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Modeling EEG source dynamics underlying emotional experiences during natural music listening: a preliminary study

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I. Introduction

➢ Challenges in studying emotions

- Lack of a standardized protocol to elicit realistic emotional responses
- Require high temporal resolution [Davidson, 1992]
- Uncertain associations between neurophysiological signals and emotional responses
- Solutions: (1) Natural music listening
  (2) Electroencephalography (EEG)

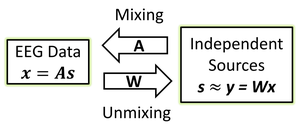
➢ Challenges in EEG-based emotion classification

- Most studies use channel (pairs) band power as features which provide limited neurophysiological interpretation.
- Emotion classification accuracy remained far from satisfaction.
- Emotion-irrelevant brain dynamics hinder accurate emotion identification; and we are currently lack of an objective criterion for informative data screening.

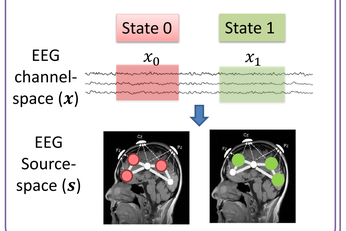
➢ Our approach

- Explore EEG source dynamics / nonstationarity underlying emotional experiences during natural music listening.
- Hypothesis: EEG correlates of different (emotional) states can be characterized by distinct sets of sources decomposed by independent component analysis (ICA) [Hsu, 2016]

Independent component analysis (ICA)



Source-state hypothesis



II. Experiment Procedure & Data Collection

➢ Participants

- 26 healthy subjects (16 male, 10 female, age: 24.4 ± 2.53)
- Non-musicians with minimal formal musical training.

➢ Natural music listening experiment

- Sixteen 30-sec music excerpts from Oscar's film soundtrack
- Procedure: 15-sec eye-closed rest → 30-sec eye-closed music listening → self-paced report of emotional states.
- Emotional states (valence-arousal emotion model):
  Valence: Positive / Negative; Arousal: High / Low
  4 classes: Joy, Anger, Sadness, Pleasure

➢ Data Collection & processing

- 32-channel EEG (Neuroscan), International 10-20 system
- Band-pass filtering: 1-100Hz, Notch filtering: 60Hz

III. Methods

➢ Adaptive mixture independent component analysis (AMICA)

AMICA learns multiple ICA mixture models with adaptive mixture sources and performs unsupervised segmentation of nonstationary data [Palmer, 2008].

1. Multiple ICA mixture models k [Lee, 2000]

$$x(t) = A_k s_k(t) + c_k, \qquad k = \{1, \dots, K\}$$

2. Adaptive source densities (mixture of generalized Gaussian density) with possible shared components.

$$p(s_k(t)) = \sum_{j=1}^{M} \alpha_{kj} \beta_{kj} GG\left(\beta_{kj}\left(s_k(t) - \mu_{kj}\right); \rho_{kj}\right)$$

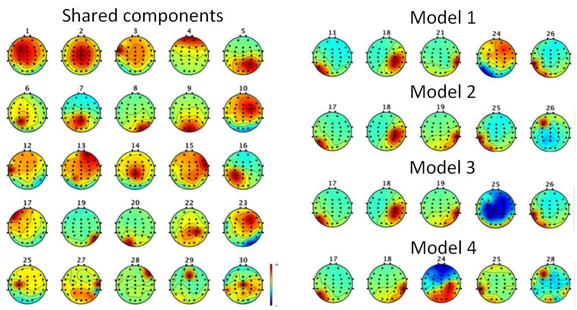
3. Maximum likelihood with Newton-based method & EM parameter estimation

$$\max_{\Theta} \log\left(p(X) = \prod_{t=1}^{T} \sum_{k=1}^{K} p(x(t) \mid k) \cdot p(k)\right) \qquad \Theta = \{A_k, c_k, \alpha_{kj}, \beta_{kj}, \mu_{kj}, \rho_{kj}, p(k)\}$$

4. Model probability $p(k)$
5. Online available as a binary program with parallel implementation at (https://sccn.ucsd.edu/~jason/amica_web.html)

IV. Results

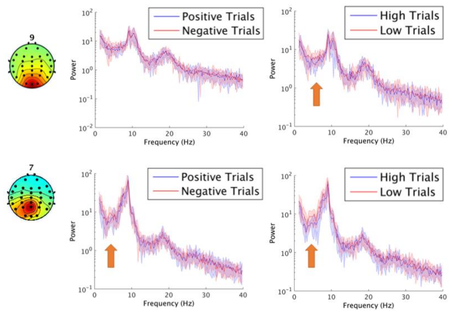
1. Multiple (Four) ICA models shared similar sources



Spatial distribution of each source activity over electrodes (scalp maps) from four models solved by AMICA with K=4 and shared components (correlation threshold 0.95) applied to the concatenated EEG data from a representative subject listening to 16 music excerpts.

25 out of 30 components were shared across the 4 models. Each model only has one to three distinct components.

2. Source power spectra showed moderate differences between positive- vs. negative-valence trials and between high- vs. low-arousal trials

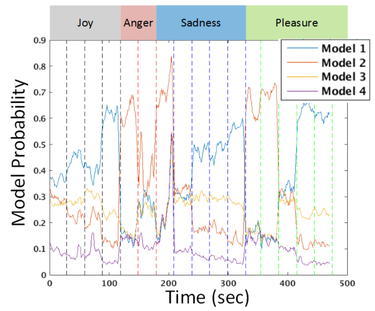


Source power spectra of the two (occipital and parietal) shared components averaged across positive- vs. negative-valence trials (left panel) and across high- vs. low-arousal trials (right panel).

Arrows indicates moderate differences between the two conditions, e.g. occipital theta and parietal delta / theta power [Rogenmoser, 2016]

IV. Results (cont')

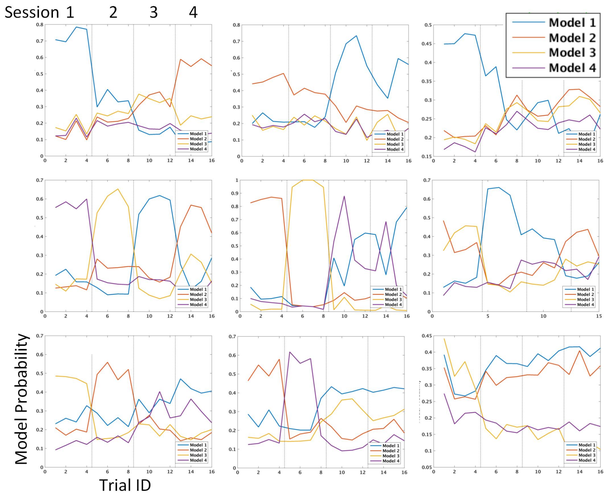
3. ICA models didn't correspond to specific emotional responses



Model probabilities of the 4 ICA models solved by AMICA fitted to the segmented EEG data (5-sec sliding window with 1-sec overlap) within each trial from the representative subject. All 16 trials were rearranged and sorted based on the four emotional labels rated by the subject.

Every trial had one dominant ICA model, suggesting distinct source structure/activities were identified between trials. However, their dominant ICA models did not match their emotion labels. Although Model 1 (blue) best fitted the Joy trials and Model 2 (red) dominated in the Anger trials, the two models were mixed in the Sadness and Pleasure trials.

4. ICA model probability characterized inter-session variability for multiple subjects



Model probabilities of 4 ICA models solved by AMICA averaged within each trial from 9 subjects. The 16 trials were organized as 4 sessions according to their original experimental order.

For these subjects, ICA model probabilities characterized inter-session variability which seemed to have weak association with emotional responses or music labels.

V. Conclusion

1. This preliminary study aims to explore EEG source dynamics / nonstationarity underlying emotional experiences during natural music listening experiments.
2. We tested the hypothesis that EEG correlates of different (emotional) states can be characterized by distinct source structures / activities decomposed by AMICA, which learns multiple ICA mixture models and performs unsupervised segmentation of nonstationary data.
3. Empirical results showed that multiple ICA models could share similar sources and moderate differences in source power spectra between different emotional responses were identified.
4. For multiple subjects, AMICA model-probability characterized inter session variability instead of emotional or musical labels, ***suggesting the existence of confounding, emotion-irrelevant responses during natural music listening that might hinder the emotion classification.***
5. Future work would focus on studying and mitigating the emotion-irrelevant responses to improve emotion identification.

References

[1] Davidson, R.J., 1992. Anterior cerebral asymmetry and the nature of emotion. *Brain and cognition*, *20*(1), pp.125-151.
[2] Hsu, S.H. and Jung, T.P., 2016, July. Modeling and tracking brain nonstationarity in a sustained attention task. In *International Conference on Augmented Cognition* (pp. 209-217). Springer International Publishing.
[3] Palmer, J.A., Makeig, S., Kreutz-Delgado, K. and Rao, B.D., 2008, March. Newton method for the ICA mixture model. In *Icassp* (pp. 1805-1808).
[4] Lee, T.W., Lewicki, M.S. and Sejnowski, T.J., 2000. ICA mixture models for unsupervised classification of non-Gaussian classes and automatic context switching in blind signal separation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(10), pp.1078-1089.
[5] Rogenmoser, L., Zollinger, N., Elmer, S. and Jäncke, L., 2016. Independent component processes underlying emotions during natural music listening. *Social cognitive and affective neuroscience*, p.nsw048.