Driver Drowsiness Classification Using Data Fusion of Vehicle-based Measures and ECG Signals

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Contents

Motivation

- Drowsiness is an intermediate vigilance state between alertness and sleep, which may increase the reaction time in driving and lead to impaired driving performance.

- National Highway Traffic Safety Administration (NHTSA) reported that yearly, about **83000** traffic accidents and **900** fatalities are connected to drowsy driving in the United States.

- The probability of crashes in drowsy driving is 4-6 times higher than in alert driving.

- The goal of designing a driver drowsiness detection system is to warn drivers and to alert them when a dangerous level of drowsiness has been detected and also to use it for informative driver state monitoring in automated driving.

Experimental Setup

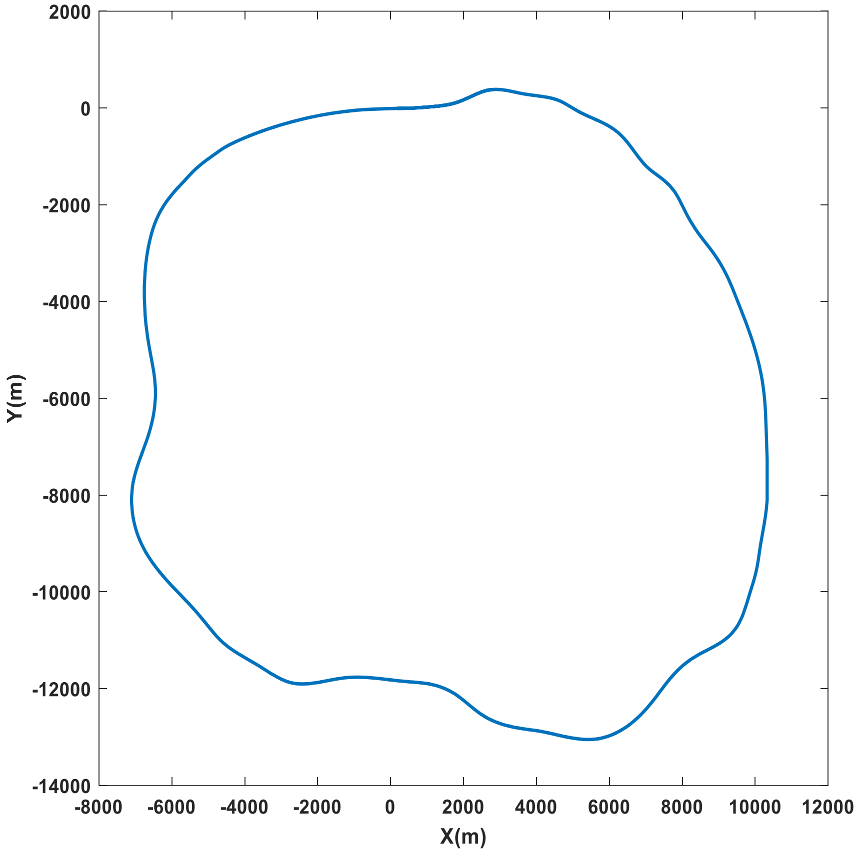
The Automated Driving Simulator of Graz (ADSG) is a modified production car, here pictured without the external housing that separates the whole simulator from the environment during the tests (left). The test track from the driver's view simulated a night drive on a highway (middle) and four different views from the drivers that are gathered using installed cameras inside the simulator (right).

Testing procedure

- **Data were collected from 93 driving tests, using 47 different subjects.**
- **Two age groups are considered including younger than 40 years (G1) and older than 40 years (G2).**

The distribution of driving tests based on age and gender of participants (including G1: younger than 40 and G2: older than 40).

Drivers' groups	No. of tests
G1-males	17
G2-males	30
G1-females	19
G2-females	27
	Sum = 93



The test track of driving tests.

Testing procedure

- Manual driving tests were performed in two driver's vigilance states: rested and tired.
- In the rested state, drivers were supposed to be alert, and they had no deviations from their usual circadian cycle.
- In the tired state, drivers were requested either to be awake for at least 16 h continuously before starting the test and to take the test at their usual bed-time or to have spent the previous night with 50% sleep restriction.

- Every driving test takes 30 minutes, and there is no traffic event to simulate a monotonous driving.

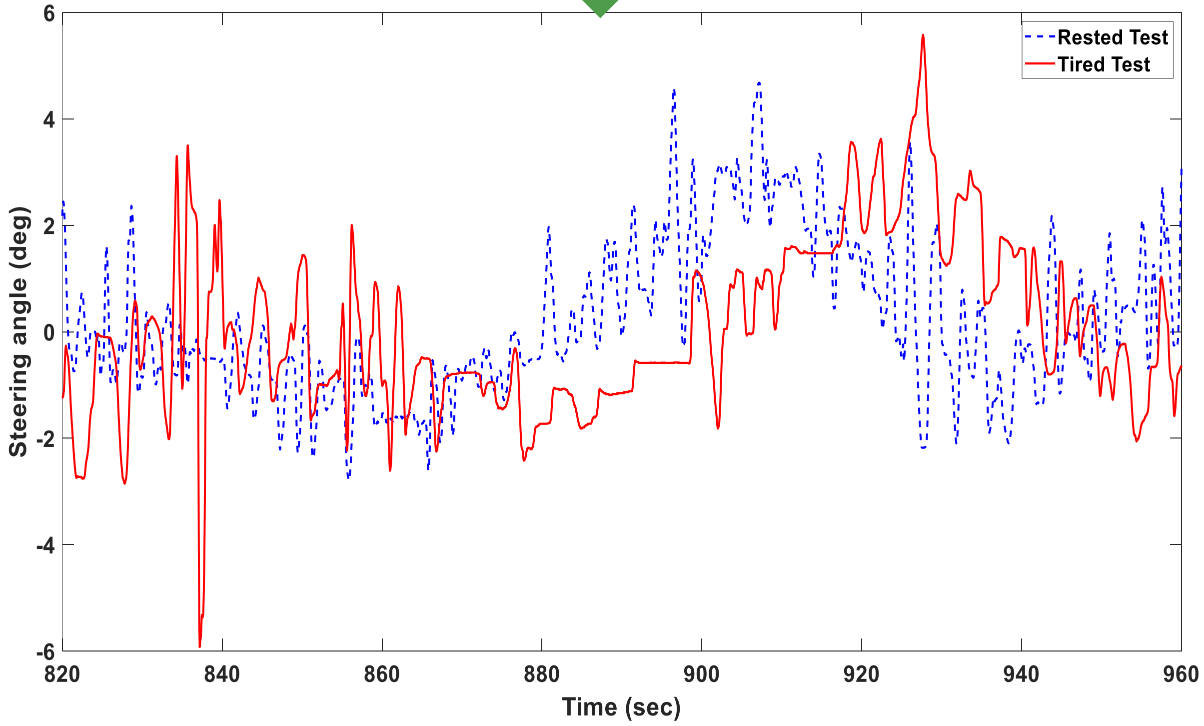
- The driven track is a closed path simulating a three lane motorway that has some smooth turns, and participants drive about 50 km during the test.

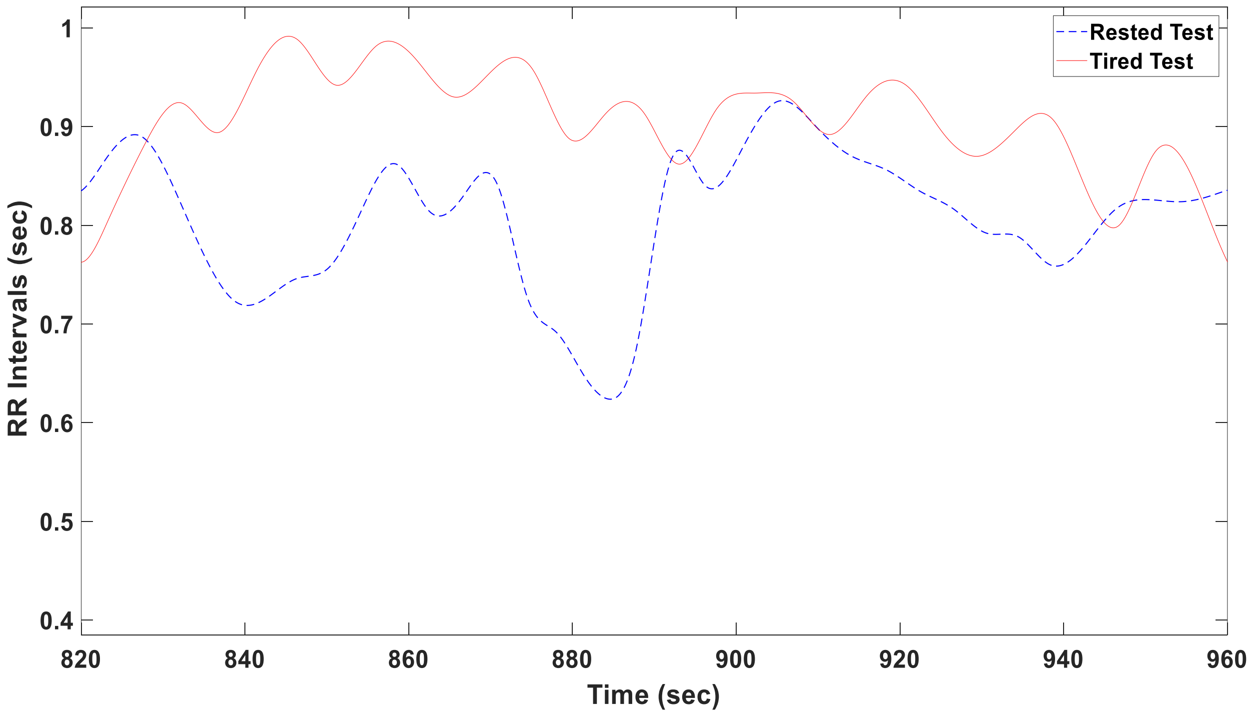
- Three levels of drowsiness, including alert, moderately drowsy, and extremely drowsy, are reported by video observing as ground truth for classification. An expert on driving observations noted different signs of sleepiness and rated the level of driver drowsiness in four levels: alert, moderately drowsy, extremely drowsy, and sleeping. For this study, the fourth level was merged to the third level

Machine Learning Methodology

Vehicle-based signals:
- **Lateral acceleration**
- **Steering wheel angel**
- **Lateral deviation from lane centerline**

ECG-based signal:
- **RR Intervals (time period between two consecutive R-peaks in ECG signals)**





Machine Learning Methodology

1. Feature extraction

- **A 40 s Hamming sliding window with the 30 s overlap between two adjacent windows is used to extract features from input data.**

Vehicle-based features; 13 features from each signal, overall 39 features.

Mean	**Signal length**
Standard deviation	**Skewness**
Energy	**Dominant Frequency**
Shannon Entropy	**Maximum of Spectrum**
Zero crossing rate	**Spectral centroid**
Slope sign change rate	**Spectral spread**
Spectral flux	

Machine Learning Methodology

1. Feature extraction

ECG-based features; 10 features from RR interval (RRI) signal	
Avg: Average heart rate	**SDNN:** Standard deviation of RRI
MeanNN: Mean of RRI	**Total Power (TP):** Variance of RRI.
RMSSD: Root mean square of the difference of adjacent RRI	**LF:** Power of low-frequency band (0.04 Hz-0.15 Hz)
NN50: The number of pairs of adjacent RRI whose difference is more than 50ms	**HF:** Power of high-frequency band (0.15 Hz-0.40 Hz)
PNN50: The percentage of NN50 in all RR intervals	**LF/HF:** Ratio of LF to HF.

Machine Learning Methodology

2. Feature selection

- Neighborhood Component Analysis (NCA) has been applied to select the most important features.

3. Classification

- Ground truth: Three levels derived from the video observations; Alert, Moderately drowsy, Extremely drowsy

- The extreme level of sleepiness was much less frequent than the two other levels→ Imbalanced dataset → Biased classifier

Machine Learning Methodology

3. Classification

- The Adaptive Synthetic Sampling Approach (ADASYN) was exploited to overcome the imbalanced classification problem.
- ADASYN is an upsampling method to generate synthetic data from the minority class (extremely drowsy) that reduces the bias introduced by the imbalanced dataset.

- The dataset has been randomly separated into the training set (75%) and test set (25%).

- K-nearest neighbors (KNN) and Random Forest (RF) are applied as two classifiers.
- Bayesian optimization method is employed to optimize their hyperparameters.

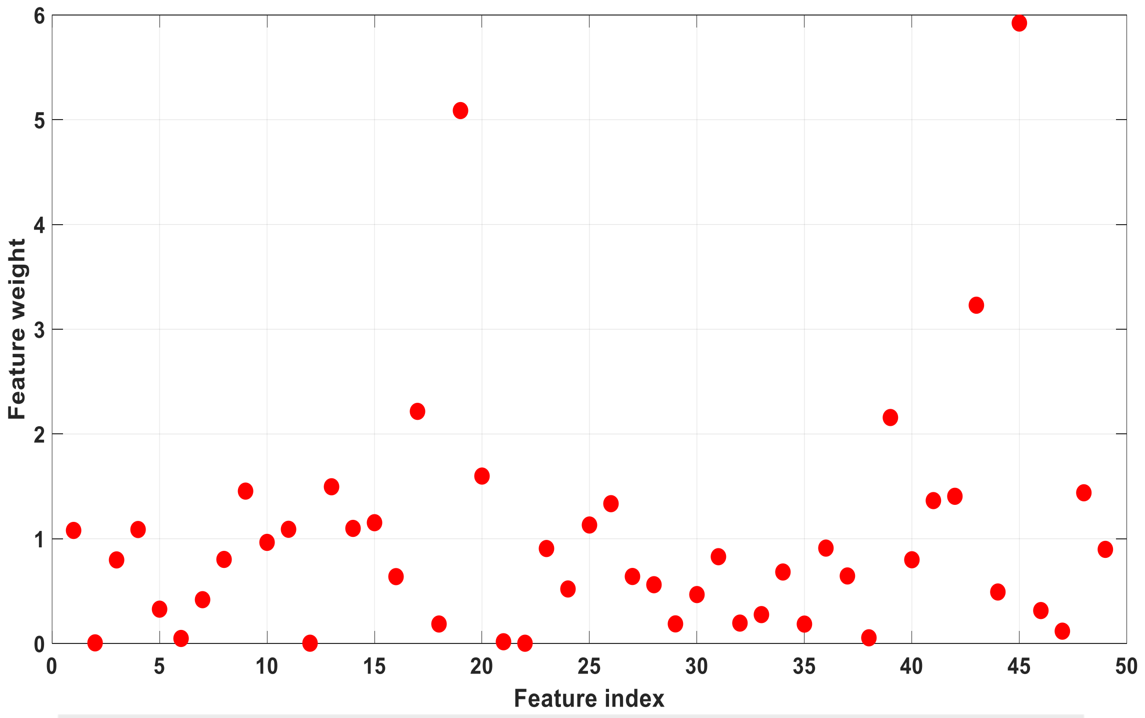
Numbers of observations for drowsiness levels

Drowsiness levels	No. of observations
Alert	11290
Moderately drowsy	4536
Extremely drowsy	15884
	Sum = 31170

Results and Discussion

Feature selection results

Twenty features that their weights are higher than 1 have been chosen by the NCA method.



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

Selected features from vehicle data and ECG signals

Data	Selected feature
ECG	NN50, Avg, HF, LF/HF
Steering wheel angle	Dominant frequency, Signal length, Shannon entropy, Spectral centroid, Slope sign change rate, Mean
Lateral acceleration	Dominant frequency, Signal length, Maximum of Spectrum, Shannon entropy, Mean, Zero crossing rate, Standard deviation
Lateral deviation	Shannon entropy, Energy, Spectral flux

Results and Discussion

Classification Results: ECG-based features and Vehicle-based features are used together.

Confusion matrices of classifiers for the whole of the feature set (ECG and vehicle data together). AL: alert, MD: moderately drowsy, ED: extremely drowsy.

		KNN-True Class			RF-True Class		
		AL	MD	ED	AL	MD	ED
Predicted class	AL	2185	60	64	2195	47	39
	MD	17	862	38	14	885	28
	ED	15	17	3084	8	7	3119

- **Classification Results show that RF detects all three levels of drowsiness with higher accuracy than KNN.**

Results and Discussion

Classification Results: ECG-based features and Vehicle-based features are used separately.

Data set	RF Accuracy%	KNN Accuracy%
ECG-based features	88.5	86.2
Vehicle-based features	82.8	80.8
ECG-based and Vehicle-based features	91.2	90.3

- **Classification results show that data fusion of ECG and Vehicle data outperforms the accuracy about 3%.**

Results and Discussion

Classification Results: Considering the human factors and by using all features.

Younger than 40		Older than 40	
KNN Accuracy %	RF Accuracy %	KNN Accuracy %	RF Accuracy %
88.4	87.7	91.1	89.1

- **Classification results show better performance (about 1.5%) for older-than-40 than for younger-than-40 participants.**

Male participants		Female participants	
KNN Accuracy %	RF Accuracy %	KNN Accuracy %	RF Accuracy %
89.2	90.6	90.1	90.7

- **Classification results show slightly better performance (about 0.5%) for female than for male participants.**

Conclusion

- **Extracted features from ECG signals and vehicle-based measures were fused to improve the performance of the driver drowsiness system in comparison with using each data source individually.**

- **KNN and RF were employed as two traditional classification methods when the Bayesian optimization method optimized the hyperparameters of classifiers. Results showed that RF outperforms the KNN for the classification of all drowsiness levels and signal sources.**

- **According to the results, data fusion improved the performance by about 3% accuracy in comparison to ECG signals only and by about 8% in comparison to vehicle-based measures only.**

- **Two human factors of age and gender also were considered in the classification process. Results showed that the method obtained a slightly better performance for older than for younger drivers.**

Acknowledgment

http://humanresearch.at/ https://tugraz.at/ https://avl.com/ https://factum.at/

Thanks for your attention!

If you have any question, please do not hesitate to contact me: s.arefnezhad@tugraz.at

Here is my Visit Card.

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