

## Motivation

Distraction is one of the most frequent causes for car accidents (Horberrry et al., 2006). During driving, it leads to a delay in recognition of information that is necessary to safely perform the driving task (Regan and Young, 2003).

TWT developed a tool to detect cognitive distraction while driving: the cognitive distraction classifier (CDC). Cognitive distraction cannot be directly observed (in contrast to visual or bio-mechanical distraction), since there is no direct indicator of this process (Liang et al., 2008). We assessed the level of cognitive distraction using several indicators:

**Facial features** of the driver (e.g. head tilt, eyebrow position) based on video data

**Eye movements** (e.g. saccades, gaze direction)

**Acoustic features** (e.g. pitch of driver's voice, MFCC)

**Behavioural features** (e.g. the jitter of the steering wheel, speed, pedal use)

The CDC is essential for the adaption of the car to the driver's level of cognitive distraction to enhance comfort and safety during driving. The CDC is planned as a tool to evaluate adaptive systems offline, but mainly as an in-car application working in real-time (online).

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## Methods, Techniques, Tools

This is a ...  Method  Technique  Tool

Tool Cognitive Distraction Classifier (CDC)

## CDC offline classification

### Final validation of the CDC – driving simulator

After investigating several distraction paradigms and analysis approaches (Naïve Bayes, Linear Discriminant Analysis, AdaBoost) for the development of the CDC, a final validation was conducted.

**Methods:** Six participants drove in a driving simulator while conducting a n-back task with three levels of distraction (undistracted, slightly distracted, strongly distracted). Each condition lasted for 135 seconds with a break of 120 seconds in-between. They had to keep a defined distance to a pace car ahead of them that randomly de- or accelerated. Two cameras recorded the driver's face (see figure 2a+b). Facial features were extracted and behavioural driving data was recorded. The entire signal processing chain has been integrated in an RTMaps diagram. The data was fed into a machine learning algorithm.



### Results:

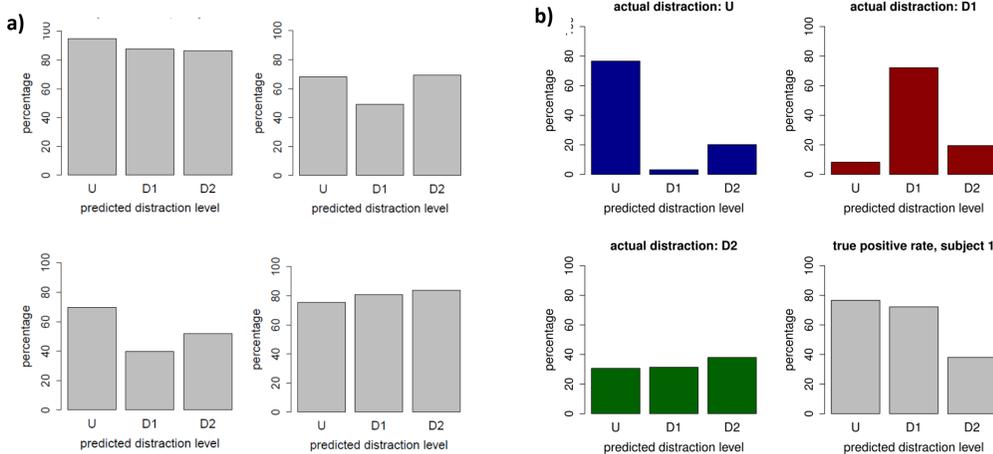


Figure 1: a) Offline classification using Linear Discriminant Analysis of the level of cognitive distraction detailed for one participant and b) summarized for four further participants (U=undistracted, D1=slightly distracted, D2=strongly distracted).

After the training, the classifier maps a given synchronized set of feature values to a distraction level with highly significant accuracy. For the subjects analyzed so far, true positive rates are above chance level (33%), with the lowest values at about 39%. Most of the true positive rates were well above 60%.

## CDC online classification

### Validation of the CDC – driving simulator

For online classification (real-time during simulated driving), we required an algorithm with low demand of computational power and therefore favoured Naïve Bayes. Classification, however, did not differ significantly from chance. Reasons might be a (possibly) inferior classification algorithm, a drastically reduced training set (only facial video data) or that feature pre-processing had to be simplified in our online classification code in order to meet real-time requirements. These factors are currently under investigation.

### Validation of the CDC & AdCoS integration

The CDC has been integrated with the AdCoS Adapted Automation in the IBEO car. Vehicle data was sent to the CDC via Ethernet. The CDC output (estimated level of distraction and reliability value) were sent from RTMaps to the vehicle CAN using a USB-to-CAN adapter and dedicated RTMaps CAN signal processing packages. It can be then used to adapt the driving style of the car to the level of cognitive distraction of the individual. Due to legal restrictions, the driving style was not actually adapted, but the associated driving mode was displayed in the vehicle. The CDC output was 'distracted' or 'undistracted'.



Figure 2: a)-b) Cameras positioned in the car; c) RTMaps showing the CDC; d) CAN-connection; e) CDC-based adaption of the chosen driving style.

So far, two participants were tested in a real vehicle. For subject 1, the distraction levels were correctly identified in most cases (82% for undistracted, 72% for distracted), while the classification for the other participant was not significantly different from chance level (correct classification 43% and 58% for undistracted and distracted, respectively; chance level 50%). We currently investigate the observed increase in CDC performance during the second half of the experiment. First results indicated that the current traffic situation –as expected– additionally influenced the classification. Next steps are to reliably quantify and analyse the effect of the traffic itself.

Subj. 1	U	D2
U	0.82	0.18
D2	0.28	0.72

## Consortium



## Acknowledgments

This research has been performed with support from the EU ARTEMIS JU project HoliDes (<http://www.holides.eu>) Any contents herein are from the authors and do not necessarily reflect the views of ARTEMIS JU.