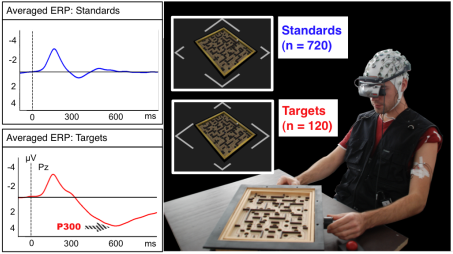
Minimizing Calibration Time for Brain Reading

Jan Hendrik Metzen[1], Su Kyoung Kim[1,2], and Elsa Andrea Kirchner[1,2]

[1] Universität Bremen, AG Robotik [2] DFKI GmbH, Robotics Innovation Center



Contact: jhm@informatik.uni-bremen.de

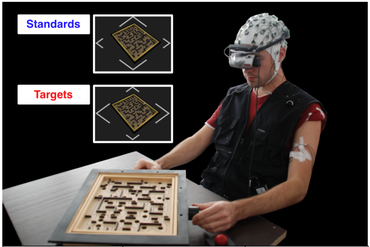
More information: `http://www.informatik.uni-bremen.de/~jhm/`

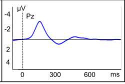
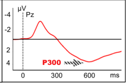
1. Motivation
2. Methods
   - Baseline
   - Ensemble approaches
3. Evaluation
   - Experimental Setup
   - Results
   - Outlook

Operator Monitoring in Telemanipluation

Did the operator get an alert that was presented to him or her?

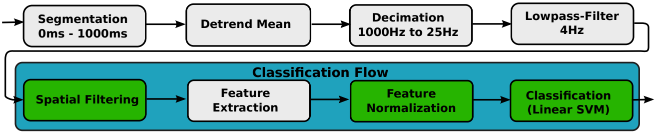
Real-time detection of the “P300 potential” can answer this question!



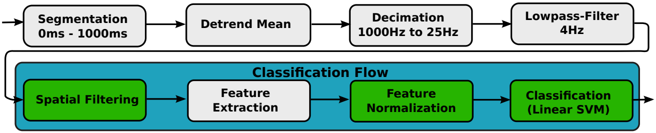
Stimulus type	Standards	Targets
Number of stimuli per run	720	60
Averaged event-related potentials		

BRIO Oddball paradigm: Experimental setup to evaluate methods for single-trial P300 detection

Machine learning approach for P300 detection

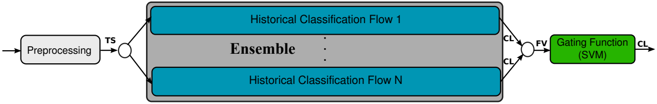


Machine learning approach for P300 detection



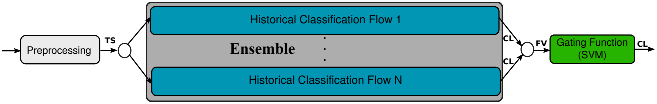
- Requires labeled training data acquired during a calibration procedure prior to usage session
- **Objective:** Achieve high predictive performance with minimum amount of training data ($\Rightarrow$ short calibration proc.)
- **Approach:** Reuse classification flows that have been trained in prior usage sessions of the same/other users

"Pure" ensemble



- Based on Fazli et al.: "Subject-independent mental state classification in single trials"

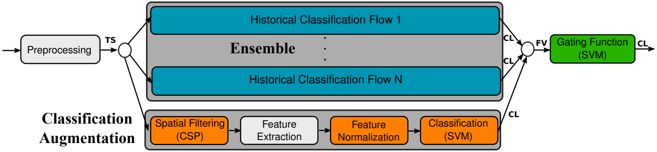
"Pure" ensemble



- Based on Fazli et al.: "Subject-independent mental state classification in single trials"
- Advantage: Learning problem becomes lower-dimensional and thus less training data may suffice for high predictive performance
- Disadvantage: Cannot adapt to session-specific patterns that haven't been observed in any prior usage session

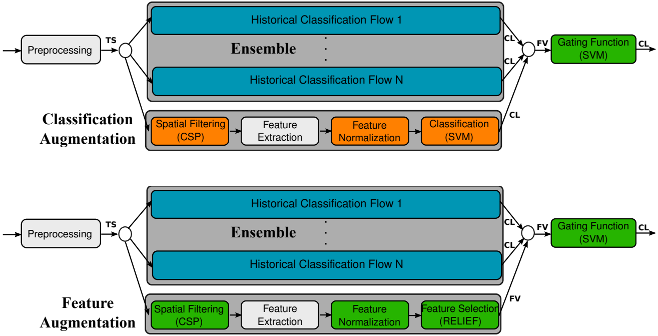
Augmentation approaches

Idea: Use ensemble not instead but in addition to standard session-specific flow.



Augmentation approaches

Idea: Use ensemble not instead but in addition to standard session-specific flow.



Experimental Setup

- Dataset recorded in BRIO Oddball paradigm consisting of 12 sessions of 6 subjects (2 sessions each)
- Generated one classification flow per historic session
- Flows generated on current session (all sessions of current user respectively) have been omitted from ensemble

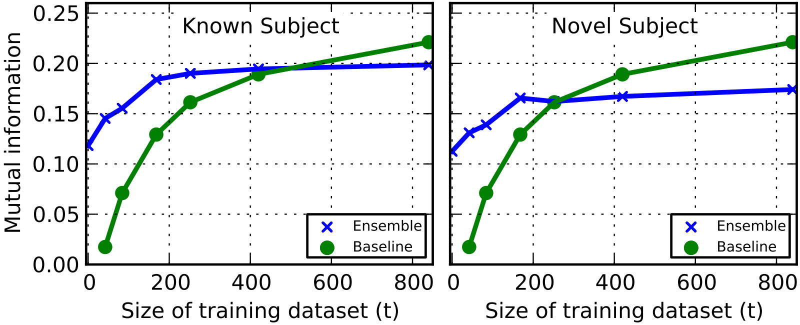
Experimental Setup

- Dataset recorded in BRIO Oddball paradigm consisting of 12 sessions of 6 subjects (2 sessions each)
- Generated one classification flow per historic session
- Flows generated on current session (all sessions of current user respectively) have been omitted from ensemble
- First run of session (partially) used as training data, remaining 4 runs for evaluation
- Parameters of SVM gating function have been optimized using 5-fold crossvalidation on respective training data

Experimental Setup

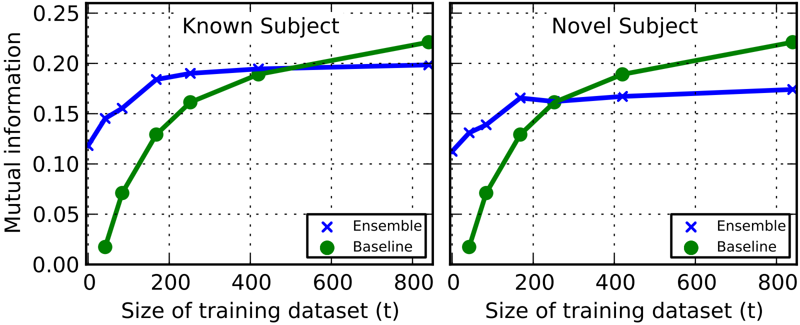
- Dataset recorded in BRIO Oddball paradigm consisting of 12 sessions of 6 subjects (2 sessions each)
- Generated one classification flow per historic session
- Flows generated on current session (all sessions of current user respectively) have been omitted from ensemble
- First run of session (partially) used as training data, remaining 4 runs for evaluation
- Parameters of SVM gating function have been optimized using 5-fold crossvalidation on respective training data
- Performance measured using mutual information $I(T;Y) = H(T) - H(T|Y)$ of class label T and classifier's prediction Y ($H(T) \approx 0.533$)

Effect of size of training dataset



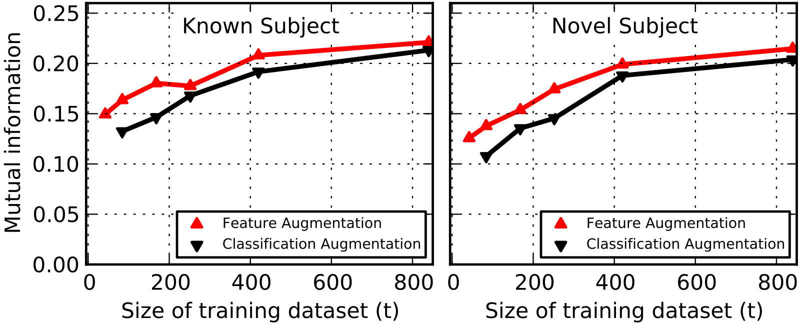
- "Baseline" worse than "Pure Ensemble" for small training datasets but better for large ones

Effect of size of training dataset



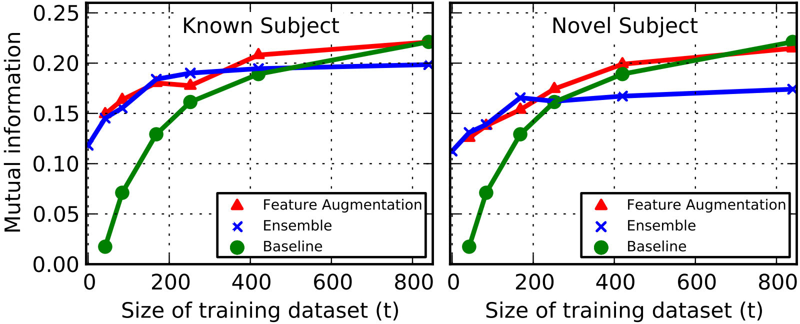
- “Pure Ensemble” worse for novel subjects than for known subjects

Effect of size of training dataset



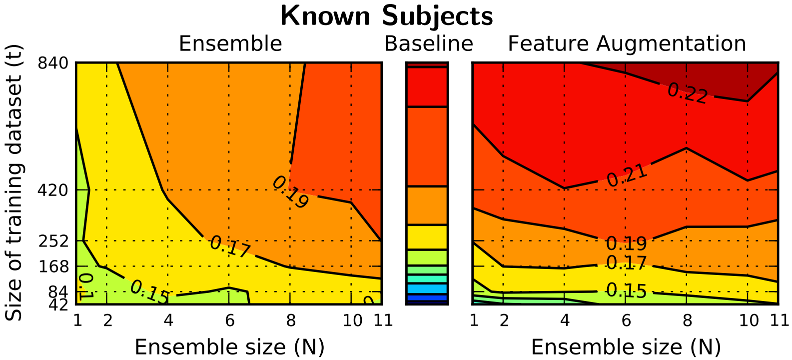
- "Feature Augmentation" superior to "Classification Augmentation" because of more efficient utilization of training data

Effect of size of training dataset



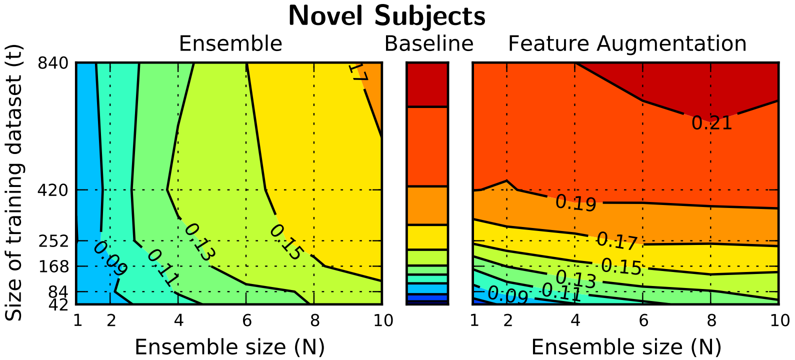
- "Feature Augmentation" combines advantages of "Baseline" and "Pure Ensemble"

Effect of ensemble size (1/2)



- Performance of "Feature Augmentation" depends less strongly on number of historic sessions than "Pure Ensemble"

Effect of ensemble size (2/2)



- Performance of "Feature Augmentation" depends less strongly on number of historic sessions than "Pure Ensemble"

Outlook

- Evaluation of augmentation approaches in an online-study where training data is acquired concurrently to usage session
- Analysis of intra-ensemble diversity/agreement

Thank you for your attention

—

Questions/Comments are welcome!

Contact: jhm@informatik.uni-bremen.de

More information: `http://www.informatik.uni-bremen.de/~jhm/`

Additional material