Introduction to EEG Decoding for Music Information Retrieval Research

RESOURCES

Software

- MNE: M/EEG analysis and visualization (Python)
 http://martinos.org/mne http://mne-tools.github.io/mne-python-intro/
- EEGLAB: M/EEG analysis and visualization (Matlab) https://sccn.ucsd.edu/eeglab/
- FieldTrip: M/EEG analysis (Matlab) http://www.fieldtriptoolbox.org/
- Brainstorm: M/EEG analysis (Matlab) http://neuroimage.usc.edu/brainstorm/
- libraries for OpenBCI hardware (C++/Arduino, Python/Matlab) https://github.com/OpenBCI/
- OpenViBE: BCI platform supporting real-time EEG acquisition, processing and visualization for a wide range of hardware (C++) http://openvibe.inria.fr/
- BBCI Toolboxes for running BCI experiments, signal acquisition and feedback control (Python, Matlab) https://github.com/bbci
- deepthought: deep learning library for EEG (Python/Theano)
 (to be updated soon) https://github.com/sstober/deepthought
- Reliable Components Analysis toolbox (Matlab) https://github.com/dmochow/rca
- Visualizing confusion matrices for RSA (R) https://github.com/hskim08/RConfMatrixPlots

EEG Datasets

- BCI Datasets (various tasks and contributors). http://bnci-horizon-2020.eu/database/data-sets
- OpenMIIR Dataset. Stober S et al. (2015). Towards Music Imagery Information Retrieval: Introducing the OpenMIIR Dataset of EEG Recordings from Music Perception and Imagination. In ISMIR, 2015. https://github.com/sstober/openmiir
- Preprocessed visual responses for classification. Kaneshiro B et al. (2015). EEG data analyzed in "A Representational Similarity Analysis of the Dynamics of Object Processing Using Single-Trial EEG Classification". Stanford Digital Repository. https://purl.stanford.edu/bq914sc3730
- Chord progression stimuli and preprocessed data. Kaneshiro B et al. (2015). EEG-Recorded Responses to Short Chord Progressions. Stanford Digital Repository. http://purl.stanford.edu/js383fs8244
- Preprocessed responses to intact and scrambled Hindi pop songs. Kaneshiro B et al. (2016). Naturalistic Music EEG Dataset Hindi (NMED-H). Stanford Digital Repository.
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References – general EEG

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- ICA for EEG artifact rejection. Bell AJ and Sejnowski TJ (1995). An information-maximization approach to blind separation and blind deconvolution. Neural Computation 7:6, 1129–1159.
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- **Spatial filtering of EEG (CSP).** Blankertz B et al. (2008). Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal Processing Magazine 25:1, 41–56.
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- Forward models for EEG. Haufe S et al. (2014). On the interpretation of weight vectors of linear models in multivariate neuroimaging. NeuroImage 87, 96–110.

References – EEG classification (music studies)

- **Naturalistic music segments**. Schaefer et al. (2011). Name that tune: decoding music from the listening brain. NeuroImage 56, 843 849.
- Subjective accenting of beat sequence (BCI aim). Vlek RJ et al. (2011). Sequenced subjective accents for brain-computer interfaces. Journal of Neural Engineering 8:3, 036002.
- Training imagery classifier on responses to perceived events (BCI aim). Vlek RJ et al. (2011). Shared mechanisms in perception and imagery of auditory accents. Clinical Neurophysiology 122:8, 1526–1532.
- **Chord progression endings**. Kaneshiro et al. (2012). An Exploration of Tonal Expectation Using Single-Trial EEG Classification. In ICMPC12-ESCOM8.
- Rhythms. Stober et al. (2014). Classifying EEG recordings of rhythm perception. In ISMIR, 649–654.
- Rhythm classification with convolutional neural networks. Stober S et al. (2014). Using Convolutional Neural Networks to Recognize Rhythm Stimuli from Electroencephalography Recordings. Advances in Neural Information Processing Systems, 1449-1457.
- Attended oddball events in polyphonic music (BCI aim). Treder MS et al. (2014). Decoding auditory attention to instruments in polyphonic music using single-trial EEG classification. Journal of Neural Engineering 11:2, 026009.
- **Pre-training filters for EEG classification.** Stober S et al. (2015). Deep Feature Learning for EEG Recordings. *arXiv preprint arXiv:1511.04306*.

References – classification and BCI/RSA

- Introduction to BCI. Blankertz B et al. (2002). Classifying single trial EEG: Towards brain computer interfacing. Advances in Neural Information Processing Systems, 157–164.
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- **RSA (EEG classification) with vision**: Kaneshiro B et al. (2015). A Representational Similarity Analysis of the Dynamics of Object Processing Using Single-Trial EEG Classification. PLoS ONE 10:8, e0135697.

References – RCA, ISCs

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- Introduction of RCA and EEG-ISCs. Dmochowski et al. (2012). Correlated components of ongoing EEG point to emotionally laden attention—a possible marker of engagement? Frontiers in Human Neuroscience, 6:112.
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Thank You

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