EEG spectral modulations during emotional imagery

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Outline

Emotional imagery experiment

Unmixing power modulations with ICA

Broadband high frequency modulations

Power modulations during emotional imagery

Emotion classification using power modulations

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Experimental procedure

- Pre-session eyes closed baseline
- Guided relaxation (~5 min)
- > 15 emotions
 - balanced positive and negative valence
 - introduced verbally via headphones
 - self-paced emotional experience
- Subject pressed a button when feeling became intense
- Instructed to image for ~4 min
- Post-session eyes closed baseline





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Separate mixed source activities



Independent component analysis (ICA)

x = scalp EEG	
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Channels

W = unmixing matrix

 $W^*x = u$ ICA

u = sources



 $\mathbf{x} = \mathbf{W}^{-1} \mathbf{u}$

mmmmmm

u = sources

*

ICA Components



Dynamic changes in frequency power over time

Frequency (Hz)

Complexity of on-going EEG spectral power



Independent (Co-)Modulators of EEG Source Activities





Log-spectral decomposition





Example IM templates + mean power spectrum



Clusters of spectral modulators (33 Ss)



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Broadband gamma modulator clusters



Muscle is not co-modulated with brain



Muscle is not co-modulated with brain



Gamma power up to 250 Hz



Sorted broadband IM weights



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IM weights for different emotions



Excitement

IM weights for different emotions



Momentary and mean IM weights



IM weights during emotional imagery



Broadband gamma modulator clusters





Valence-correlation-weighted dipole density of γ IMs



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Emotion classification procedure

IMs

Inv Wt

Matrix

windows

- 1) ANOVA across columns of W⁻¹ (IMs)
- 2) Sort IMs by ANOVA F-score
- 3) Select IMs with highest F-scores for classification (bet. 3-17)
- 4) Remove 10% of each emotion period as 'test' data
- 5) Classify each non-overlapping 1-sec of 'test' data with SVM
- 6) Calculate % correct classification across all 1-sec 'test' epochs
- 7) Separate classification IMs into theta, alpha, beta, gamma categories



Classification accuracy (1-sec, non-overlapping epochs)



Brain sources with emotion-related IMs

F-score standard deviation-weighted dipoles



Summary

- ☑ ICA isolates independent brain activity from scalp EEG
 - Separates high frequency brain from scalp muscle
- ☑ IC power is affected by independent modulator processes
 - possibly neuromodulatory influences
- If High frequency IM strength is related to emotional valence
- IM strengths can differentiate between subjective states
 - > high freq. IMs are more likely to differentiate between emotions

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