Discomfort Detection in Autonomous Driving Using Artificial Neural Networks

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Abstract

With the role change from driver to passenger inhered in driving automation, human factors such as driving comfort are considered important requirements for the broad acceptance and usage of this technology. Potential indicators of discomfort include physiological, environmental, and vehicle parameters from different sensors. The reliable detection of discomfort based on a combination of such indicators contains a lot of complexity. Machine learning methods have led to rapid solving of problems with high complexity and particularly artificial neural networks are among the most prominent methods with the ability to deal with these type of challenges.

Objectives

We aim to detect discomfort by:

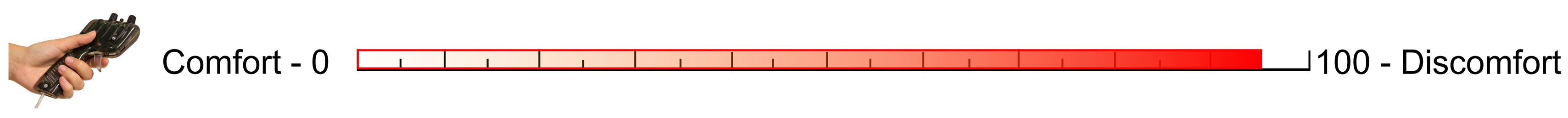
- **(a)** Identify suitable input signals (features) that could help us in detecting discomfort.
- **(b)** Using a cascade Long Short Term Memory (LSTM) model to identify discomfort.
- **(c)** Compare the ability of models to identify discomfort with different input signals.

Dataset

- **Experimental Design and Participants:** To achieve a highly immersive presentation of real driving situations a modular simulator was used [3].

Participants	25 drivers (25-84 years old)
Driving style	Highly automated driving
Driving simulator softeware	SILAB
Projection View	180° + rear, and side mirrors

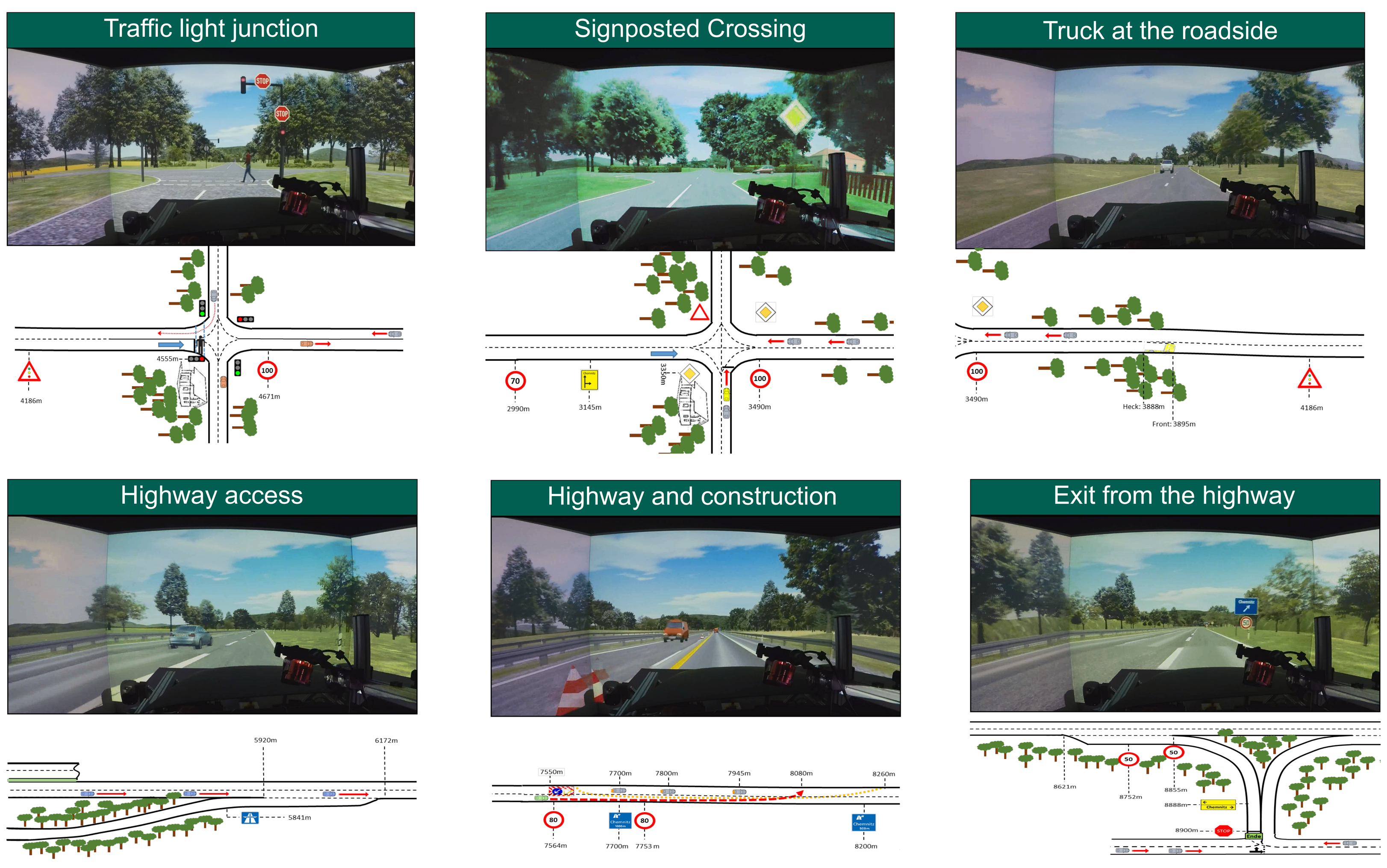
- **Hand-Set-Controller:** The participants should press the hand controller corresponding to their perceived discomfort.



- **SMI-EYE-TRACKER:** SMI eye tracker glasses can record the pupil diameter of participants and track which area is interesting for participants at each time steps.

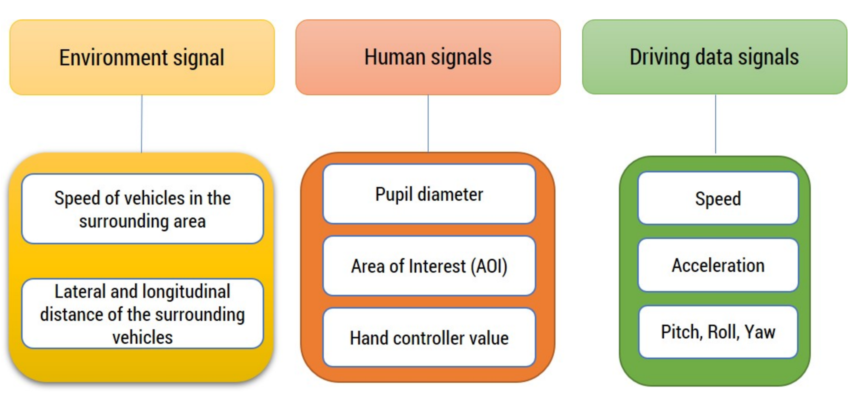
SMI eye tracker glasses

- **Different Critical Traffic Situation:** Every driving session is composed of a 9-km long highly automated trip on a rural road, carriageway, highway, and six different traffic situations.



Features

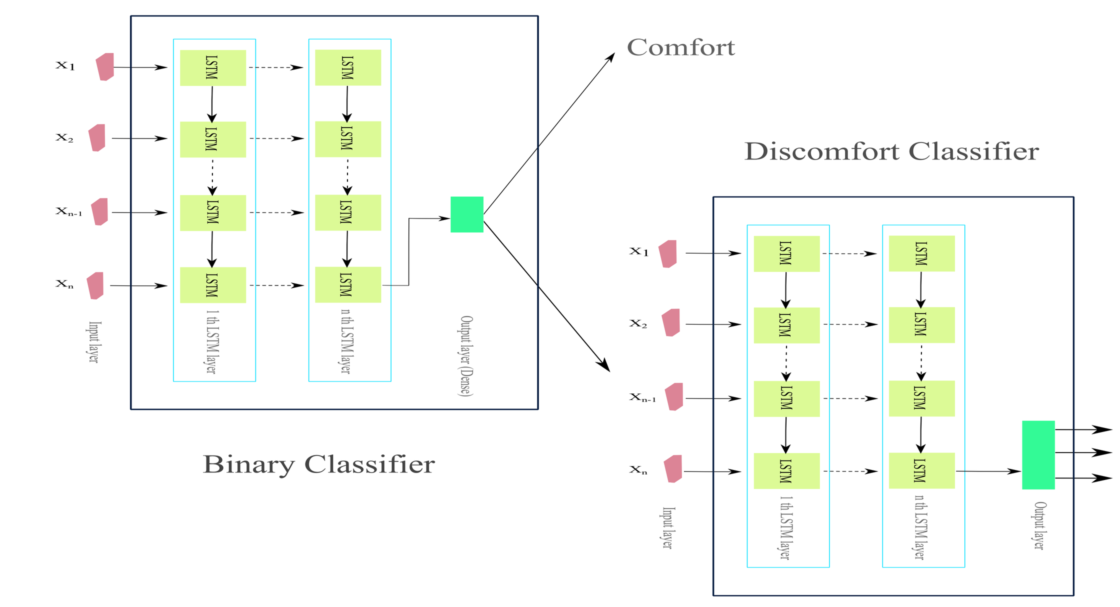
Input signals are divided into three sub-groups, the features from environment, from the human, and from the automated vehicle, which provide the concept of the interaction between human and technology.



Models

To identify discomfort, two models with different input signals are considered. An binary LSTM model for recognizing the comfort and discomfort of the driver and discomfort LSTM model for recognizing three different levels of discomfort (High, Low, and Medium). The optimal architectures of models are found by the *hyperopt* hyperparameter optimization method [2]. The Dataset has 25515 train samples and 32 available input signals ($x_1, \ldots, x_{32}$).

LSTM Cascade Classifier Model



Cascade Classifier

- **Train the cascade model with all available input signals:**
After preprocessing, we train an LSTM cascade model with the remaining input signals, which we call them All input signals here.We also chose the cascade architecture model because the multi-classifier was not able to classify 4 classes from each other. The cascade model contains a binary and a discomfort classifier.
- **Train the cascade model with selected input signals:**
In the next step, we apply a feature elimination method [1] to determine the most important input signals for recognizing discomfort and afterward evaluate the model with the selected features.
- **Train the cascade model with Expert input signals:**
In order to assess the performance of the model, we train another cascade model with a predetermined set of input signals, which is called *Expert*, since this set of input data was selected by an expert (psychologist).

Technical Details

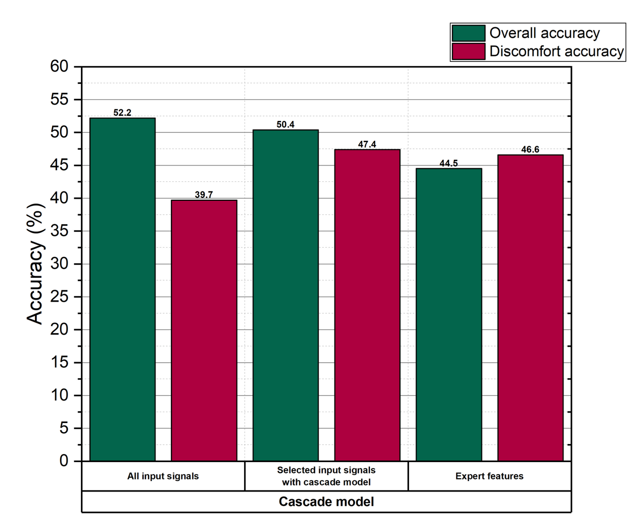
The binary model with all input signals contains two LSTM layers and one dense layer, while the binary model with selected input signals contains three LSTMs and the expert binary classifier contains only two LSTM layers. The discomfort models for all and selected input signals contain two LSTM layers. However, the expert discomfort classifier contains three LSTM and a dense layer with the different number of nodes. All binary and discomfort models used a time step size of 20, and the RMSprop as optimizer.

The name of input signals

All input Fatures		Selected features with the feature elimination method	Expert features
1	Speed	●	●
2	Acceleration		●
3	Steering wheel angle	●	●
4	yaw		●
5	Pitch	●	●
6	Roll	●	●
7	rpm		●
8	Blinker	●	
9	Right circular pupil diameter	●	●
10	Left circular pupil diameter	●	●
11	AOI1	●	●
12	AOI3	●	●
13	AOI4	●	●
14	AOI5	●	●
15	AOI6	●	●
16	AOI8		●
17	Traffic_Front_v	●	
18	Traffic_Front_dist	●	●
19	Traffic_Behind_v	●	
20	Traffic_Behind_dist	●	
21	Traffic_Right_Front_v	●	
22	Traffic_Right_Front_dist_long	●	
23	Traffic_Right_Front_dist_lat		
24	Traffic_Left_Front_v	●	
25	Traffic_Left_Front_dist_long		
26	Traffic_Left_Front_dist_lat		
27	Traffic_Right_Behind_v		
28	Traffic_Right_Behind_dist_long	●	
29	Traffic_Right_Behind_dist_lat	●	
30	Traffic_Left_Behind_v	●	
31	Traffic_Left_Behind_dist_long		
32	Traffic_Left_Behind_dist_lat	●	

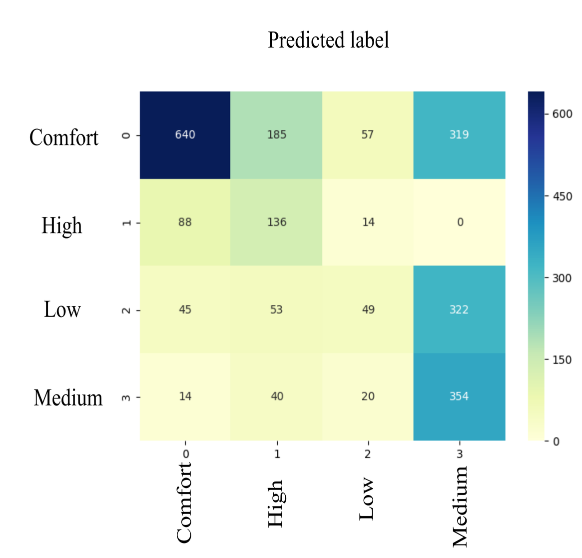
Result

Result of three models:



The result of the models for all, selected, and Expert input signals.

Confusion matrix:



The confusion matrix of cascade model with selected input signals.

Conclusion

We have build different models to predict discomfort in automated vehicles. The Cascade model with all input signals presented the best overall performance with an accuracy of 52.2% for detecting comfort and discomfort. However, all the two models with selected and Expert input signals have roughly the same ability to detect discomfort. The analysis of the models has shown that input signals, which are selected by the cascade model are more efficient to identify discomfort in comparison to the other one with an accuracy of 47.4% .

References

[1] Feature extraction: foundations and applications, Guyon, Isabelle and Gunn, Steve and Nikravesh, Masoud and Zadeh, Lofti A, 2008.

[2] Hyperopt: a python library for model selection and hyperparameter optimization, Bergstra, James and Komer, Brent and Eliasmith, Chris and Yamins, Dan and Cox, David D, 2015.

[3] Using smartbands, pupillometry and body motion to detect discomfort in automated driving, Beggiato, Matthias and Hartwich, Franziska and Krems, Josef, 2018.