Observing shifts in EEG features, *9th GBCIC*. `https://doi.org/10.3217/978-3-99161-014-4-028`

Ongoing work: Continuous Prediction is Hard

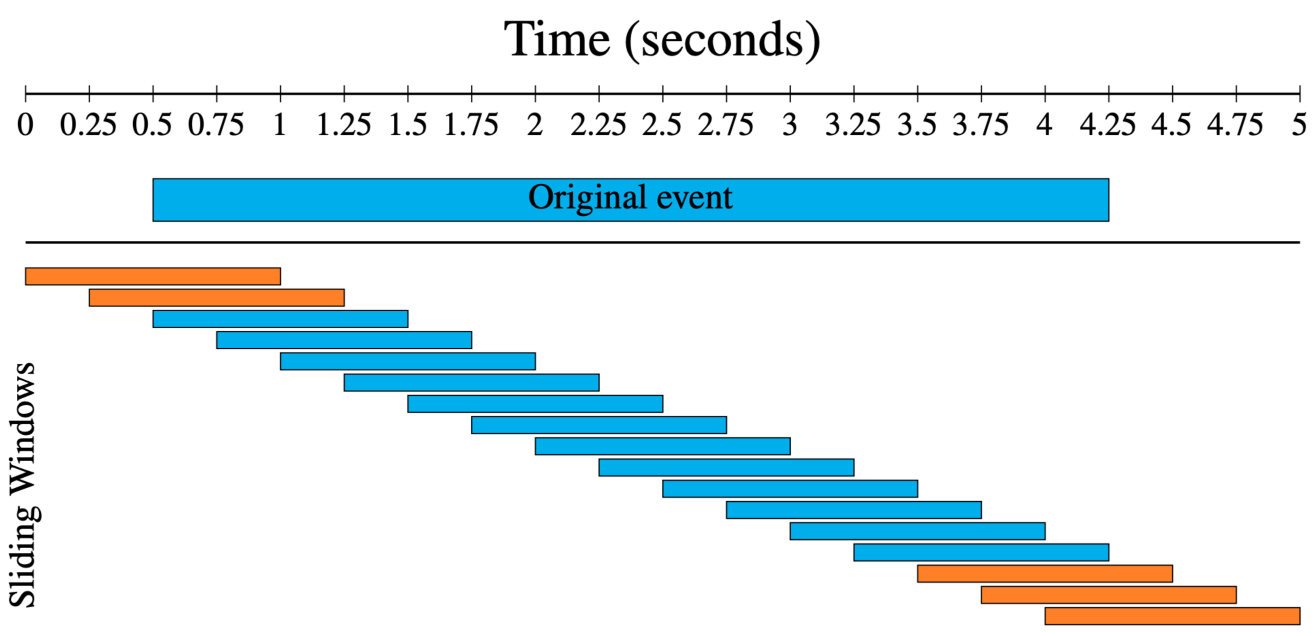


Figure 4. Sliding-window decoding: predictions every 200ms using 1s of EEG. Partial overlap is disregarded.

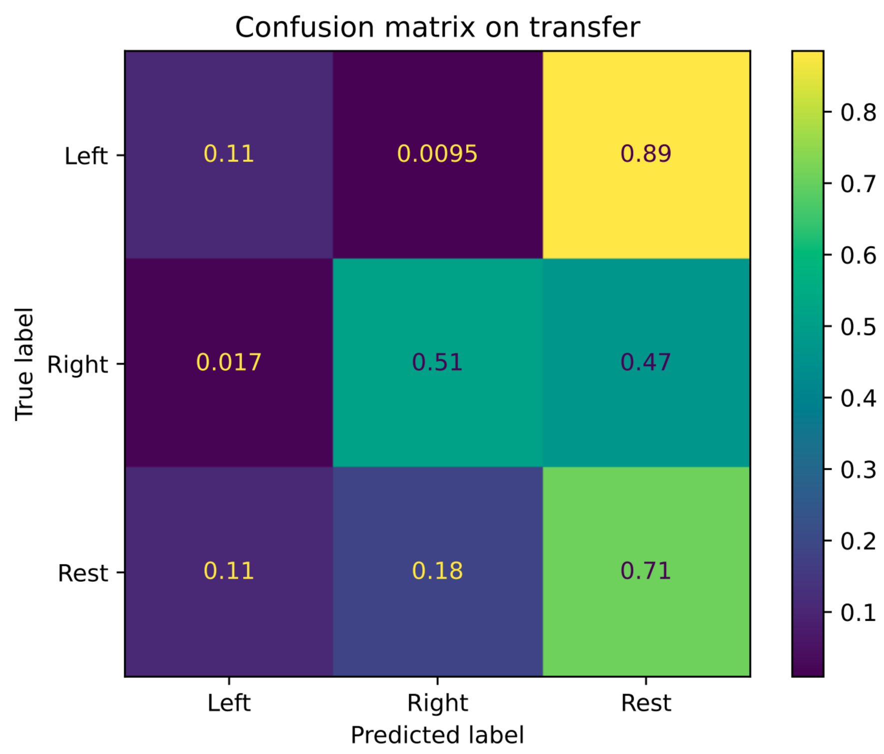


Figure 5. Rest vs movement becomes ambiguous; left/right is separable.

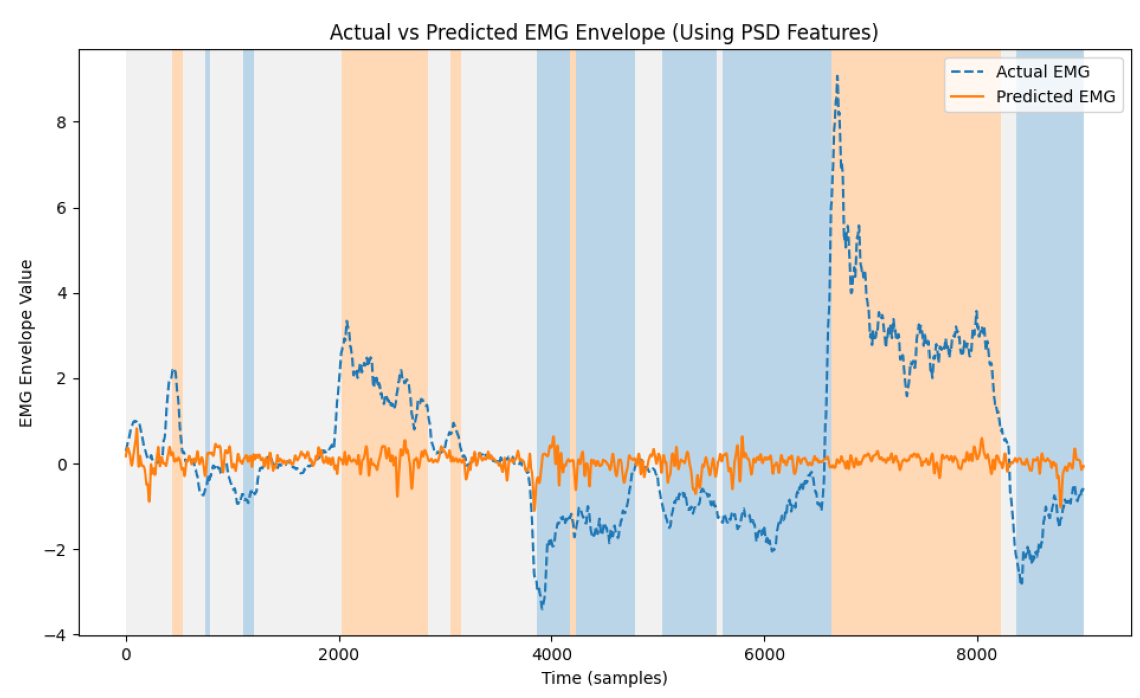


Figure 6. Direct EMG prediction from EEG remains challenging. Which neural correlates exist?

Research on Motor BCIs uses time-locked paradigms. Models, neural correlates, and analysis are needed before we can build BCIs with continuous control.