Karlsruhe Institute of Technology

INSTITUTE OF INFORMATION SYSTEMS AND MARKETING

Heart Rate Extraction from Around-The-Ear EEG for Live Biofeedback Applications

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Agenda

- Motivation / Appetizer (1min)
- Related Work (1min)
- Problem Analysis / RQ (2min)
- Methodology (3min)
- Evaluation Procedures (3min)
- Key Findings (1/2) (3min)
  - Results (1/2) (3min)
- Limitations (2min)
- Conclusion (1min)
- Future Research (1min)

Motivation / Appetizer

- Why Flow?
- Why Interoceptive Biofeedback (cardiac, auditory)?
  (see Potential Application Context)

- Why simultaneous EEG and ECG?

- (Research Gaps / Needs in that regard?)
- (Necessary Definitions and Concept Explanation?)

Related Work

- Ear-centered ECG vs/and Wearable EEG systems
  (for simultaneous ECG and EEG)

- -> Research Gap / Need in that regard?

- Why ExG Headphones?

Objective and Research Questions

- Utilizing ATE-EEG for live cardiac biofeedback by extracting heartbeat via ICA
  - **Feasibility Assessment**
- Requirements resulting from envisioned application context (explicit/implicit)
  - Temporal delay threshold of 200 ms between heartbeat and feedback [B] [C]

- **RQ 1**: How robustly can recorded ATE-EEG be used, to extract ECG or heartbeat by means of ICA?
- **RQ 2**: How feasible is the utilization of unobtrusive ATE-EEG recordings for the online extraction of R-peaks by means of ICA?

Objective and Research Questions (2)

- Feasibility was operationalized in terms of
  - Computational Complexity (“costs”), using algorithmic execution time as indicator
  - ICA Result Quality / R-peak Detection Performance (“benefit”), using specific quality *(pTp-SNR)* and accuracy *(JF score)* measures as indicator

Independent Component Analysis

- Probabilistic method for separating multivariate data (e.g., multichannel EEG data) into maximally independent subcomponents / sources
  - Assuming independence and non-gaussianity (unlike, e.g., PCA)

- Special case of *Blind Source Separation (BSS)*
  - Separate a set of sources from a mixture of signals without knowing the original sources or mixing process

- Commonly, model estimation is derived in two steps:
  1) Linear transformation *("whitening")* and dimension reduction of data first, to simplify problem (e.g., using PCA or SVD)
  2) Actual iterative ICA estimation afterwards (using prior obtained PCs)

Sinus Rhythm of Healthy Individual

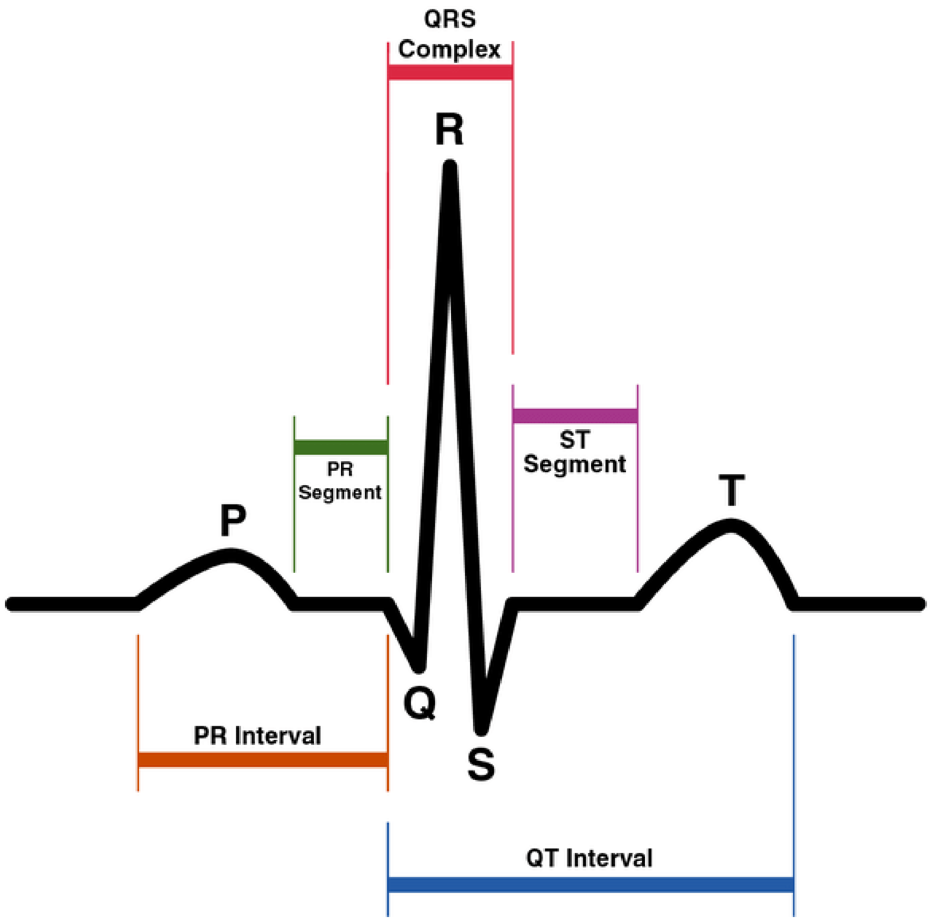
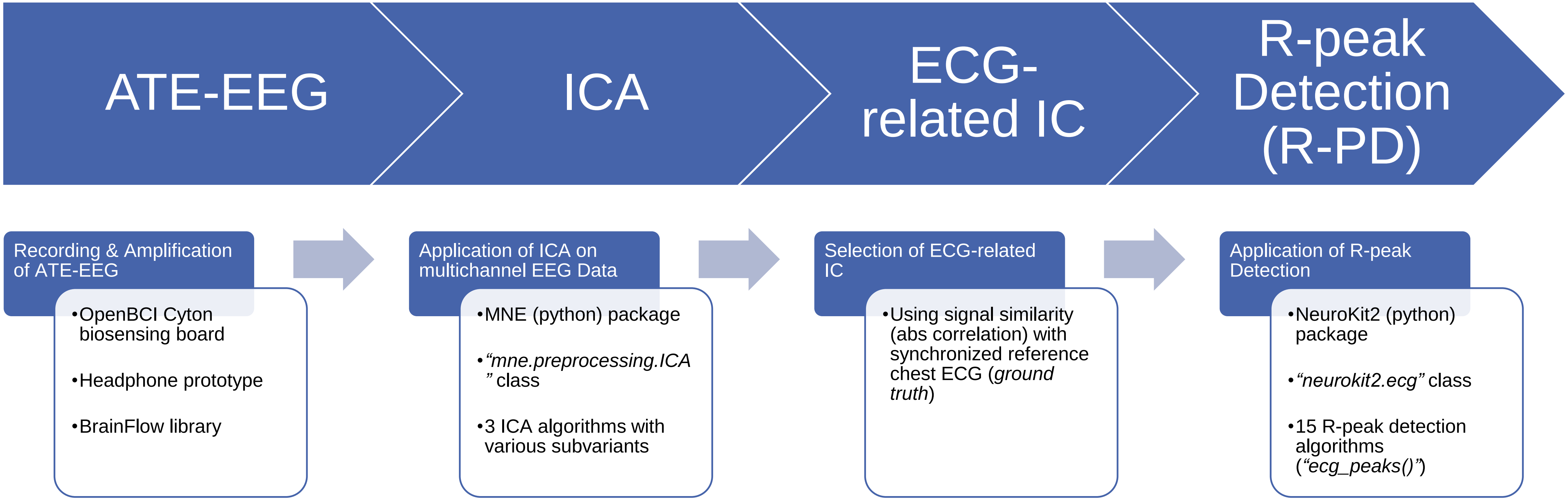


Figure taken from [A]

Overview: Proof of Concept Pipeline



Methodology

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- Hardware used:
  - *Cyton* bio-amplifier (OpenBCI, NY, USA) for 8 channel ExG recordings with 250 Hz sampling frequency
  - Headphone prototype for unobtrusive ATE-EEG recording, based on *Open ExG Headphones* [D] with 16 dry electrodes integrated into each earpad

- Software packages (python) used:
  - MNE (v1.5.1) for ICA, in total 8 (sub-) variants investigated
  - NeuroKit2 (v0.2.7) for R-PD, in total 16 R-peak detection variants investigated (some algorithms provide own pre-cleaning routine – *"ecg_clean()"*)

Methodology (2)

- Data Collection
  - ATE-EEG recordings from 5 study participants (3 males & 2 females with different hair length, 22-28 years old)
  - For each, simultaneous reference chest-ECG recording for *ground truth*, with conventional wet (pre-gelled adhesive Ag/AgCl) electrodes (bipolar)
  - Each recording yielded 13 observation segments of 60 s length, 104 ICA results and 1,664 *possible* R-PD results

- Preliminary Hardware Configuration evaluated with *"Proband 01"*
  - Selection of 7 promising recording electrodes around the ear for unipolar ATE-EEG channels (8^{th} channel for bipolar chest ECG - *ground truth*)
  - Suitability evaluation based on *skin-electrode impedance* (in kΩ) [E]

Quality and Performance Measures

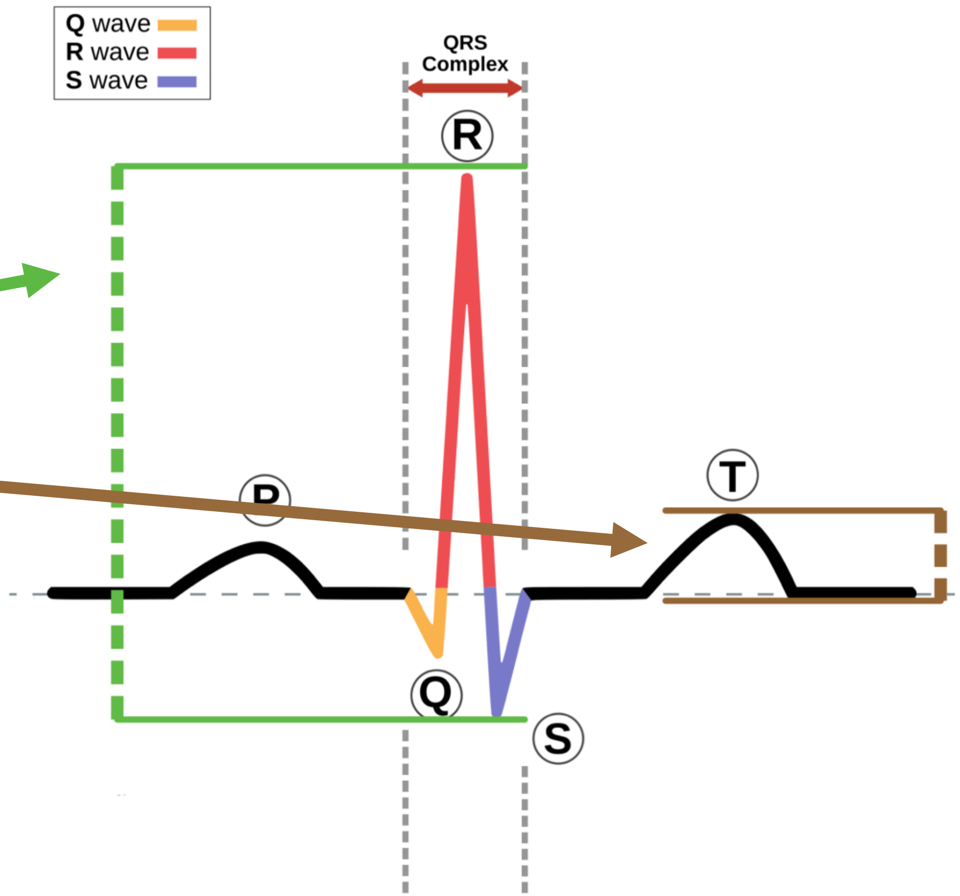
- Performance measures used:
  - Skin-electrode impedance (in kΩ) as proxy for ATE-EEG signal quality to expect
  - *Peak-to-peak SNR* (pTp-SNR) to assess quality of extracted ECG-related ICs regarding subsequent R-peak detection
  - *JF score*, to assess the (sample-wise) accuracy of R-peak detection algorithms on the ECG-related ICs

ICA Quality Measure

- Peak-to-peak SNR (pTp-SNR) in dB, adapted from [F]

$$SNR = \frac{V_{pp}^{signal}}{V_{pp}^{noise}}$$

$$SNR\ [dB] = 20 \cdot log_{10} \frac{V_{pp}^{signal}}{V_{pp}^{noise}}$$



R-peak Detection Performance Measure

- Popular QRS detector performance metrics ignore temporal inaccuracies, e.g., *sensitivity SE*

$$SE = \frac{TP}{TP + FN}$$

- *JF* score (in percentage), *“combining temporal jitter and F-score”* [G], for more meaningful comparison instead

$$JF = F_1 \cdot f(\overline{\Delta}) \cdot 100\,,$$

with F_1 *- score* as performance measure of detection accuracy [H]
and *“jitter score”* $f(\overline{\Delta})$ penalizing (temporal) R-peak displacements

Methodology

- Overview: Necessary Steps of a proof-of-concept pipeline
- Overview: Used Hard- and Software (+ justification)
  - Present used Hard- and Software in more detail (inclusive configuration/parameterization)

- Necessary Explanation for ICA and R-peak detection?
- Overview: Performance Measures for ICA Quality and R-Peak Detection Accuracy

  (Brief explanation and justification)
  - Explain Validation of each pipeline step / used quality and performance measures

- Data Collection and Preliminary Hardware Configuration

Overview: Evaluation Procedures

Preliminary Hardware Evaluation → ICA Evaluation → R-Peak Detection Evaluation → Combined Evaluation

Preliminary Hardware Evaluation

- Investigate skin-electrode impedance changes for various recordi...

Why?

- Cyton Board only offers 8 ExG recording channels
- Find promising recording configurations
- Minimize possible signal quality impairment, e.g., due to (facial) hair, bones etc.

ICA Evaluation

- Appy ICA algorithms on ATE-EEG recordings, with ICA

1) allowed for convergence

2) allowed for single

Why?

- Estimate upper bound of ICA quality
- Estimate lower bound of ICA execution time
- Assess influence of preliminary hardware configuration (Good Case vs Bad Case)

R-Peak Detection Evaluation

- Employ R-peak detection algorithms on all converged ECG-related ICs

(regardless of ICA variant used)

Why?

- Investigate JF score compared to other metric (sensitivity)
- Provide performance reference for every R-PD algorithm (Best Case for R-PD performance) independent of ICA variant used

Combined Evaluation

- Separately investigate performance of all 128 ICA x R-PD combinations, with ICA

1) allowed for convergence

Why?

- Estimate upper bound of combined (R-PD) performance
- Estimate lower bound of combined execution time
- Narrow down most promising combinations for use in live biofeedback pipeline

Overview: Evaluation Procedures

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Preliminary Hardware Evaluation	ICA Evaluation	R-Peak Detection Evaluation	Combined Evaluation
What? - Investigate skin-electrode impedance changes for various recording configurations	**What?** - Appy ICA algorithms on ATE-EEG recordings, with ICA 1) allowed for convergence 2) allowed for single iteration	**What?** - Employ R-peak detection algorithms on all converged ECG-related ICs (regardless of ICA variant used)	**What?** - Separately investigate performance of all 128 ICA x R-PD combinations, with ICA 1) allowed for convergence 2) allowed for single iteration
Why? • Cyton Board only offers 8 ExG recording channels • Identify promising recording configurations • Minimize possible signal quality impairments, e.g., due to (facial) hair, bones etc.	**Why?** • Estimate upper bound of ICA quality • Estimate lower bound of ICA execution time • Assess influence of preliminary hardware configuration (Good Case vs Bad Case) • Answer RQ 1	**Why?** • Investigate JF score compared to other popular metric (sensitivity) • Provide performance reference for every R-PD algorithm (Best Case for R-PD performance), independent of ICA variant used	**Why?** • Estimate upper bound of combined (R-PD) performance • Estimate lower bound of combined execution time • Narrow down most promising combinations for use in live biofeedback pipeline • Answer RQ 2

Key Findings (1)

- RQ 1: How robustly can recorded ATE-EEG (with presented prototype) be used, to extract ECG or heartbeat by means of ICA?

Key Findings (2)

- RQ 2: How feasible is the utilization of unobtrusive ATE-EEG recordings (with presented prototype) for the online extraction of R-peaks by means of ICA?

Results (2.1)

- Single Evaluation R-Peak Detection (on converged ICA results)
  - JF score is better suited performance measure than, e.g., sensitivity
  - Mean temporal jitter of R-peak Detection across ICA variants between 7 and 75ms
  - Execution Time of R-peak detection mostly below 65 ms (promising compared to ICA exec time, therefore no further exec time minimization conducted for R-PD)
  - 5 are most promising variants (having JF above 90%)

Results (2.2)

- Combined Performance Evaluation
  - When ICA allowed for convergence, combined exec above 200ms threshold (-> employ “naïve” runtime minimization)
  - Elimination of combinations with combined exec time above 200ms, almost all of the remaining stayed even under 125ms

Limitations

- Small Sample Size
- Ground truth for R-peak detection not manually annotated
- Automatic RT selection of ECG-related IC for live biofeedback pipeline

Conclusion

- What are the key findings?
- What are my own contributions?

Future Research

- Study with bigger sample size and automatic (RT) selection of ECG-related IC to generalize the results / feasibility
- Create annotated data set with fusion of ATE-EEG and ECG data (synchronized) for ground truth in further investigation
- Further hardware development to improve recorded signal quality
- More extensive hardware configuration and software parameterization for optimal trade-off between quality and execution time using expert domain knowledge (also investigate other performance measures for ICA/PD)

References

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- [C]: Meyerholz, L., Irzinger, J., Witthöft, M., Gerlach, A. L., & Pohl, A. (2019). Contingent biofeedback outperforms other methods to enhance the accuracy of cardiac interoception: A comparison of short interventions. Journal of behavior therapy and experimental psychiatry, 63 , 12–20.
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1-4.

Appendix

- JF-Score

JF Score

- JF score defined as follows:

$$JF = F_1 \cdot f(\overline{\Delta}) \cdot 100,$$

- Apart from *True Positives (TP)*, encompasses all types of detection errors that can occur
  - *False Negatives (FN)* and *False Positives (FP)*
  - *"Temporal jitter"* $\overline{\Delta}$ (mean displacement of R-peaks regarding ground truth)

- F_1 – *score* is defined as follows:

$$F_1 = \frac{2TP}{2TP + FP + FN} ,$$

- *"Jitter score"* is defined as follows:

$$f(\overline{\Delta}) = \frac{1}{1 + \frac{\overline{\Delta}}{12ms}} ,$$

JF Score vs Sensitivity *SE*

- **TODOooo**