A Comparison of Two Methodological Approaches for Emotion Recognition from EEG Data

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INTRODUCTION

Emotions are essential to everyday human life and may appear trivial. However, numerous questions concerning emotions remain unanswered in psychological research. For example, are emotions categorial or dimensional constructs? Recent studies have used electroencephalogram (EEG) experiments to gain further insight into human emotions. This poster investigates two methodological approaches for recognizing human emotions from EEG data, both based on Russel's emotion theory.

EMOTION IN PSYCHOLOGICAL RESEARCH

Selected influential theories:

- Ekman (1992): basic emotions anger, surprise, disgust, enjoyment, fear, sadness
- Russel (1980): two-dimensional circumplex model (Arousal, Valence)

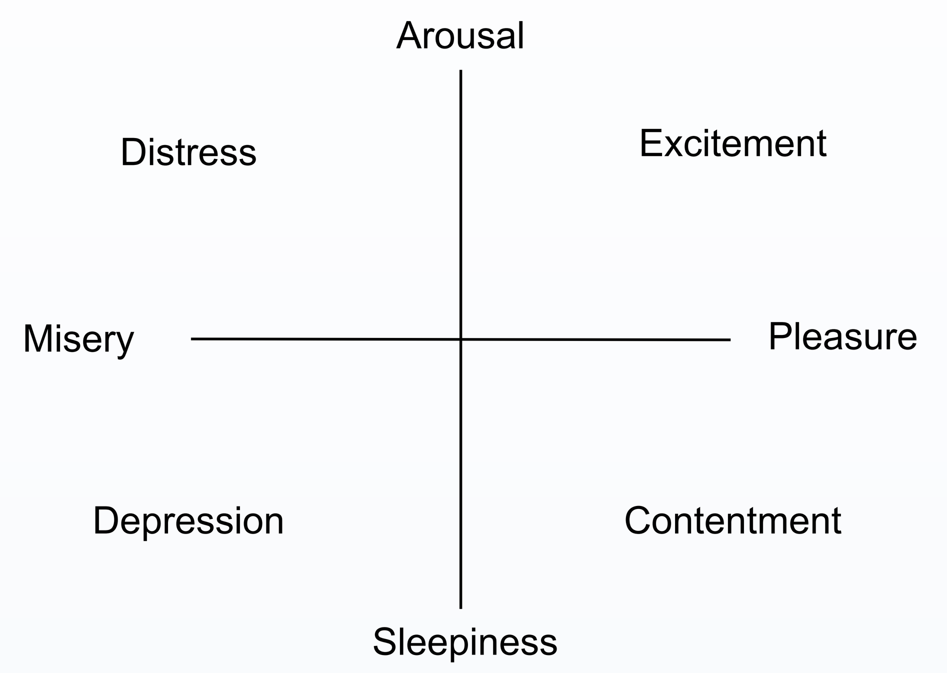

Fig. 1 Russel's two-dimensional circumplex model with the dimensions Arousal (vertical) and Valence (horizontal) (Russel, 1980)

EEG SIGNALS

- Electroencephalogram (EEG): flow of neuronal ionic currents, measured using pair of electrodes (Im, 2018)
- Excellent temporal resolution, deficient spatial resolution (Im, 2018)
- EEG signal are usually very noisy and contain artifacts that must be removed before the data can be used for analyses (Kim, 2018)

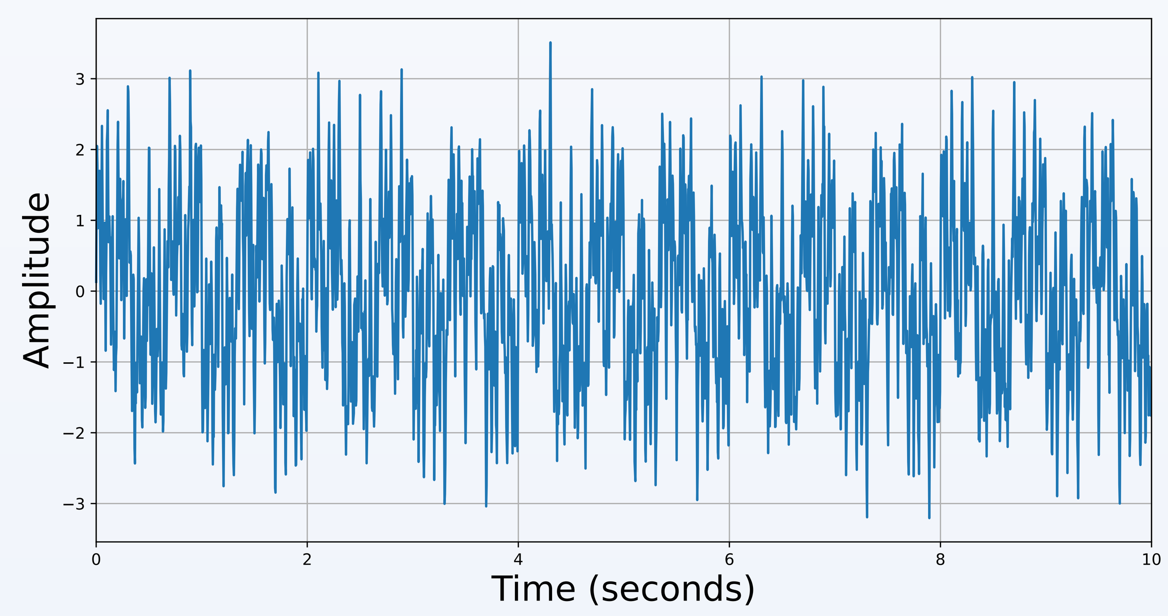

Fig. 2 Example EEG signal obtained from simulated data

DEAP DATASET (Koelstra et al., 2012)

- 32 healthy participants (50% female, ages 19-37, M = 26.9)
- 40 one-minute-long music videos
- Arousal and valence rating for every video (continuous scale from 1-9)
- Valence: unhappy/sad – happy/joyful
- Arousal: calm/bored – stimulated/excited

APPROACH 1: INTRINSIC MODE FUNCTIONS (Pandey & Seeja, 2022)

1. Extraction of Intrinsic Mode Functions (IMFs) from EEG signal
   - Empirical Mode Decomposition (EMD): IMFs obtained from signal $s(t)$ through shifting

$$s(t) = \sum_{i=1}^{k} I_i(t) + x_k(t)$$

   - Variational Mode Decomposition (VMD): optimization approach to extract IMFs
2. Calculating peak value of PSD and first difference of the extracted IMFs
   - Power spectral density (PSD): distributed of signal power over frequency
   - First difference = $y_t - y_{t-1}$
3. Emotion Classification with a Deep Neural Network (DNN)
   - Type of used layers not publicly disclosed
4. Model evaluation using training and test datasets

APPROACH 2: EEG FEATURE MAPS (Topic & Russo, 2021)

- Selected features from EEG signal: fractal dimension, Hjorth activity, mobility, complexity, peak-to-peak, root-mean-square, band power, differential entropy, power spectral density
- Inclusion of spatial positioning of the electrodes

1. Creation of feature maps
   - TOPO-FM: topographic map for spatial positioning and a specific feature, interpolation of "missing" data
   - HOLO-FM: holographic feature map (feature value in the spatial area as object), projection into two-dimensional image
   - TH-FM: fusion of TOPO-FM and HOLO-FM

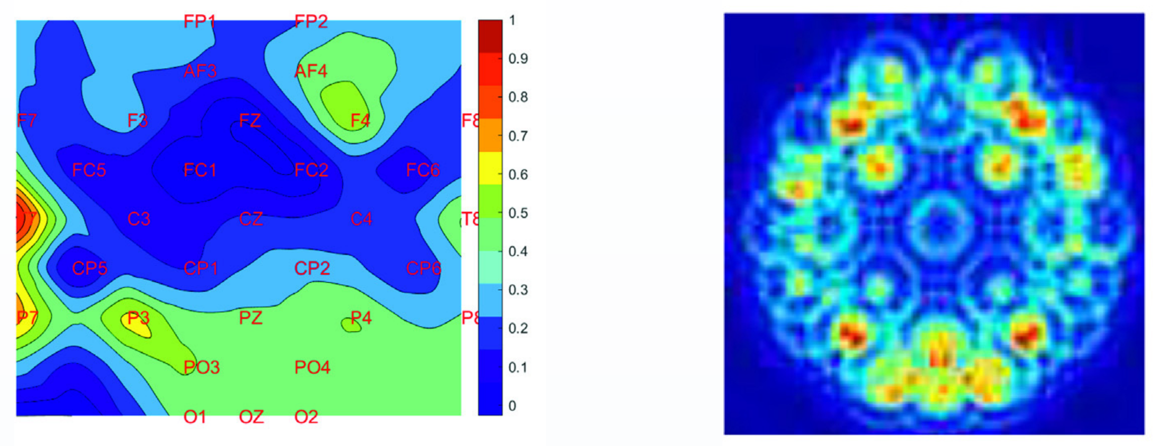

Fig. 3 Example TOPO-FM (left) and HOLO-FM (right) feature map (Extracted from Topic & Russo, 2021)

2. Deep learning feature extraction using a separate CNN for every signal characteristic
3. Feature fusion
4. Super-Vector-Machine classification
5. Model evaluation using 10-fold cross validation

RESULTS

Study	Valence Accuracy	Arousal Accuracy
Approach 1: Pandey & Seeja (2022)	EMD (3 IMFs): 91.75% (training) 56% (test) VMD (4 electrodes): 62.50% (test)	EMD (3 IMFs): 94% (training) 60% (test) VMD (4 electrodes): 61.25% (test)
Approach 2: Topic & Russo (2021)	TOPO-FM: 76.30% HOLO-FM: 76.61% TH-FM: 74.91%	TOPO-FM: 76.54% HOLO-FM: 77.72% TH-FM: 75.44%

Tab. 1 Comparison of key results, highlighting best-performing models for the DEAP dataset

- Approach 1 achieves high training accuracy but only marginally above guessing accuracy for test data, however VMD outperforms EMD
- Approach 2 suggests highly generalizability evidenced by consistently high accuracy with CV over all types of feature maps

CONCLUSION

- Approach using feature maps produces most promising results
- IMFs provide simpler feature extraction and interpretability
- Only binary classification (high/low Arousal/Valence)
- Future research: continuous multidimensional predictions to properly depict emotional facets rather than rough estimates

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