Deep Neural Network for Real-Time EEG Decoding of Musical Rhythm Imagery

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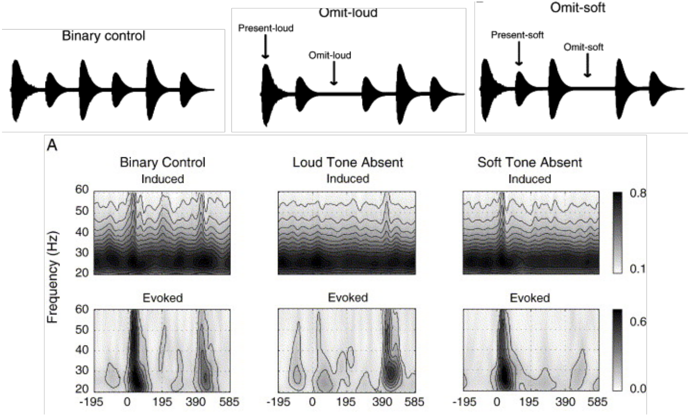
Pulse and Meter as Neural Resonance

- Pulse: (aka beat) the repeating, periodic *pulsation* that we *perceive* through time when we listen to music
  - Tempo: the pulse's frequency over time
- Meter: The patterns of accentuation between pulses (i.e. march or waltz)
- Neural Resonance: Music can trigger rhythmic bursts of high-frequency neural activity, which may enable communication between auditory and motor cortices (Large & Snyder 2009)

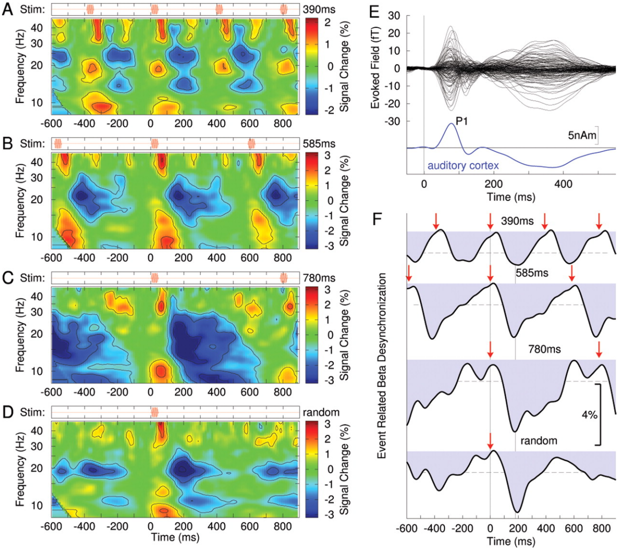
Early EEG Evidence for Neural Resonance

Induced and evoked oscilatory activity reflect the processing and expectation of periodic stimuli



Snyder & Large 2005

Pulse timing is reflected in beta- and gamma-bands



Fujioka et al. 2009

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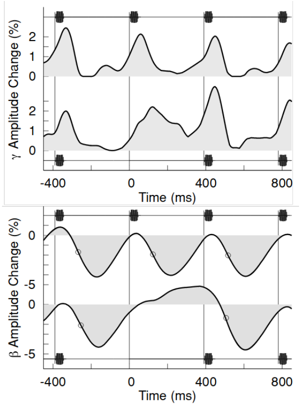
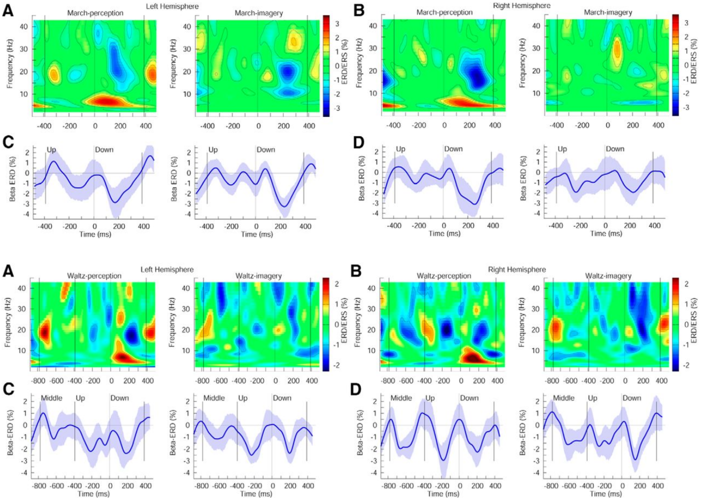


Fujioka et al. 2012

This kind of analysis involves the averaging of hundreds of trials

Imagined meters are also reflected in the beta-band

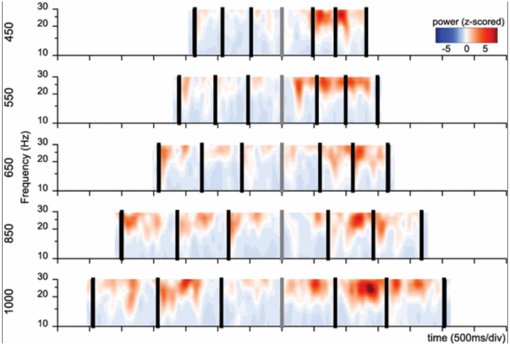
Imagination of different meters (i.e. binary march vs ternary waltz) results in different beta-band patterns



Fujioka et al. 2015

Primate oscillations reflect the metronome tempo

Dorsal putamen LFPs of macaques in a metronome tapping task



Merchant & Bartolo 2017

Bottomline: gamma reflects stimulus processing, while beta reflects the entrainment of large basal ganglia networks during internally driven pulse tapping

Research question and hypothesis

- Pulse, tempo and meter can be observed in the neural correlates measured with EEG and MEG.
- To maximize the SNR, these observations require the analysis of hundreds of trials.
- **Research Question:** could these features be identified in single trials? and if so, can we decode from human brain data, in real-time, perceived and imagined musical features like pulse, tempo and meter?
- **Hypothesis:** Deep neural networks, like CNNs, can learn to identify these musical features on a single-trial level.

Lit Review: What can CNNs learn from EEG data?

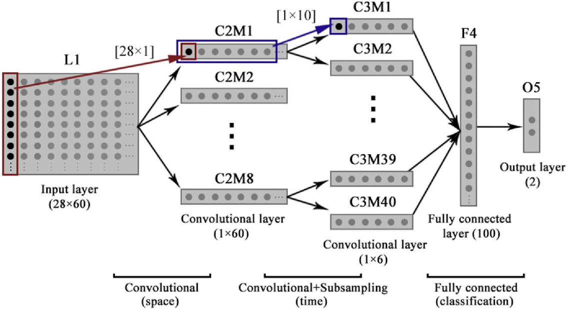
- Individual subject classification with resting-state data (Ma et al. 2018)
- Motor imagery classification: left vs rigt hand (Tang et al. 2017)
- Motor imagery with Riemannian Geometry Classifiers (Barachant et al. 2011)
- Music imagery information retrieval (Tan et al. 2018)
- The key problem: domain adaptation and transfer learning (Lotte et al. 2018)

Individual subject classification (Ma et al. 2018)

- Task: resting state with open and closed eyes
- CNN input: 64x160 EEG "images"
  - 64 EEG channels
  - 1 second-long epochs ($fs = 160$)
  - 50 (5) seconds of training (test) data per subject
  - 10 participants
- CNN architecture: LeNet (6 channels in each conv layer)
- Performance: **88% accuracy**
- Significance:
  - EEG for biometrics

Motor imagery classification: left vs right hand (Tang et al. 2018)

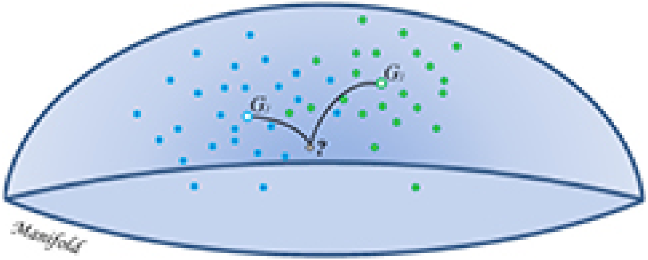
- Task: imagination of right or left hand movements during 5 second trials (460 total)
- CNN input: 28x60
  - 28 EEG channels
  - 3 seconds, 50ms fft frames (1 frequency band per subject)
  - 350 (100) trials of traning (test) data per subject
  - 2 participants
- CNN architecture



- Performance: **87% accuracy**

Motor imagery with Rimennian Geometry Classifiers (Barachant et al. 2011)

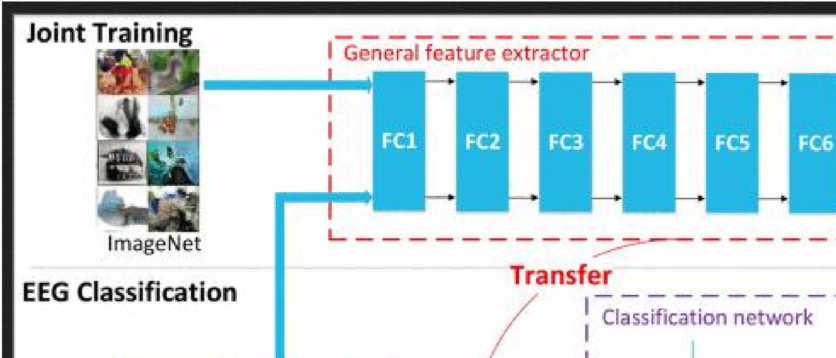
- Riemannian geometry studies smooth curved spaces that can be locally and linearly approximated with tangents
- Assumption: each EEG mental state has different power and spatial distribution
- The covariance matrix of the EEG data can code this information



- Performance: **70% accuracy** in a four-class, motor imagery task (four extremities)
- Significance:
  - This method is considered to be the *state-of-the-art* (Lotte et

Music imagery information retrieval (Tan et al. 2018)

- OpenMIIR dataset: listening and imagination of 12 known musical stimuli (Stober et al. 2015)
- CNN input: raw EEG signal
  - 64 EEG channels
  - 240 trials per participant (12 stimuli x 4 conditions x 5 blocks). Avg trial length (1̃0 sec)
  - 10 participants
- CNN architecture



The key problem: domain adaptation and transfer learning (Lotte et al. 2018)

- In EEG, major changes in data distribution can occur between subjects or across time.
- Solution: transfer learning (calibration) to optimize the algorithm across time and across subjects
  - Learn the transformation that explains the change in the data distribution
  - Reweighting
  - Find the common features between the two distributions

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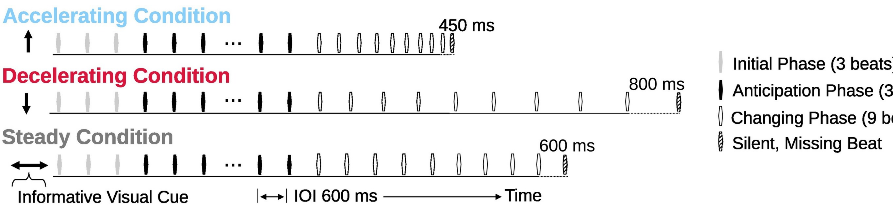
Methods: EEG dataset task



- 21 Participants listened 450 trials, each consisting of ~18 metronome clicks that either:
  - accelerate
  - decelerate
  - remain isochronous
- The metronome starts at 1.67Hz (600ms inter-stimulus-interval)
- The three types of trials are equally likely to appear and are presented randomly.
- Stimuli presentation was evenly divided across eight blocks
- At the beginning of each trial, participants see a visual cue that tells them what the metronome will do

Methods: EEG equipment

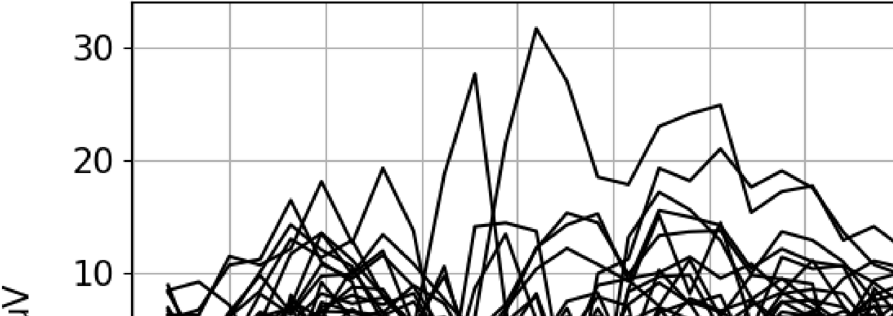
- 64 channel Neuroscan
- 500Hz sampling rate
- 2 electro-oculogram channels to record horizontal and vertical eye movements
- Insert earphones and a monitor delivered the stimuli

Methods: EEG data processing

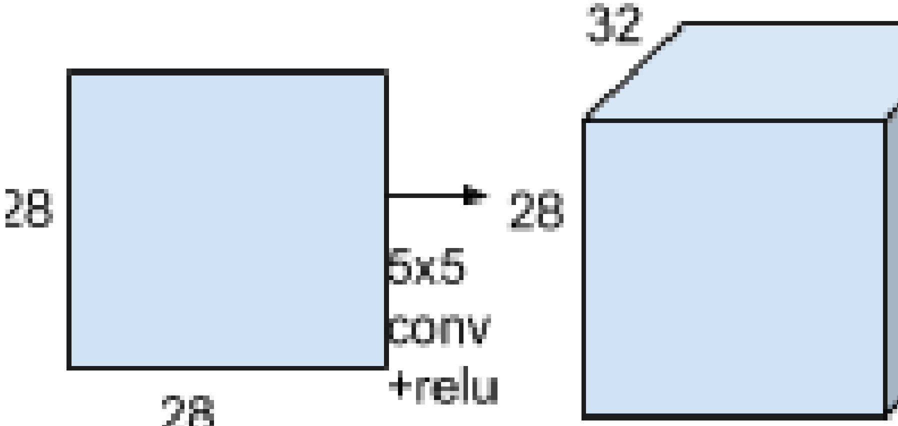
- 10 noisy EEG channels were eliminated from all recordings.
- The noisy EEG channels were at the edge of the EEG cap.
- Eye movement artifacts were removed using the signal-space projection method.
- 200ms epochs were calculated starting 16ms before each click or visual cue.
- Epochs were baseline corrected with the mean of the eeg amplitude before each click (100ms).
- Epochs were downsampled from 500Hz to 125Hz sampling rate.
- Rejected epochs with EEG peak-to-peak difference greater than 100μV in any channel.

Methods: CNN input data

- 10% of all epochs were held-out as validation data
  - 133,813 training epochs (7,363 visual epochs)
  - 14,791 validation epochs (803 visual epochs)
- ˜6,300 epochs per participant (21 total)
- Epochs were multiplied by 10^6 and cast to be float32
- Data shape is: `[None, 54, 1, 25]`



Methods: LeNet architecture



Methods: EEG classification experiments

- Subject classification
- Audio vs visual stimulus classification
- Accelerating vs decelerating vs steady beat classification