Robust, Accurate and Predictive Driver Drowsiness Detection Fusing Vehicle and Bio-signals for Application in Automated Driving

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Automotive Innovation Workshop (AUIN Workshop)

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SCIENCE
PASSION
TECHNOLOGY

Agenda

- Motivation
- Experiments in the Driving Simulator
- WACHsens data base
- AI-based drowsiness classification
- Results
- Summary

Motivation for driver drowsiness research: Vehicle Safety

Classification

- Importance of drowsiness difficult to **quantify**
- Likelihood of accidents **4-6 times** higher [1].

Application

- Warning vehicle systems
- **Precondition** for handover procedures at SAE L3 (UN regulation for certification of “ALKS” systems)

[1] M. Awais, N. Badruddin, and M. Drieberg, “A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability,” *Sensors*, vol. 17, no. 9, 2017.

Experimental test design and test procedure

“WACHSens” Project

Experimental test design and test procedure

- 1.5.2017 - 31.10.2019: Austrian research project **"WACHsens"**
- Consortium: TU Graz, Human Research Institute, Factum und AVL Powertrain UK

- Goals
  - Improve accuracy of AI-assisted drowsiness classification.
  - Augment vehicle data with physiological measurement data

- Method:
  - Driving simulator tests
  - 368 driving tests
  - 92 participants
  - Four different driving modes: rested-automatic, rested-manual, tired-manual and tired-automatic
  - Duration per test drive approximately 30 minutes
  - Total length about 184 hours

Experimental test design and test procedure

- **92 Participants:** valid driver's license, annual mileage greater than 1000km/year, no known propensity for motion sickness, ~equally distributed by age and sex.

- Rested state
- Tired state
    - At least 16 hours of sleep deprivation, test at usual bedtime
    - Or previous night with 50% sleep restriction.

95 measured data channels

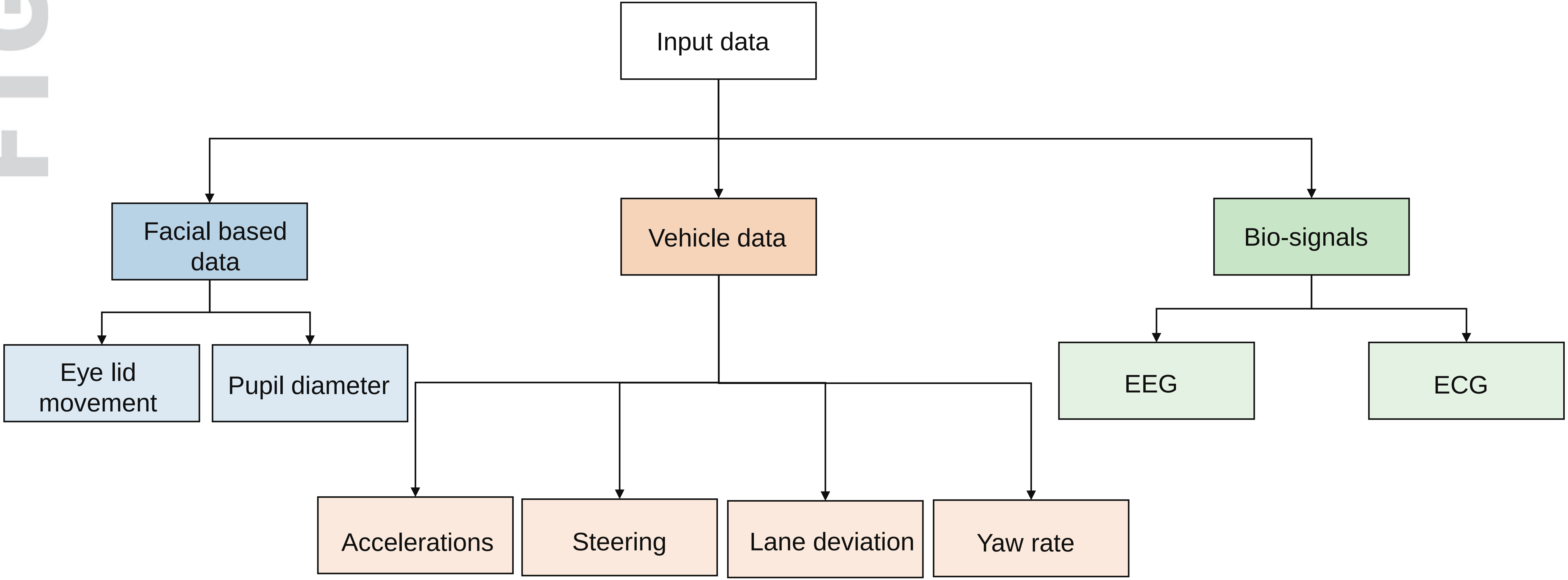
For example:

- ## Vehicle data: 20 channels
  - Speeds, position angles: 8 channels
  - Steering angle, speed and steering torque: 2 channels
  - Throttle and pedal positions and forces: 3 channels
  - Engine speed and gear: 2 channels
  - Indicator: 1 channel
  - ACC and LKA control: 4 channels

- ## Physiological data: 41 channels
  - EEG: 8 channels plus one reference channel
  - ECG: 2 electrodes
  - EOG (eyelid activity): 2 channels
  - Respiratory rate: 1 channel
  - Skin resistance: 1 channel
  - Head acceleration: 3 channels
  - Head position and rotation : 6 channels + 2 times quality assessment
  - Gaze direction: 12 channels + quality assessment
  - Pupil diameter: 3 channels + 3 times quality assessment
  - Eyelid movement: 3 channels + 3 times quality assessment

Example for test drive

Input Data for drowsiness classification



“Ground Truth” for drowsiness classification: video observation

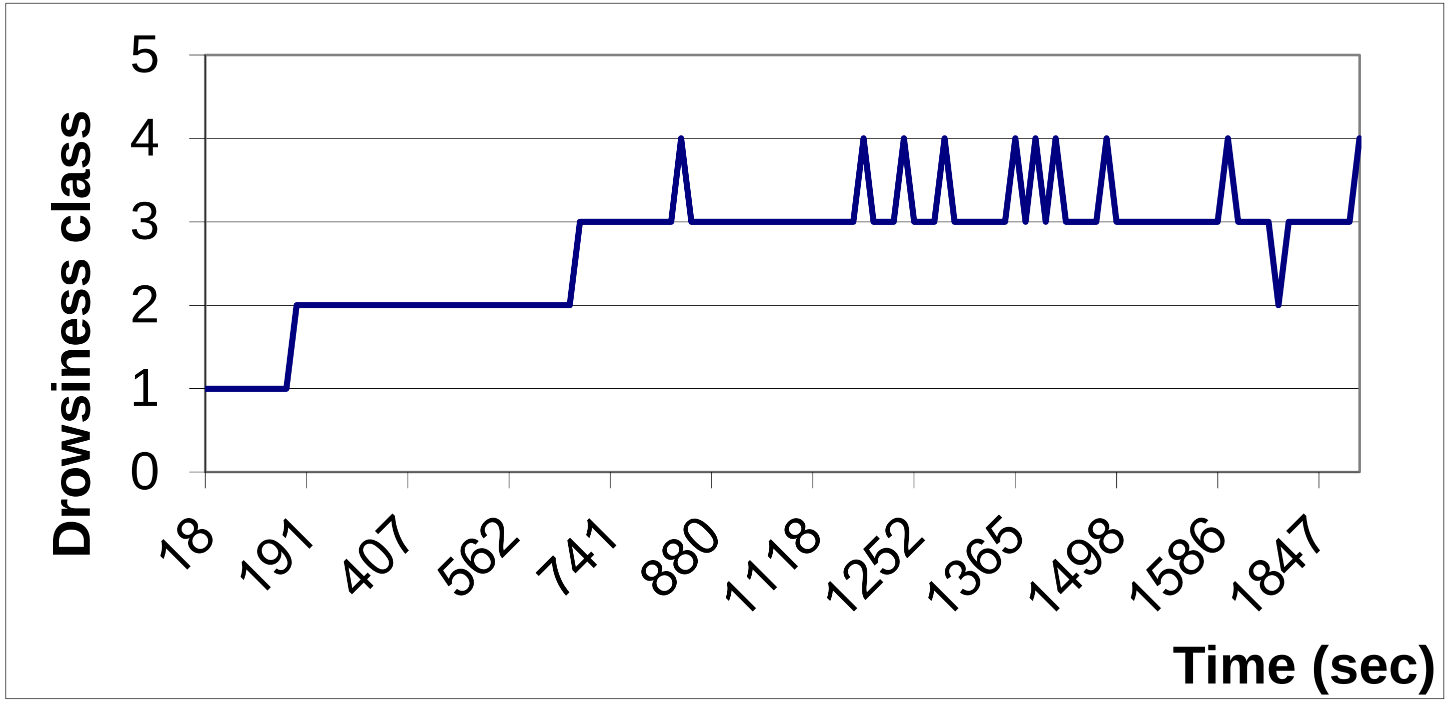
An expert in traffic psychology notes various signs of sleepiness and rates the driver's level of sleepiness in four stages: awake, moderately sleepy, extremely sleepy, and asleep [2]. Here, the third and fourth stages are merged because the 4th stage occurs too infrequently in the dataset.

1: Alert

2: Moderately drowsy

3: Extremely drowsy

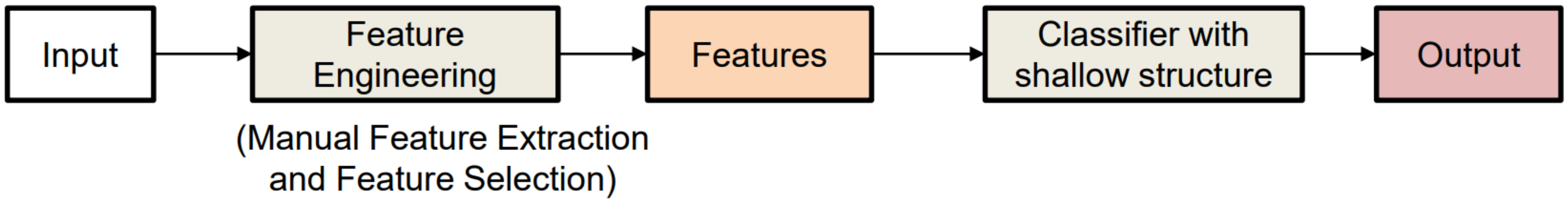
4: Asleep



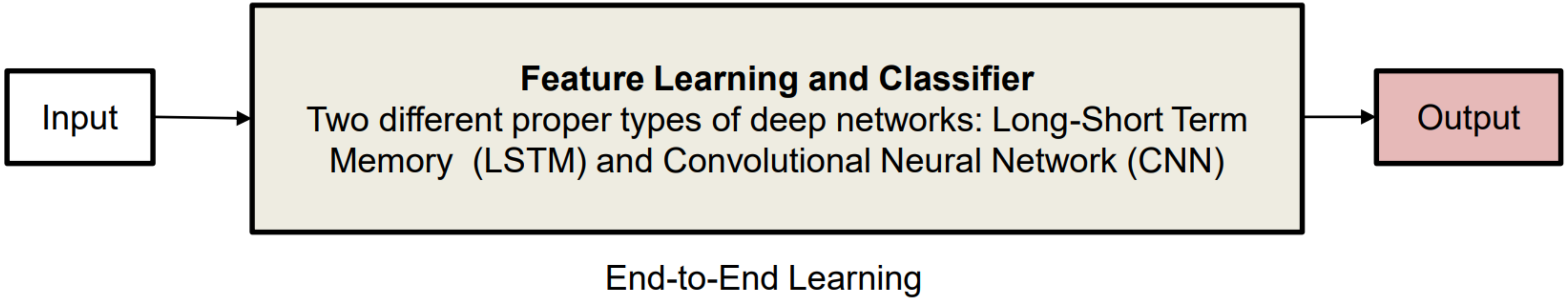
[2] Kaufmann, C., Frühwirth, M., Messerschmidt, D., Moser, M., Eichberger, A., & Arefnezhad, S. (2020). Driving and tiredness: Results of the behaviour observation of a simulator study with special focus on automated driving. Transactions on Transport Sciences, 11(2), 51-63. https://doi.org/10.5507/tots.2020.011

AI-based method for drowsiness classification

- **Machine Learning**



- **Deep Learning**



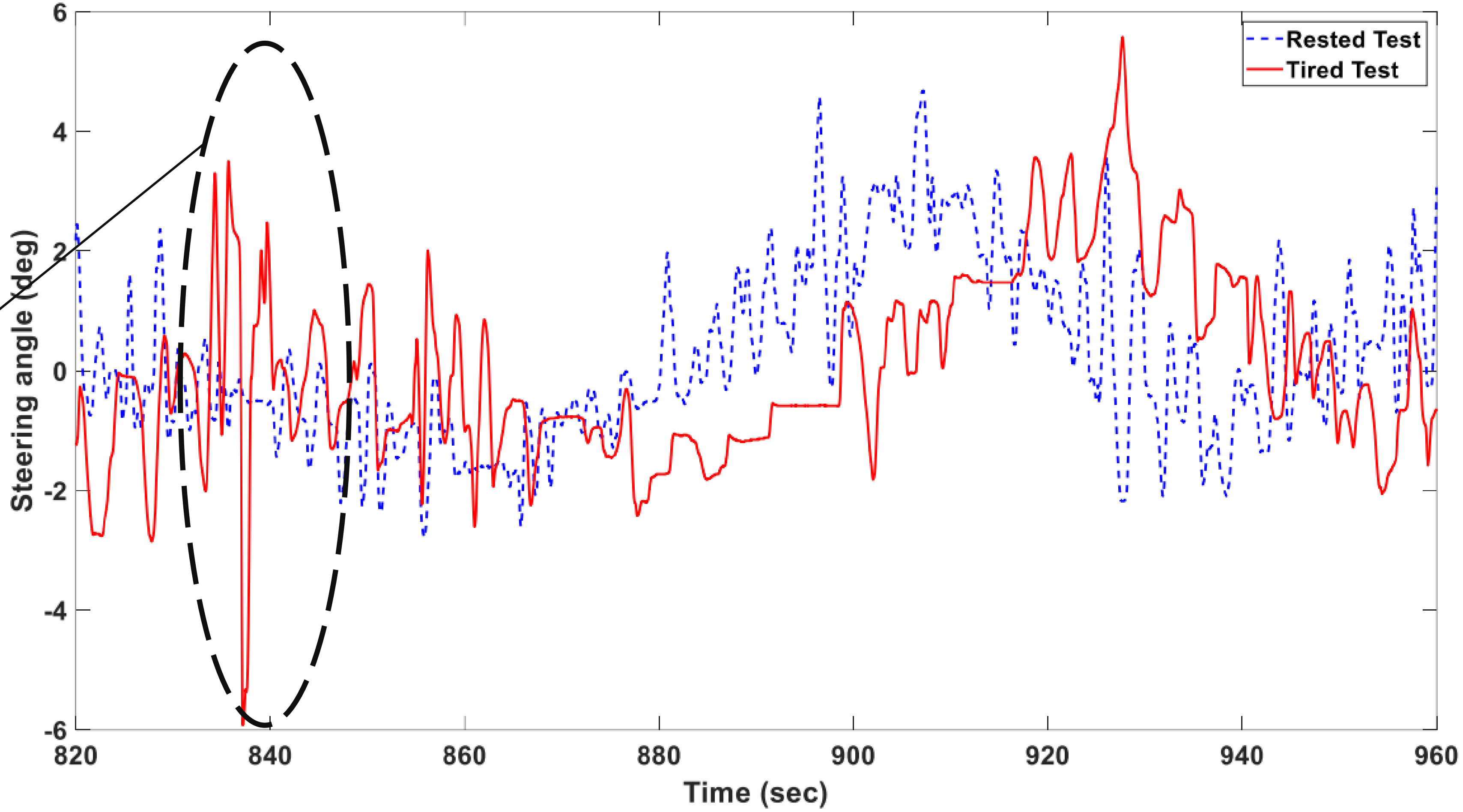
Comparison between: a) traditional machine learning, b) deep learning [3].

[3] J. Wang, Y. Ma, L. Zhang, R. X. Gao, D. Wu, Deep learning for smart manufacturing: Methods and applications, Journal of Manufacturing Systems, Volume 48, Part C, 2018, pp. 144-156.

Traditional Machine Learning methods for drowsiness classification

Drowsiness classification using vehicle based features

Large and fast steering wheel correction in the test for tired drivers



Drowsiness classification using vehicle based features

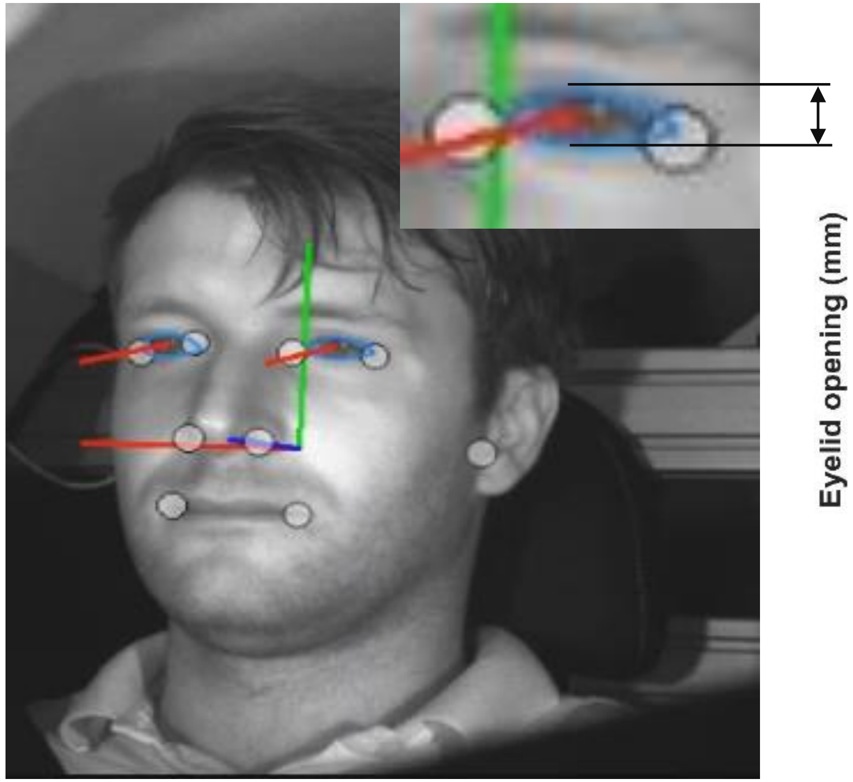
Vehicle-based data used: Steering wheel angle, yaw rate, lateral acceleration, lateral deviation from road centerline, steering wheel speed.

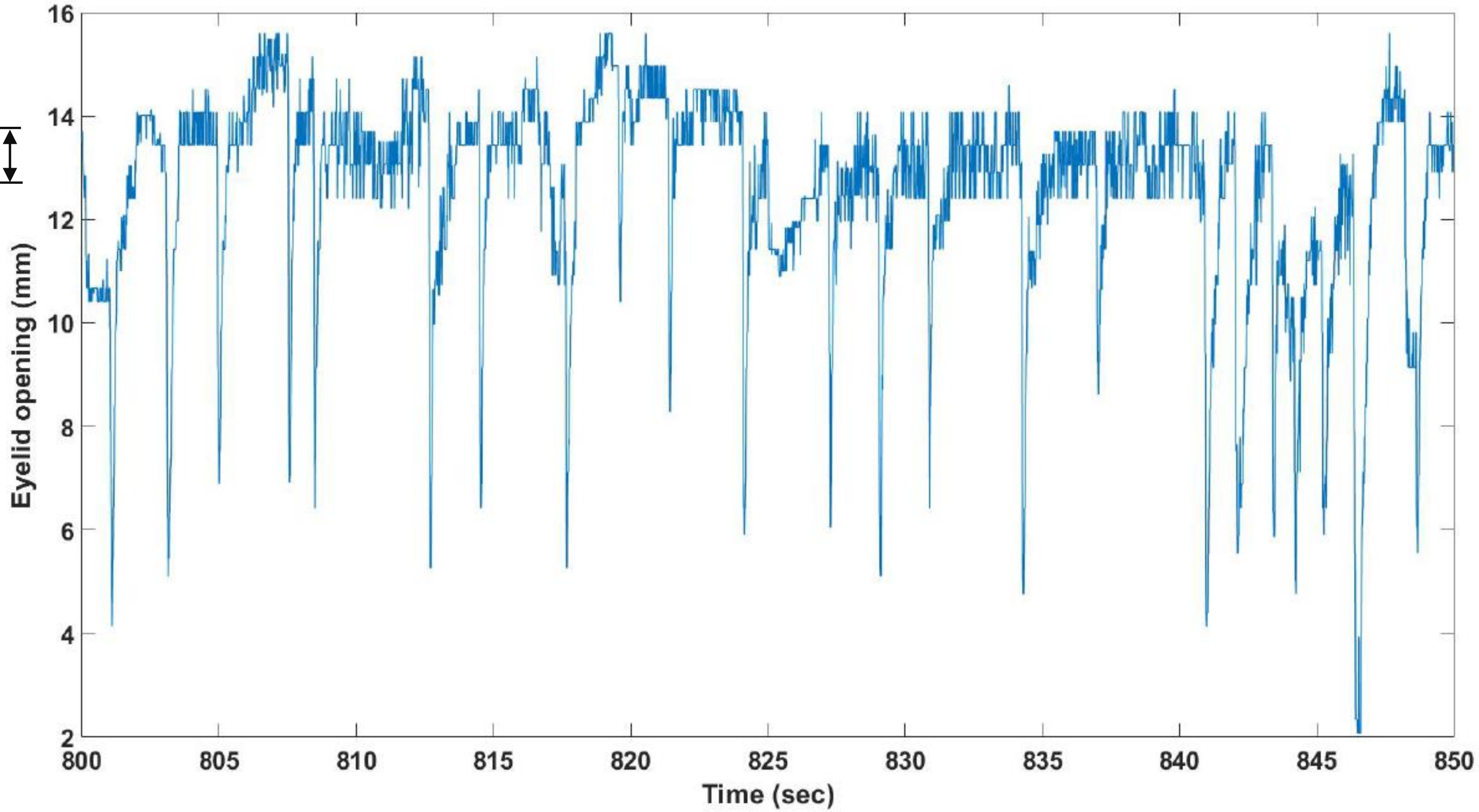
Extracted features from vehicle-based data to classify driver drowsiness [4]:
These features are extracted from all vehicle-based data.

Feature	Description
Mean	Average value of the signal in every sliding window
Standard Deviation	Dispersion of the data around mean value
Energy	Sum of the square of signal magnitude
Zero Crossing Rate (ZCR)	Number of steering or steering velocity direction changes per second
First Quartile	Middle number between the smallest number and the median of the signal in sliding window
Second Quartile	Median of the signal in the sliding window
Third Quartile	Middle value between the median and the highest value of the signal in sliding window
Skewness	A measure for signal similarity
Approximate Entropy (ApEn)	Complexity of signal in time domain based on distance in embedding dimension
Shannon Entropy (ShEn)	Complexity of signal in time domain based on probability function
Spectral Entropy (SpEn)	Complexity of signal in frequency domain
Dominant Frequency	The frequency that has maximum value of the Power Spectral Density (PSD)

[4] Arefnezhad, S.; Samiee, S.; Eichberger, A.; Nahvi, A. Driver Drowsiness Detection Based on Steering Wheel Data Applying Adaptive Neuro-Fuzzy Feature Selection. *Sensors* 2019, *19*, 943.

Drowsiness classification using facial data



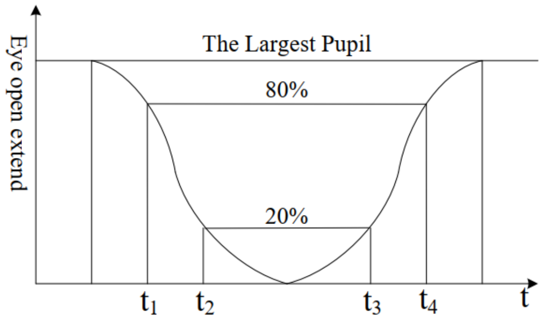


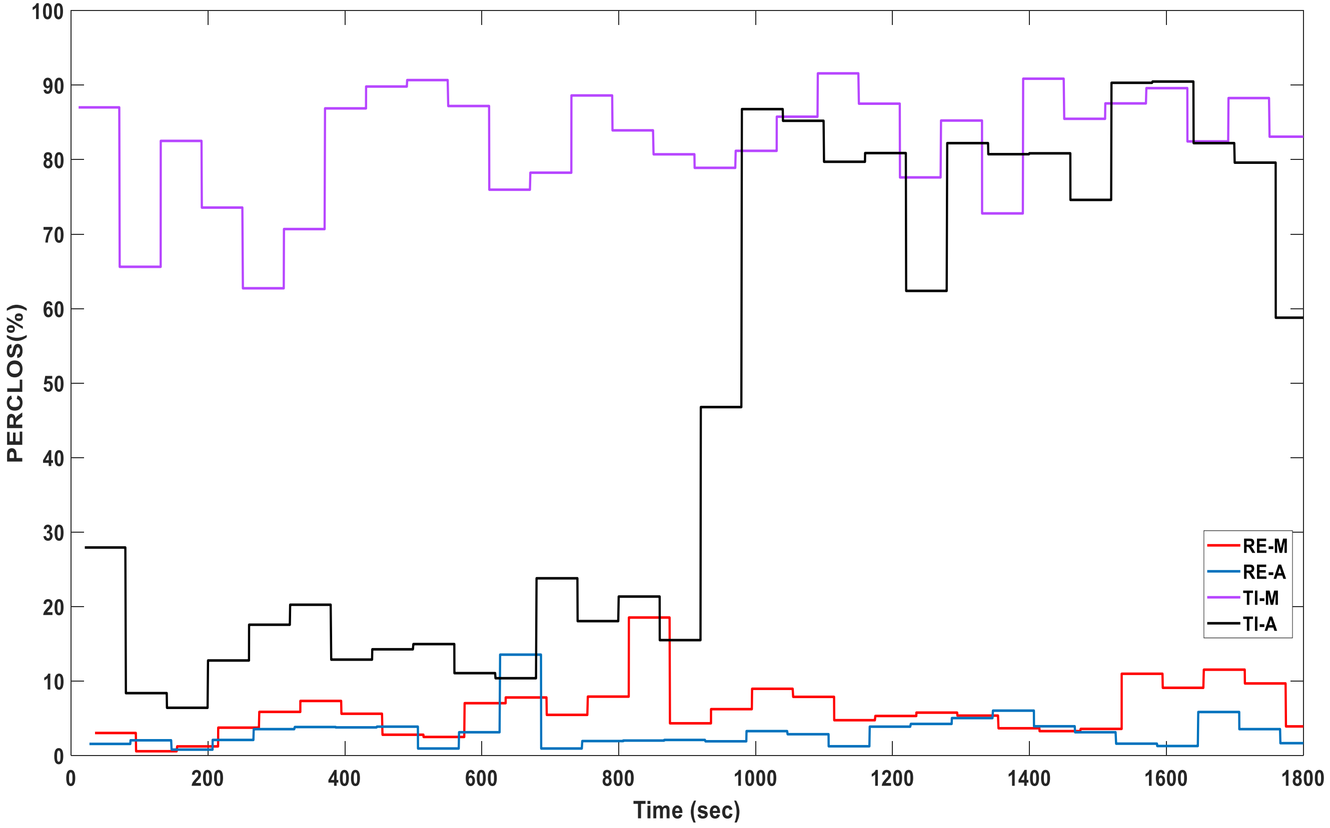
Drowsiness classification using facial data based features

Percentage of Eyelid Closure (**PERCLOS**):

- The percentage of time per minute that the eyes are closed more than 80% of the time.
- PERCLOS is a proven, objectively measurable ground truth for detecting drowsy driving.

$$PERCLOS(\%) = \frac{t_3 - t_2}{t_4 - t_1} \times 100$$

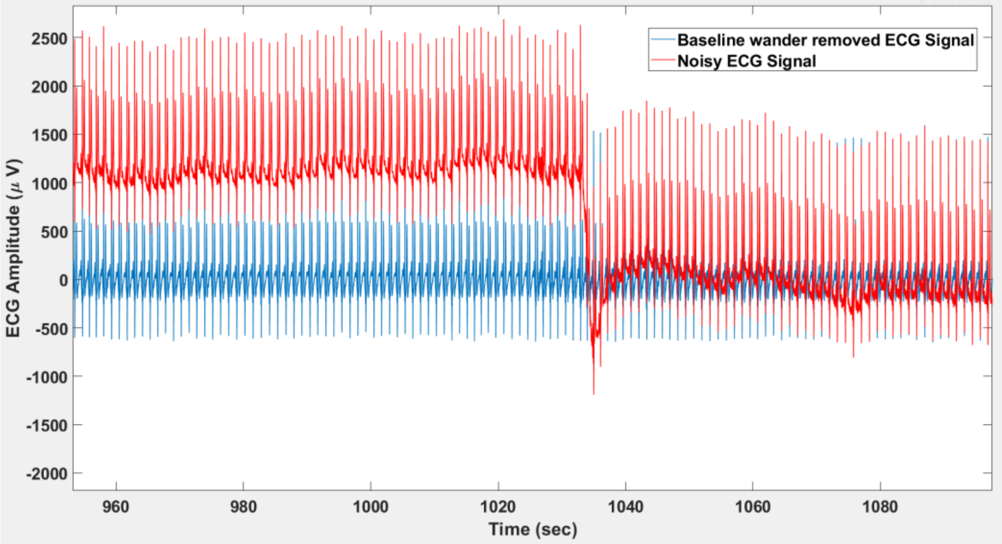




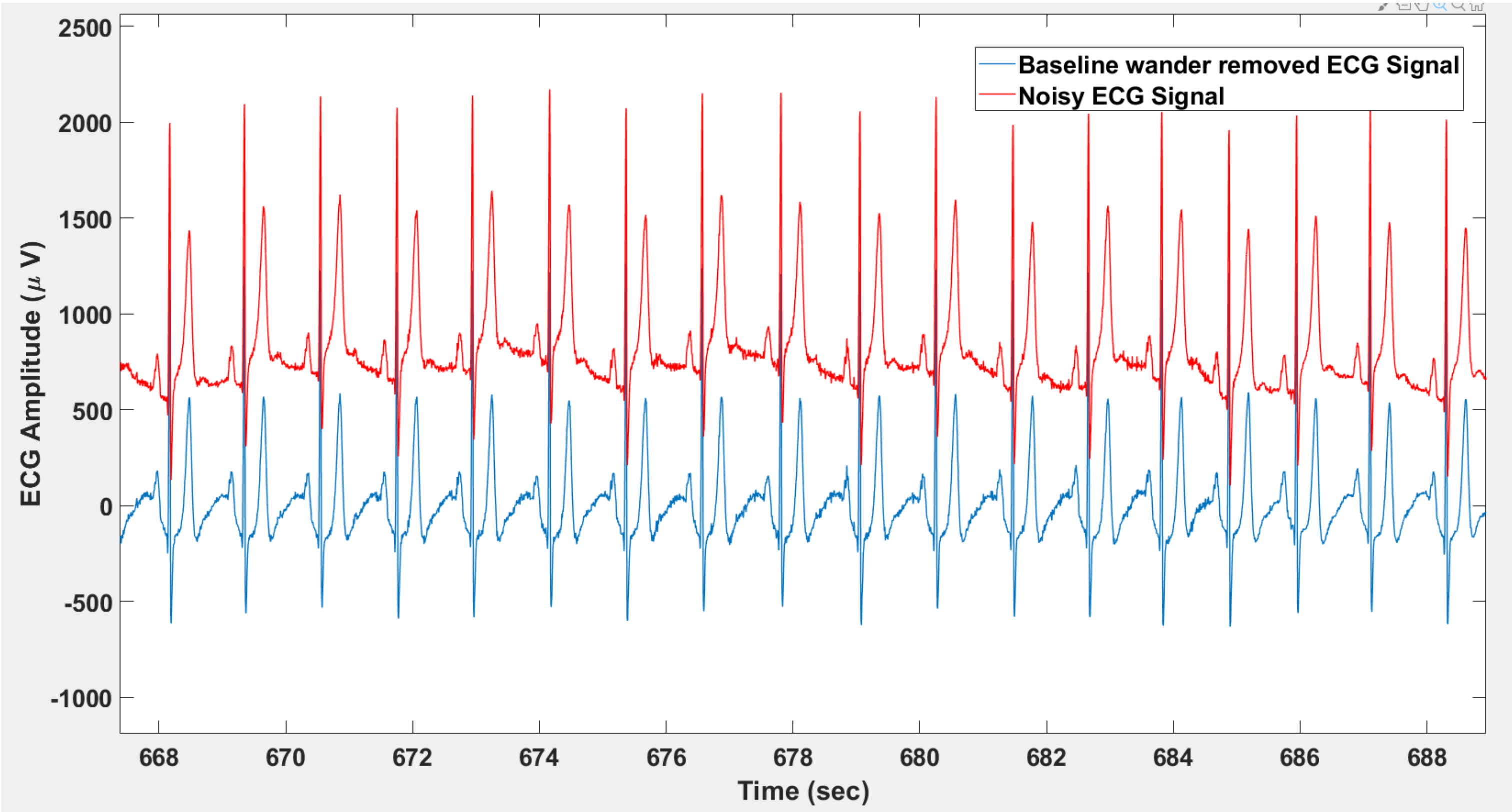
PERCLOS values for 4 driving modes: rested-manual (RE-M), rested-automatic (RE-A), tired-manual (TI-M) and tired-automatic (TI-A).

Drowsiness classification using ECG based features

Preprocessing of ECG signals to remove measurement noise

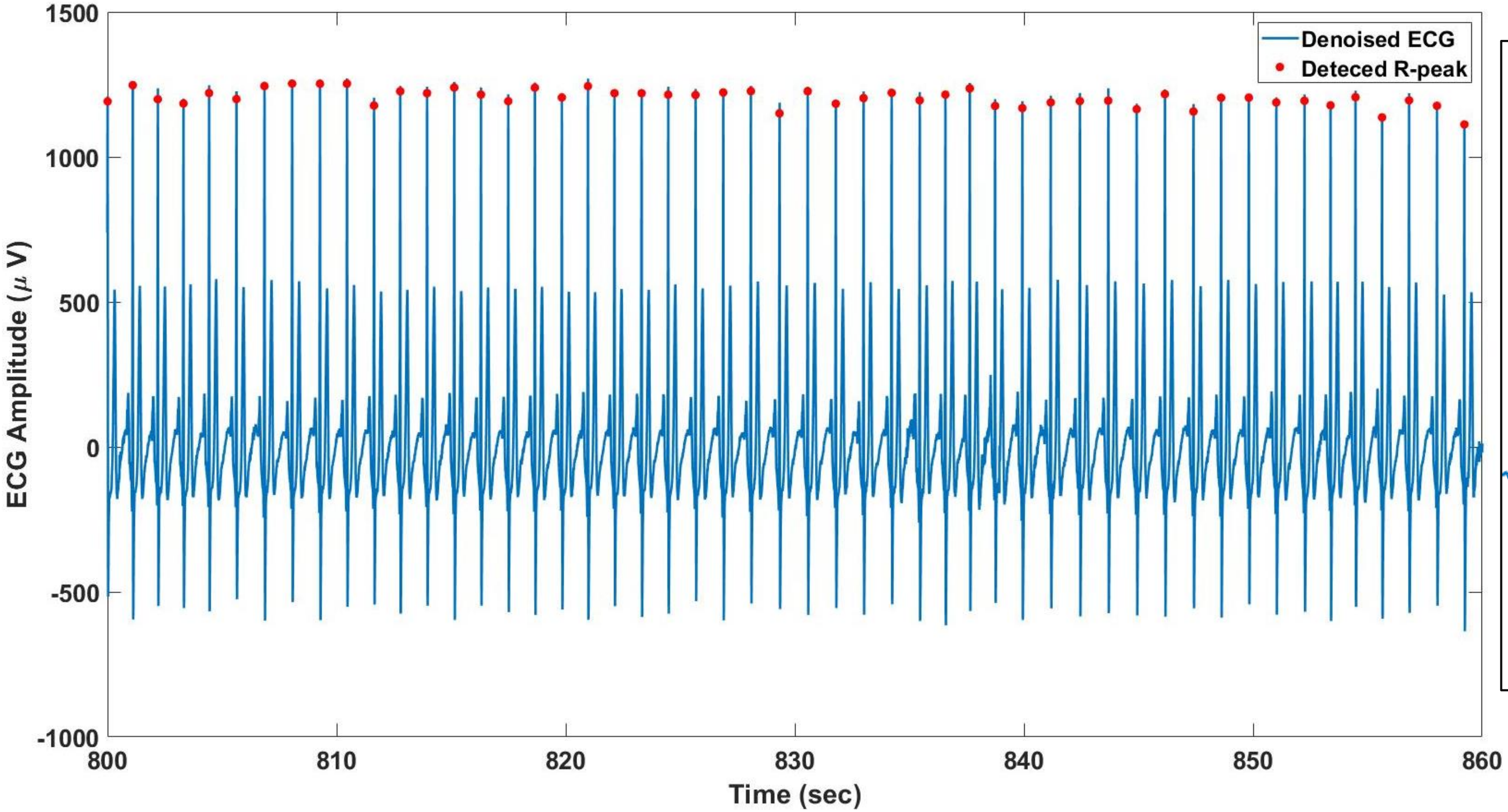


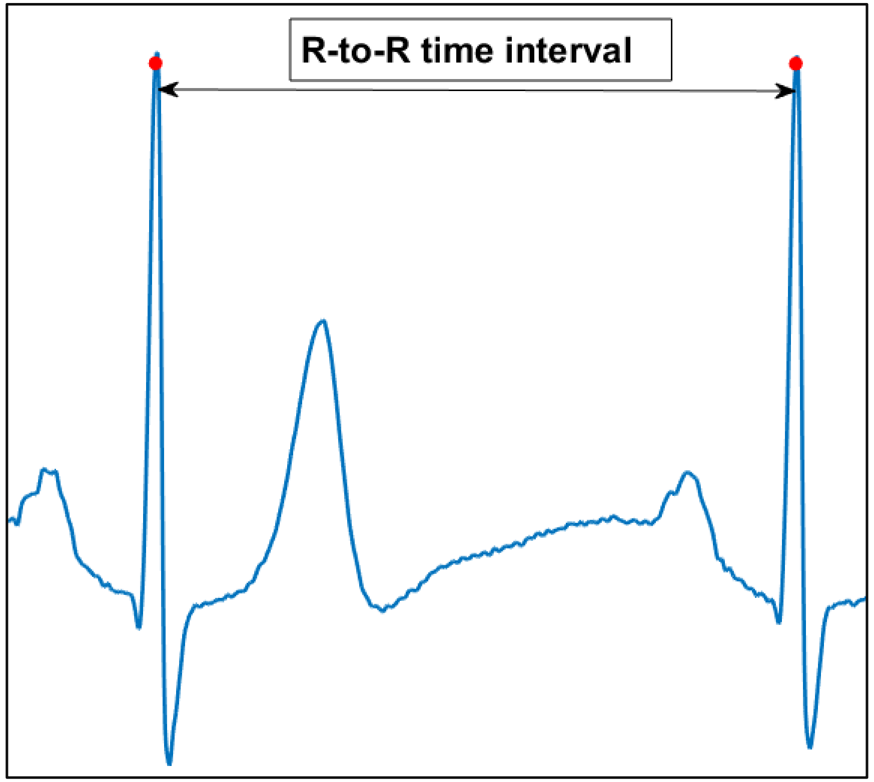
The nonlinear trend was removed with a Chebyshev Type II high-pass filter.



Drowsiness classification using ECG features

R-peak detection for heart rate variability extraction

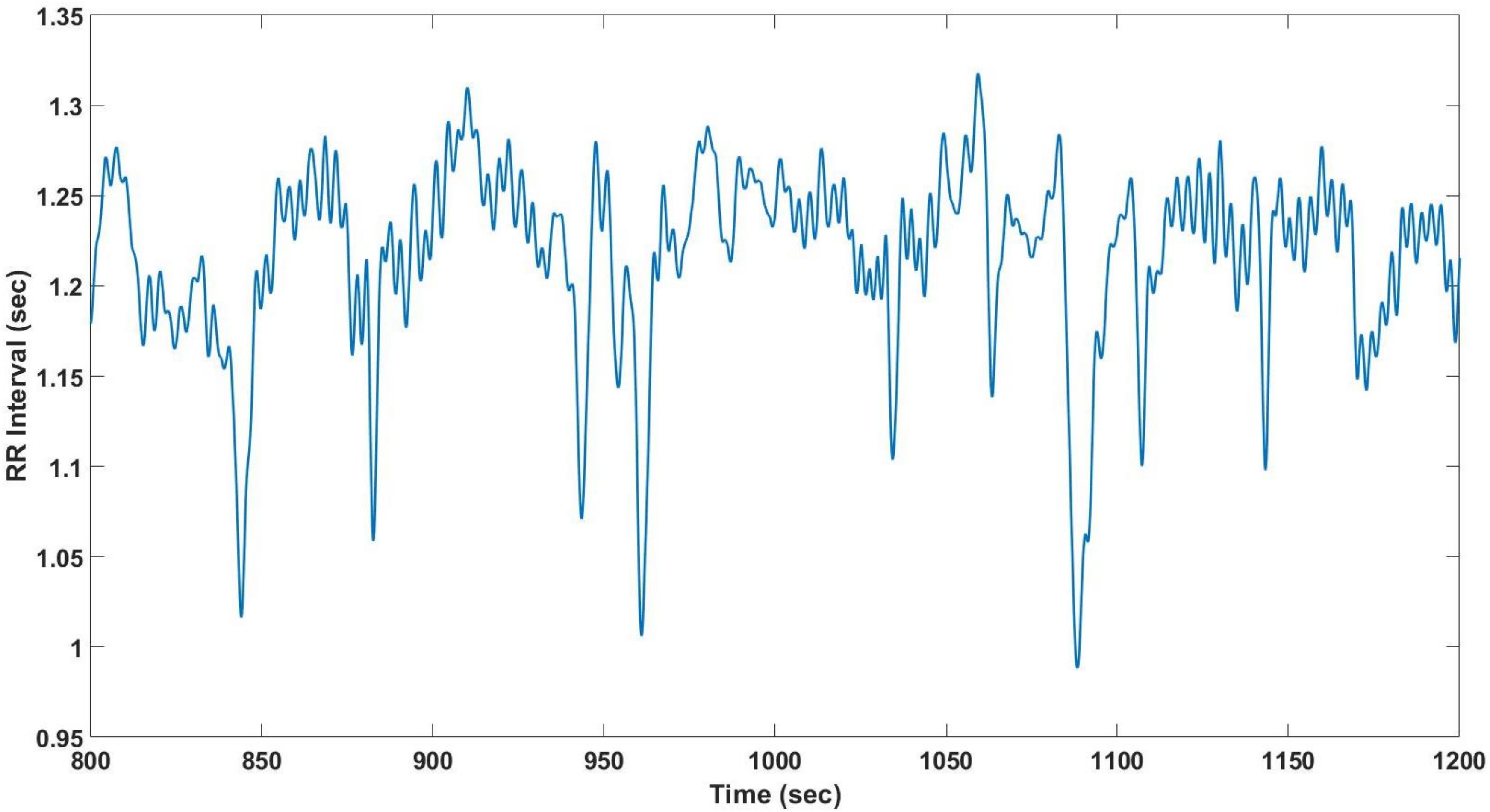




Drowsiness classification using ECG features

Extraction of RR interval (RRI) information based on detected R peaks.

This image shows the rapid oscillations of the heart rate during the test, which can be good information for distinguishing the alertness levels of the driver.

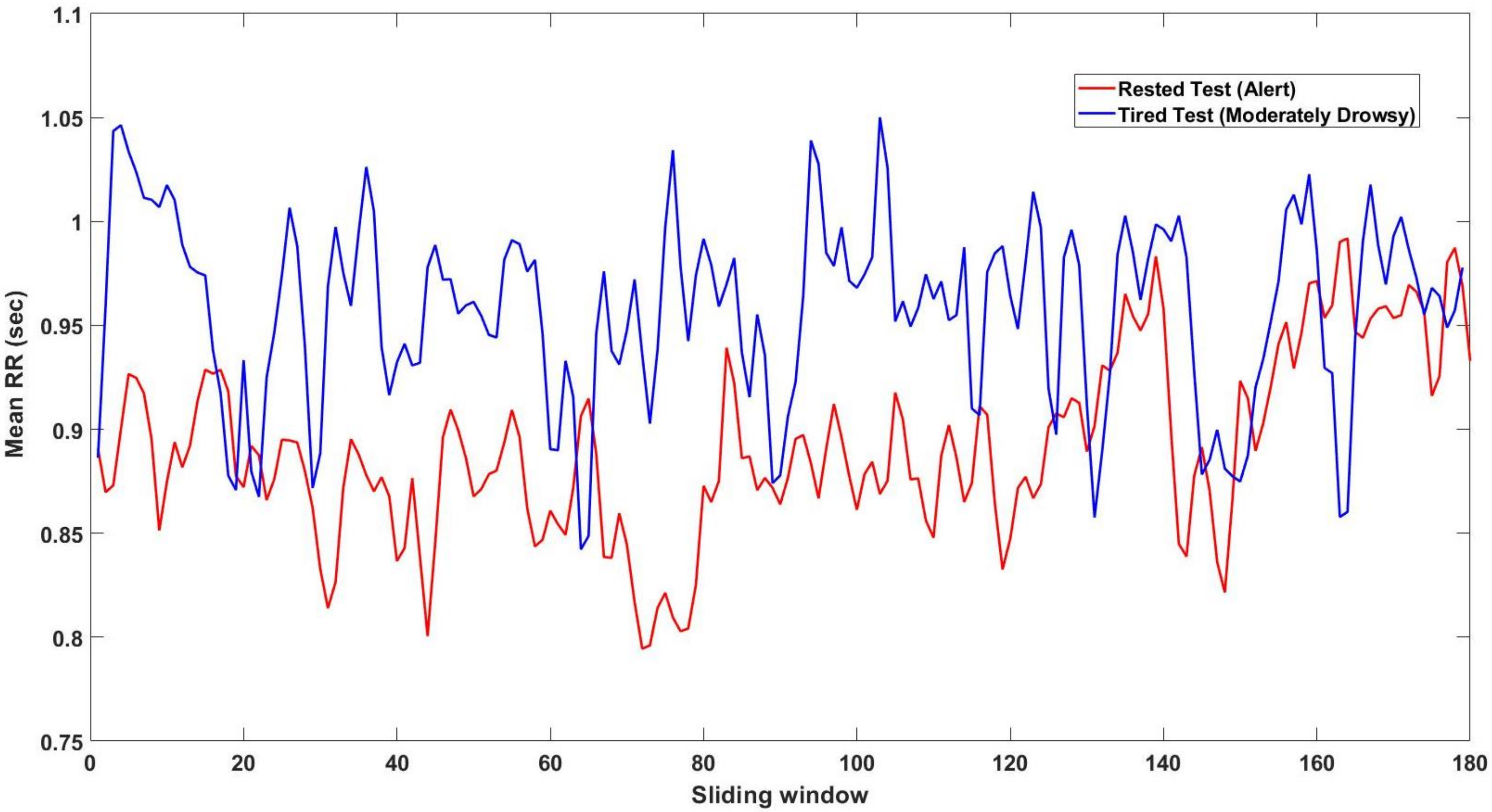


Drowsiness classification using ECG features

Extracted features from RR interval (RRI) signal	
Avg: average hear rate	**SDRR:** Standard deviation from RRI
MeanRR: average RRI	**Total Power (TP):** Variance of RRI.
RMSSD: Root-Mean-Square of the difference between adjacent RRIs	**LF:** Power of the low frequency range (0.04 Hz-0.15 Hz)
RR50: The number of pairs of adjacent RRI whose difference is more than 50ms	**HF:** Power of the high frequency range (0.15 Hz-0.40 Hz)
PRR50: The percentage of NN50 in all RR intervals	**LF/HF:** Ratio LF to HF.

Drowsiness classification using ECG features

- This figure shows the MeanRR for two different tests (rested and tired) for the same driver.
- Overall, the MeanRR is greater in the Tired test than in the Rested test.
- A lower MeanRR value means a higher heart rate.



Feature Selection Methods for selecting the feature with the highest information content

Data source	Input signal	Number of features
Vehicle data	Lateral acceleration, lateral deviation from the center of the road, steering wheel angle, steering wheel speed and yaw rate	64
ECG data	RR Intervals	10
Facial based data	Pupil diameter, eye lid opening	6
		Sum = 80

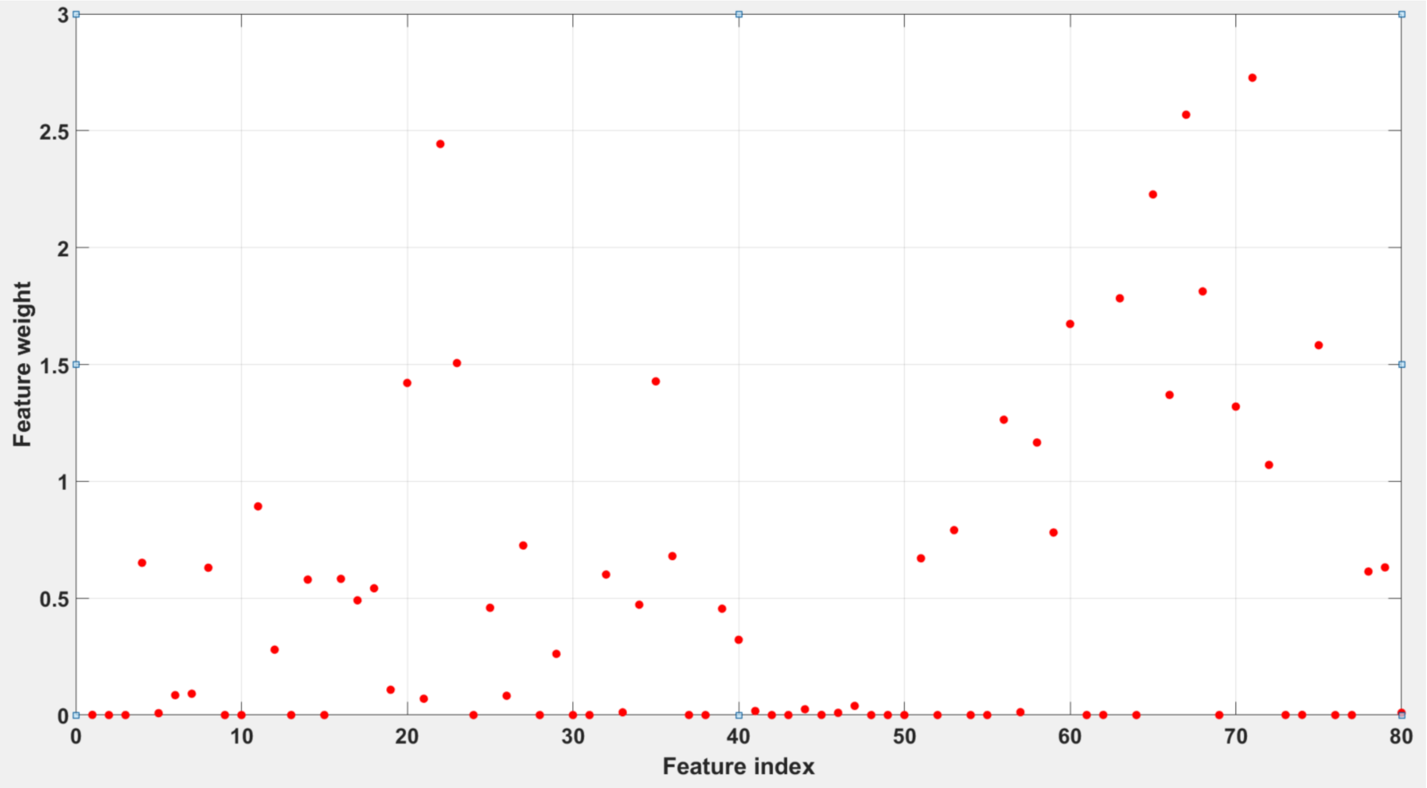
- Vehicle-based data have only be exploited in the manual driving tests because in the automated tests, drivers insert no input to the vehicle.

Feature Selection Methods for selecting the feature with the highest information content

Neighbourhood Component Analysis (NCA)

- NCA is a non-parametric feature selection algorithm. The feature weights are adjusted to maximize the leave-one-out probability of correct classification.

- Features that have no weight or a very low weight are removed from the feature set.



Feature weights calculated using the Neighborhood Component Analysis (NCA) method.

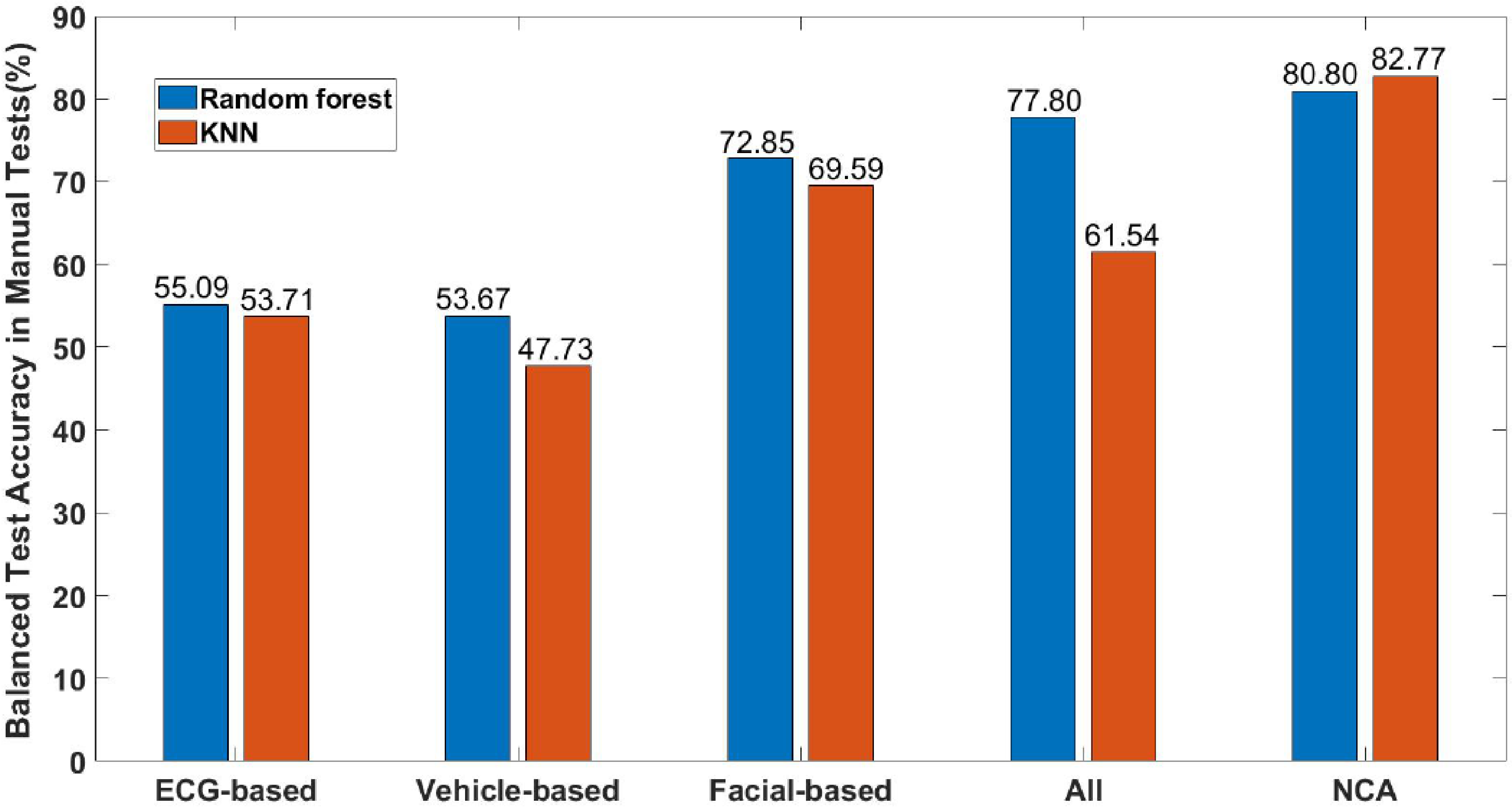
Feature Selection Methods for selecting the feature with the highest information content

Selected features by NVA (weight >0.2)

Data Source	Selected Features	No. Selected Features
Vehicle signals	First quartile of SWA, zero-crossing-rate of SWA, Approximate Entropy of SWA, OutPer of SWA, NMRHold of SWA, Energy of SWV, First quartile of SWV, Third quartile of SWV, Standard deviation of SWV, Approximated Entropy of SWV, First quartile of YR, Standard deviation of YR, Zero-crossing-rate of YR, Approximate entropy of LA, Skewness of LD, First quartile of LD, Third quartile of LD, Standard deviation of LD, Zero-crossing-rate of LD, Approximate Entropy of LD	20
ECG signals	MeanRR, SDRR, PRR50, LFrel, HFrel	5
Facial signals	Mean of Eyelid, Standard deviation of Eyelid, Mean of Pupil diameter, Standard deviation of Pupil diameter, PERCLOS	5
		Sum = 30

Classification accuracy

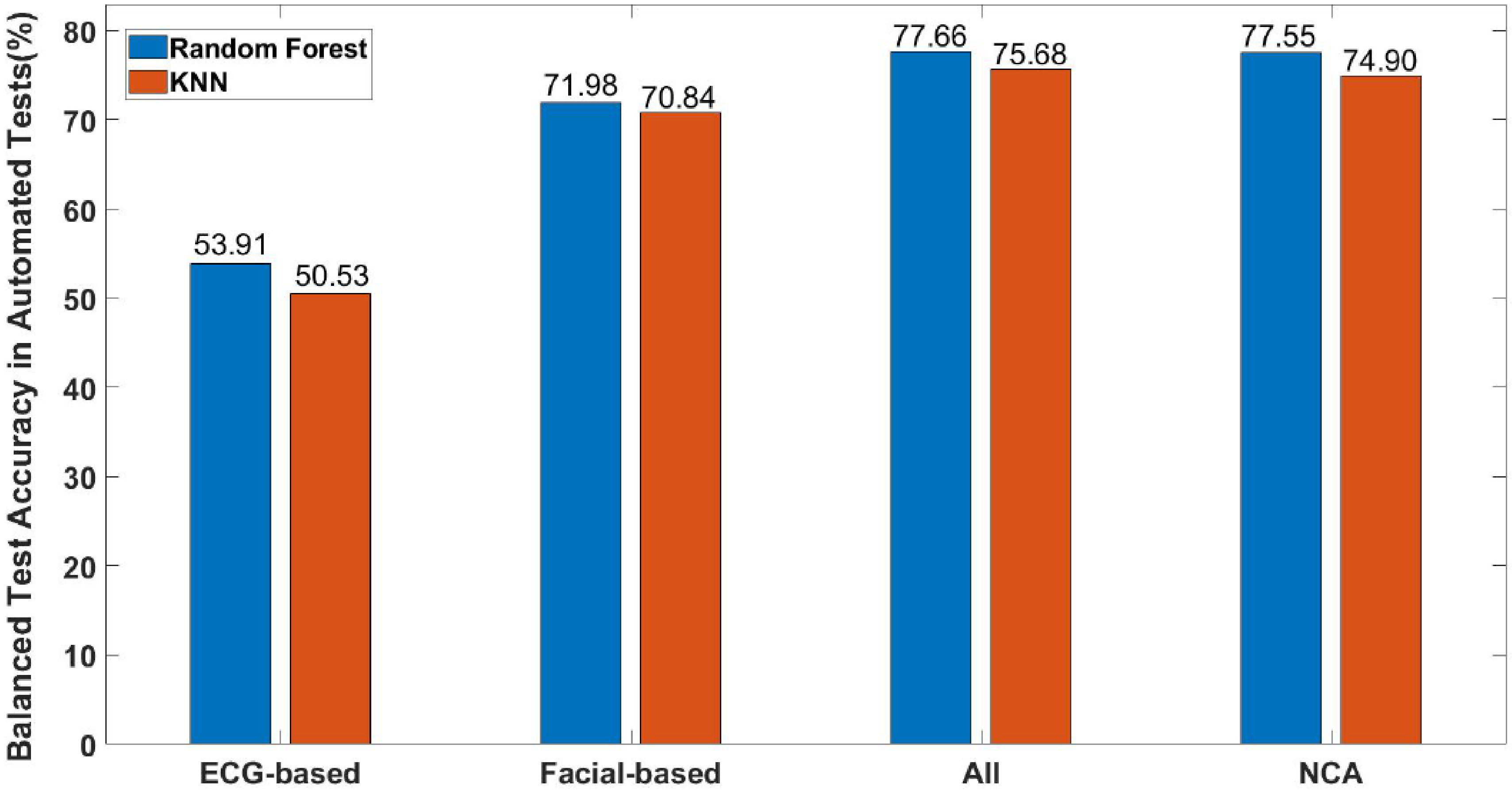
Classifier:
KNN, Random Forest
Driving mode: manual



Classification accuracy

Classifier:
KNN, Random Forest
Driving mode: automated

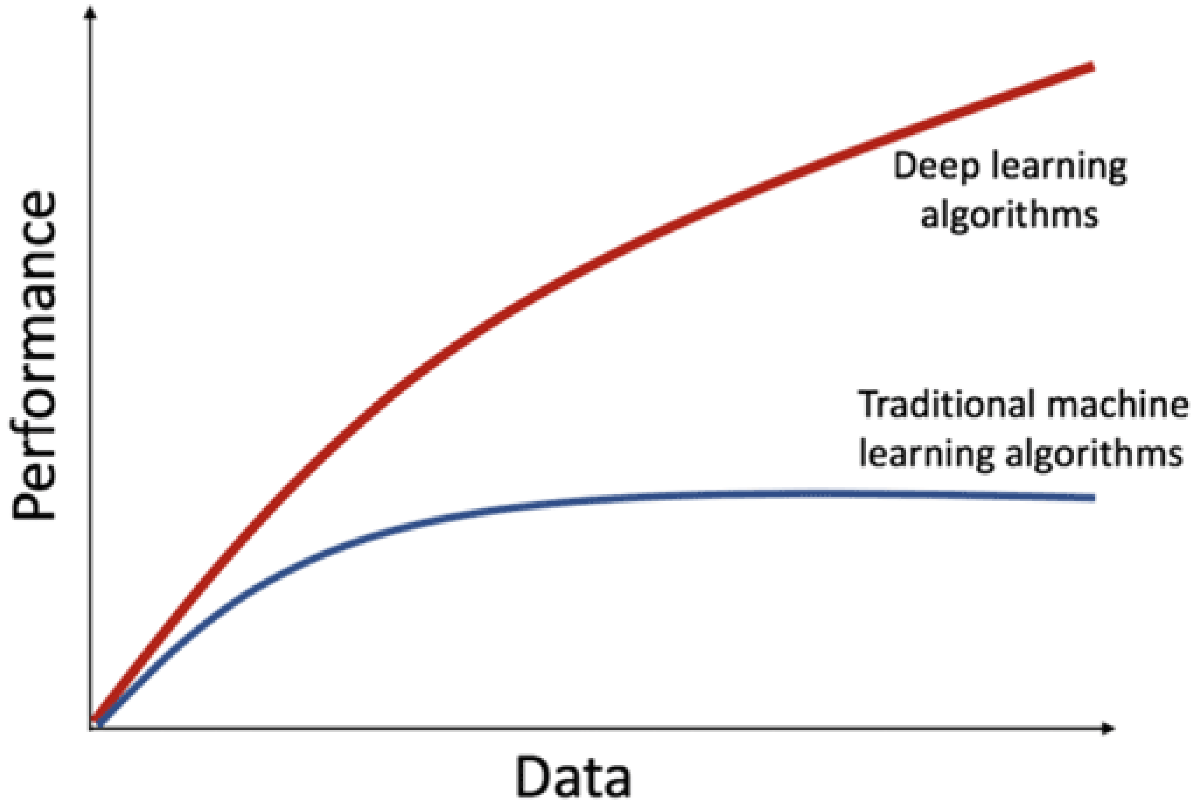
Vehicle-based data cannot be used to classify driver drowsiness in automated mode.



Deep Neural Networks for drowsiness classification

Why use deep learning methods?

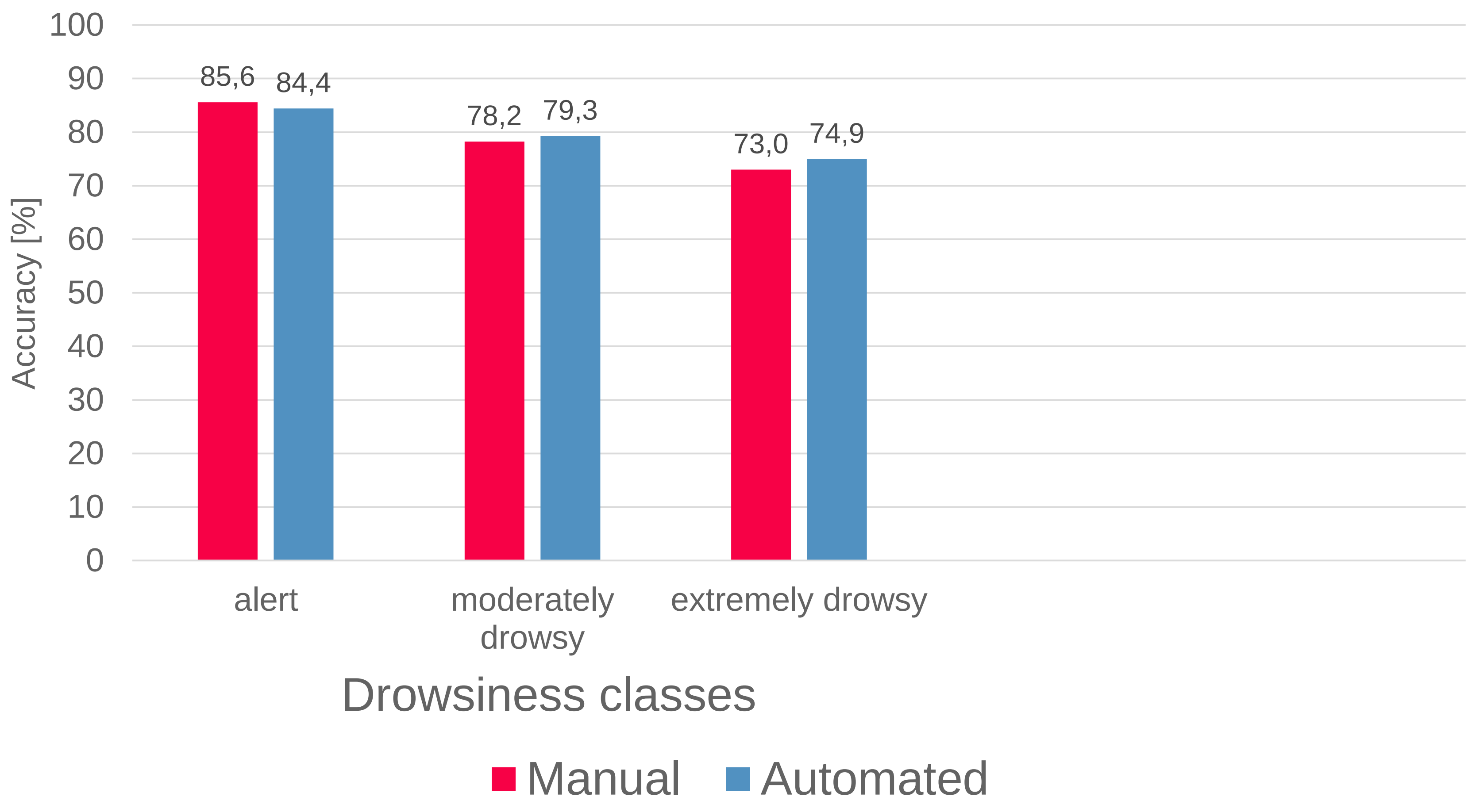
- When sufficient data is available, the performance of deep learning is superior to machine learning
- The main limitation of Deep Learning methods:
    - Difficulties in the training process e.g. getting stuck in local minima
    - or "overfitting".



https://idm.net.au/article/0012488-what-deep-learning-and-how-it-different-machine-learning

Accuracy of classification with Deep Learning

Higher data volumes in the "awake" state increase the accuracy
→
Further increase in the number of tests

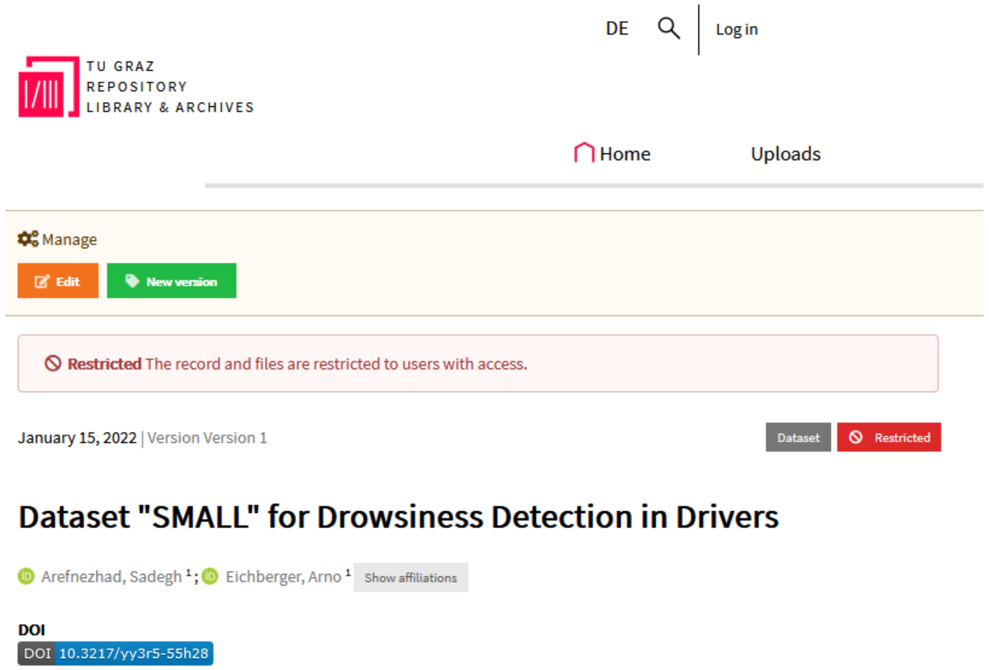


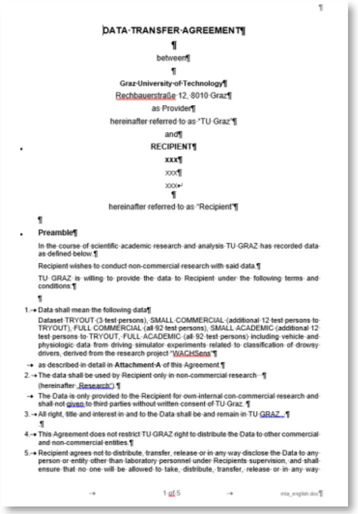
Datasets soon available on: **repository.tugraz.at**

1. Select model for usage

	Commercial use	Academic use
Dataset TRYOUT	free	free
Dataset SMALL	TBD	TBD
Dataset FULL	TBD	TBD

3. Download data sets





DATA TRANSFER AGREEMENT

between

Graz University of Technology
Rechbauerstraße 12, 8010 Graz
as Provider
hereinafter referred to as "TU Graz"

and

RECIPIENT
xxx
xxx
xxx

hereinafter referred to as "Recipient"

Preamble

In the course of scientific academic research and analysis TU GRAZ has recorded data as defined below.

Recipient wishes to conduct non-commercial research with said data.

TU GRAZ is willing to provide the data to Recipient under the following terms and conditions:

1. Data shall mean the following data
   Dataset TRYOUT (3 test persons), SMALL COMMERCIAL (additional 12 test persons to TRYOUT), FULL COMMERCIAL (all 92 test persons), SMALL ACADEMIC (additional 12 test persons to TRYOUT, FULL ACADEMIC (all 92 test persons) including vehicle and physiologic data from driving simulator experiments related to classification of drowsy drivers, derived from the research project "WACHSens"
   as described in detail in **Attachment A** of this Agreement.
2. The data shall be used by Recipient only in non-commercial research (hereinafter „Research").
   The Data is only provided to the Recipient for own internal con-commercial research and shall not given to third parties without written consent of TU Graz.
3. All right, title and interest in and to the Data shall be and remain in TU GRAZ.
4. This Agreement does not restrict TU GRAZ right to distribute the Data to other commercial and non-commercial entities.
5. Recipient agrees not to distribute, transfer, release or in any way disclose the Data to any person or entity other than laboratory personnel under Recipients supervision, and shall ensure that no one will be allowed to take, distribute, transfer, release or in any way

1 of 5 mta_english.doc

2. Sign data transfer agreement

Summary

- Essential: **Ground truth** definition for AI based classification methods
  PERCLOS, objectified video analysis, EEG

- **Vehicle signals** increase accuracy of classification, but only available with manual driving

- **ECG** and **eyelid motion** are robust and accurate for drowsiness classification even in automated driving mode

- Introduction of **multilevel** classification allows timely **prediction** of drowsiness

- WACHsen's database is **unique** worldwide in **quantity and quality** of data

- **Accessibility to the public** via the Research Data Management of TU Graz
  FAIR Data: Findable, **A**ccessible, **I**nteroperable, and **R**eusable

Published:

- Kaufmann, C., Frühwirth, M., Messerschmidt, D., Moser, M., Eichberger, A., & Arefnezhad, S. (2020). Driving and tiredness: Results of the behaviour observation of a simulator study with special focus on automated driving. *Transactions on Transport Sciences*, *11*(2), 51-63. https://doi.org/10.5507/tots.2020.011
- Arefnezhad, S., Eichberger, A., Frühwirth, M., Kaufmann, C., & Moser , M. (2020). *Driver Drowsiness Classification Using Data Fusion of Vehicle-based Measures and ECG Signals*. 451-456. Beitrag in 2020 IEEE International Conference on Systems, Man, and Cybernetics , Virtuell, Kanada. https://doi.org/10.1109/SMC42975.2020.9282867
- Arefnezhad, S., Samiee, S., Eichberger, A., Frühwirth, M., Kaufmann, C., & Klotz, E. (2020). Applying Deep Neural Networks for Multi-level Classification of Driver Drowsiness Using Vehicle-based Measures. *Expert Systems with Applications*, *162*, [113778]. https://doi.org/10.1016/j.eswa.2020.113778
- Eichberger, A., Koglbauer, I. V., Lex, C., & Arefnezhad, S. (2019). Menschliche Faktoren bei der Entwicklung von automatisierten Fahrfunktionen. in *16. Symposium Reifen und Fahrwerk* ÖAMTC Wien.
- Arefnezhad, S., Samiee, S., Eichberger, A., & Nahvi, A. (2019). Driver Drowsiness Detection Based on Steering Wheel Data Applying Adaptive Neuro-Fuzzy Feature Selection. *Sensors* , *19*(4), [943]. https://doi.org/10.3390/s19040943
- Arefnezhad, S., Eichberger, A., Frühwirth, M., Kaufmann, C., Moser , M., & Koglbauer, I. V. (2021). Classification of Driver Drowsiness using a Deep Convolutional Neural Network Trained by Scalograms of ECG Signals. Energies 2022, 15, 480. https://doi.org/10.3390/en15020480 .

Accepted:

- Arefnezhad, S., & Eichberger, A. (2021). Deep Learning for Driver Drowsiness Classification. Manuscript in preparation. in *Deep Learning and Its Applications for Vehicle Networks* CRC Press.
- Arefnezhad, S., Eichberger, A., Frühwirth, M., Koglbauer, I. V., & Kaufmann, C. (2021). *Driver Drowsiness Detection using Deep Neural Networks*. Postersitzung presented at 35. VDI-Fachtagung Fahrerassistenzsysteme und Automatisiertes Fahren, Aachen, Deutschland.
- Arefnezhad, S., Hamet, J., Eichberger, A., Frühwirth, M., Ischebeck, A., Koglbauer, I. V., Moser, M., & Yousefi, A. (2021). Driver Drowsiness Estimation Using EEG Signals with a Dynamical Encoder-Decoder Modeling Framework. Manuscript accepted for Scientific reports (Springer Nature).

Submitted:

- Arefnezhad, S., Eichberger, A., & Koglbauer, I. V. (2021). Effects of Automation and Fatigue on Drivers from Various Age and Gender Groups. Manuscript submitted

Thanks for the attention!

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