Decoding Melodic Acoustic Features from Neural Data

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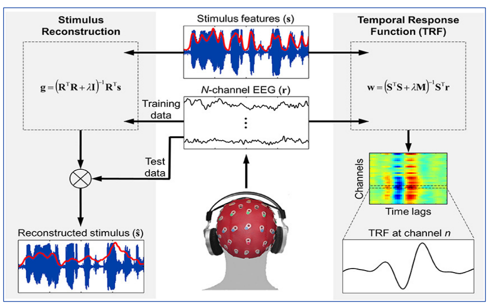
Introduction

- Understanding how **music** transforms into **neural signals** may benefit assistive technologies and neurological rehabilitation (Moses et al., 2021).
- Decoding of neural data may also open new applications in **audio engineering** (Williams, 2020).
- This late-breaking paper investigates how auditory stimuli relate to brain activity by decoding **acoustic features** of music from **EEG** using **machine learning**.

Methods

- **Dataset.** EEG (64 ch) from 10 non-musicians and 10 pianists listening to 10 melodies with 3 repeats thus 30 trials per participant (Galeano-Otálvaro et al., 2024).
- **Preprocessing.** EEG filtered into delta, theta, alpha, beta bands; melody **envelopes** and **onsets** extracted.

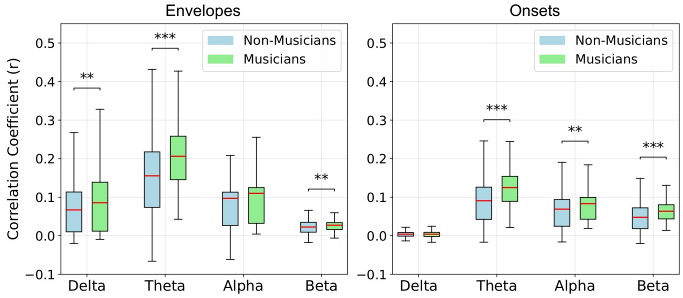


(Crosse et al., 2016)

- **Decoding.** The temporal response function (TRF) is a linear model mapping neural responses to stimulus features, and vice versa, via convolution (Brodbeck et al., 2023). **TRF models** (per participant, per feature, per band) mapped EEG to musical features using eelbrain (300 ms window). Accuracy was evaluated using Pearson's r between predicted and true features.

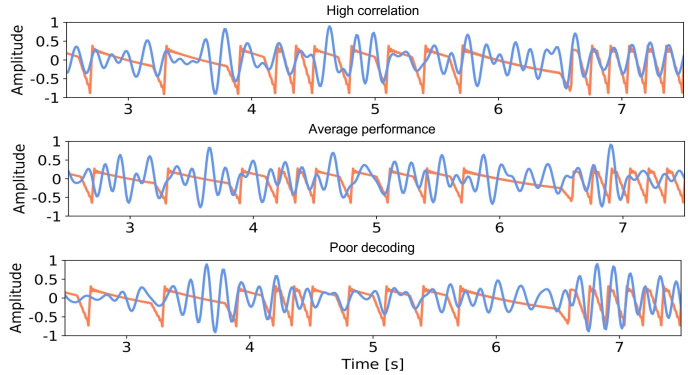
Results

1. Decoding performance across EEG frequency bands:



Correlation coefficients were **significantly higher for musicians than non-musicians**, with the **theta band** (4–8 Hz) yielding **best decoding** overall. Envelope decoding generally outperformed onsets decoding.

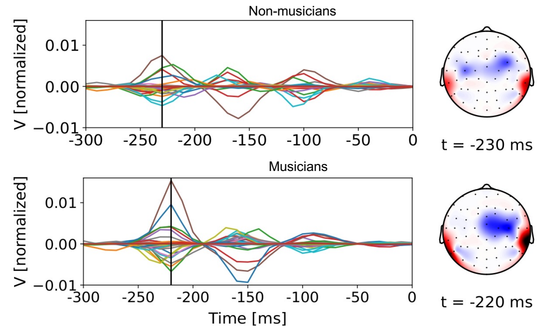
2. Three representative examples of decoded (blue) vs. true (orange) envelopes in the theta band:



Musician (top) shows **closer alignment** in shape and timing between decoded and true envelope, particularly toward the end. In contrast, **non-musicians** (middle and bottom) show **reduced synchrony**.

3. Mean filters learned to decode musical envelopes from theta-band:

Butterfly plots show the filter for each EEG channel (left). Topographic maps at peak latencies show spatial distribution of voltage field strength (right).



Musicians had stronger filter amplitudes and **stronger voltage field**, particularly over **right-lateralized channels**. This aligns with prior findings on hemispheric lateralization for musicians (Koelsch et al., 2002).

Conclusion

Musical expertise enables **more accurate decoding** of musical features from EEG. Performance was **highest** in the **theta band**. Our findings suggest that **musical training** yields **measurable differences** in brain responses to music, offering valuable insights for future neural audio engineering interfaces.

References

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Paper