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The future of driving.

Deliverable D32.2
Model of driver behaviour for the assessment of driver's state

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Revision and history chart

Version	Date	Reason
0.1	2009-11-09	Initial template and draft of structure by WIVW
0.2	2009-11-20	Contributions CAF added
0.3	2009-11-25	Version ready for review
0.4	2009-12-16	Modified version after review process
0.5	2009-12-29	Final editing and submission

Table of Contents

Executive Summary

This report describes the first release of the Driver State Assessment (DSA) software component within HAVEit. First, the general concept for Driver State Assessment is described (chapter 1). Then, the main principles of the software are summarized (chapter 2). Afterwards, the state charts of the software and their relation to drowsiness and distraction detection are presented (chapter 3). In chapter 4 all relevant constants, inputs, outputs and internal signals are described in detail. Specific documentation for the supported platforms (e.g. Windows, CSC) can be found in chapter 5. First validation studies are described in chapter 6. The results of these studies can be used to define necessary modifications of the software in a second optimized version.

1 General overview

The idea of the HAVEit system is that automation is adapted to the intentions and limits of both of the two members in a Joint system - the driver and the co-system. Based on this information the current appropriate automation level is selected. If either the co-system or the driver is not able to manage the situation, then the automation level has to be changed. This could mean either a transition back towards a higher responsibility for the driver or a transition towards a higher responsibility for the co-system. A main precondition for applying this dynamic task repartition is to constantly know the potentials and limits of both members of the Joint System.

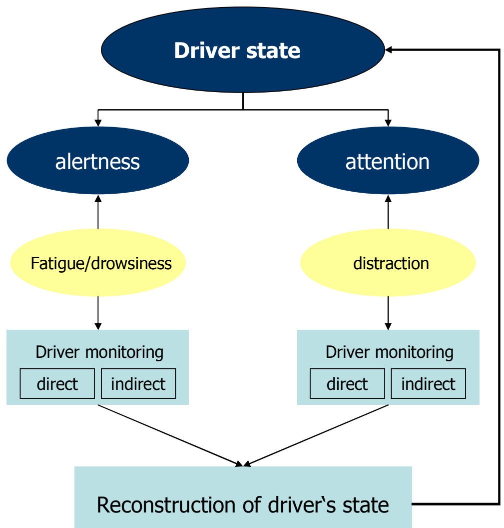

Figure 1: General concept for driver state assessment

From the human's perspective in this concept, a driver model is necessary in order to assess if the driver is able to safely manage the driving task under all various conditions and automation levels. This is required as the automation will not be 100% reliable and will not cover the whole driving task. Instead, the system will produce errors and have some limits. So the driver is required to "stay in the loop" and has to react appropriately on system limits and system errors. Limits of the driver's performance capabilities are mainly set by driver's current physiological and psychological state. To identify negatively influencing factors on the driver state, a Driver State Assessment is required which is able to detect

- long term evolving driver drowsiness / fatigue which impairs the general arousal level of the driver and
- short term driver distraction which impairs task-oriented attention.

The output of this Driver State Assessment (DSA) module can be used to identify driver's need for automation and to make decisions when automation has to be up- or downgraded. For the assessment both driver related and driving related measures will be used to derive a model of driver's behaviour (see Figure 1). Driver related measures refer to direct measures of driver state using a camera based system (Driver Monitoring System DMS) provided by Continental Automotive France (CAF). It observes driver's eye movements, blinking patterns and gaze direction. A detailed description of the DMS software is provided in deliverable D32.1 "report on driver assessment methodology". Driving related measures are indirect activity and performance measures which can be used to draw conclusions about the driver's state, e.g. reduced steering activity or decreased lane keeping performance. Both inputs will be combined to derive a driver model that can be used for detecting driver drowsiness and driver distraction.

1.1 The model for driver drowsiness assessment

Driver drowsiness monitoring has to be carried out on multiple levels with reference to the underlying energetic processes that occur in different time frames and correlate with different performance levels of the driver. It is assumed that a differentiated set of indicators is required to reflect this multi-level concept. The following levels of this drowsiness development and the related consumption of energetic resources have to be distinguished in this model:

In the "awake" state full resources are available. The driver's behaviour is not influenced in any way.

On the next "slightly drowsy" level some resources have to be invested to maintain a certain arousal level. This should be measurable by first behavioural changes, e.g. in the blinking pattern. DMS will provide an output "slightly drowsy" at this stage. Driving performance will still remain uninfluenced at this level. Therefore, no indicators will be derivable from driving behaviour on this state.

On the next "drowsy" level the driver has to invest a high effort to stay awake and to maintain an adequate driving performance. This effort can be measured again by the observation of the eye blinking behaviour (a higher frequency of medium and long blinks). DMS will provide an output "drowsy" at this stage. On this level also first hints from the observation of driving behaviour (over longer time intervals) will be available. Results from the re-analysis of driving simulator data (detailed description see D32.1) revealed that suitable indirect parameters for detecting the "drowsy state" will be the standard deviation of lateral position (SDLP) and several parameters derived from steering activity averaged over a longer time interval (e.g. mean amplitudes of steering wheel reversals)[1].

On a higher level, energetic resources are exhausted and performance capabilities are exceeded. This "sleepy" state will be observable in micro-sleep events and the accumulation of single critical attention lapses in driving. DMS will provide an output "sleepy" at this stage. Results from the re-analysis of driving simulator data revealed that e.g. the number of lane crossings rises heavily especially at the sleepy state. The driver seems to be no longer able to maintain a safe lateral control. Also, very fast steering corrections occur only on higher drowsiness states and therefore seem to be a reliable indicator for a really sleepy driver.

On the final level, a complete collapse of the energetic system occurs accompanied by a full breakdown of performance. The driver has fallen asleep and does not longer respond to critical driving situations (e.g. lane departure or imminent collisions with a lead vehicle) and e.g. takeover requests by the system (stage "unresponsive").

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[1] Other parameters for the driver activity, such as brake and accelerator pedal usage proved to be less sensitive for detecting a drowsy driver. In addition, they are much more influenced by the current traffic environment and are the first ones who will drop out when the driver is driving on higher automation levels, e.g. driving with ACC. Therefore, it was decided to rely more upon parameters that describe the steering activity and the driver's lateral control performance.

1.2 The model for driver distraction assessment

The observation of distraction can only be made within a short-term range of several seconds where it has to be monitored, whether the driver is not looking at the road and/or is operating some other tasks inside the vehicle, e.g. navigating within a complex information system or using the cell phone. It can be expected that the distraction level increases when performing more demanding secondary tasks for a longer time interval. A detailed description of the model for distraction assessment is already described in D32.1 “report on driver assessment methodology” and is not further described here. The relevant computations that are performed in the DSA software are:

- Classification of distracting tasks: eyes on/off the road (output of the DIM module by DMS system), hands-off driving, engaging in secondary in-vehicle tasks
- Definition of distraction weights per group according to their distraction potential
- Definition of a continuous distraction score by observing time sequence and task switching strategies between distracting tasks and driving task
- Definition of a discrete distraction diagnostic (distracted vs. not distracted) by setting thresholds for unacceptably long distraction, adaptable to current automation level and task demands (e.g. driven speed)

2 Main principles of the DSA module

The main principles of the DSA software architecture can be summarized as follows:

- Long-term drowsiness vs. short-term distraction are assessed separately
- Direct (output of the DMS) and indirect measures (internally calculated parameters from driving performance and driver's activity) are fused within a model of driver behaviour
- Driver's state is assessed on multiple levels with a differentiated parameter set for each level
- In a calibration phase the "normal" driving behaviour of each individual driver is assessed in order to adapt the algorithms (especially for the calculation of some indirect parameters)
- A manoeuvre detection and classification (e.g. lane changes, sharp curves) is included in order to define the appropriateness of calculated parameters (especially indirect ones from driving behaviour) and to decide on their inclusion in the output
- The current automation level (hands-off vs. hands-on) is considered for the decision on the inclusion of parameters in the output
- Signal quality (e.g. detection of lane markings) is considered for the definition of the confidence of the final output

The software delivers the following outputs (a detailed description can be found in chapter 4.2):

- 2 distraction states: distracted vs. not distracted (+ confidence level)
- 6 drowsiness states: undefined, awake, slightly drowsy, drowsy, sleepy and unresponsive (+ confidence level)

The following information will be used for the classification of the several outputs:

- For state "distracted":
  - Information about the driver looking on/off the road (output of the DIM module by Direct Driver Monitoring System DMS)
  - Information about driver's use of onboard systems, buttons pressed on the steering wheel, using the cell phone etc.
- For the multiple states of "drowsiness":
  - Direct: output of DMS diagnostic
  - Indirect: critical lane keeping behaviour, critical steering wheel activity, critical distances to a lead vehicle, critical duration of unintended hands-off driving, inadequate reaction times to take-over requests etc.
- Direct and indirect measures are currently fused by simple disjunctions on lower drowsiness levels and for the distraction diagnostic (if either the direct or the indirect monitoring detects a drowsy, sleepy or distracted driver the respective output is given by the DSA). On the unresponsive level currently a conjunction of both measures is used (if both direct and indirect monitoring detects an unresponsive driver the respective output is given by the DSA).
- The confidence level of the outputs will be mainly derived from signal quality within the observed time buffer. This will be dependent both from vehicle performance measures

(e.g. lane detection quality) and camera performance measures (e.g. face tracking performance-output by DMS).

- In the first software version information about the time of day and trip duration are not considered. They will be included in the next software version as weighting factor for the overall output of the module

The following chapters describe the software architecture of the DSA module in more detail. The basis is a description of the distinguished states of the DSA module. A further explanation of the internally calculated parameters (Debug-Outputs), the required input signals according to the interactor table and relevant constants can be found in chapter 4.

3 State charts

3.1 Top-level state chart

The following figure shows the top-level state chart of the DSA module.

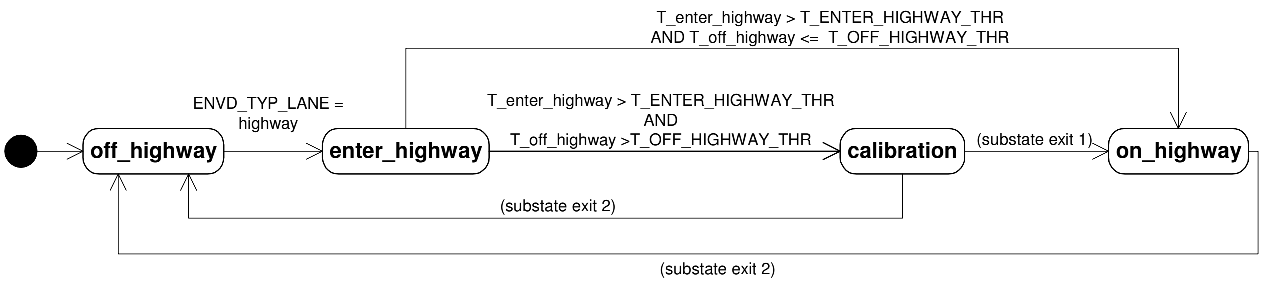


Figure 2: Top-level state chart of the DSA module

Initially, the module is in the state **off_highway**. As soon as the driver enters the highway it changes to the state **enter_highway**. After a certain time (T_ENTER_HIGHWAY_THR), the **calibration** phase starts. This calibration phase is required in order to define the “normal” driving style of each individual driver. If enough calibration data have been collected (see state charts for calibration sub-states, section 3.3), the state changes to **on_highway**. When the driver leaves the highway (e.g. drives on a rest area), the DSA module starts again in the state **off_highway**. When the driver enters the highway again within a time period T_OFF_HIGHWAY_THR, the calibration phase is skipped. Otherwise a new calibration is performed.

In the calibration phase for each of the signals AD_SWR_MEAN and SDLP four buffers of length 2.5 min are filled with data[2]. The calibration data of a signal are computed by averaging the data obtained from the four buffers. This means, that the calibration phase takes at least 10 minutes. In most cases, it will take longer depending on the availability of required data.

Table 1 below summarizes which components of the DSA module are active within which state:

Table 1: Components of the DSA module which are active in the different states

state	drowsiness	distraction
off_highway	not available	not available
enter_highway	not available	fully functional
calibration	partly available, reduced detection rate	fully functional
on_highway	fully functional	fully functional

For more details on the restrictions concerning the drowsiness detection in the calibration state see sections 3.3.1 - 3.3.5. Within the states **calibration** and **on_highway** a simple situation

[2] The time buffer of 2.5 minutes was derived from analysed simulator data (see Deliverable D32.1). There it became obvious that parameters of the driver’s steering activity and lane keeping performance have to be observed and averaged for longer time intervals of minimum 2.5 minutes in order to draw reliable conclusions about the driver’s state.

classification is used to determine which indirect measures can be included in the drowsiness detection.

Examples:

- The measure TTC is only included if a leading vehicle is present (i.e. when a **car follow** or **traffic jam** situation is detected).
- During a **lane change** situation, the steering wheel angle and the position on the lane is not a reasonable input. Therefore, no data that depend on these signals should be collected.

The following sections describe how this situation dependent drowsiness detection and calibration is performed. Please note that the distraction detection doesn't use such a situation classification at the moment. The results of the first validation studies described in chapter 6 show that this is necessary and will be included in the next version.

3.2 Situation classification for state "on_highway" (OH)

The following state chart shows how the situations **car_follow**, **free_drive**, **traffic_jam**, **lane_change** and **sharp_curve** are classified within the top-level state **on_highway** ("OH"). The signals and constants that are used in conditions for transitions are described in chapter 4.

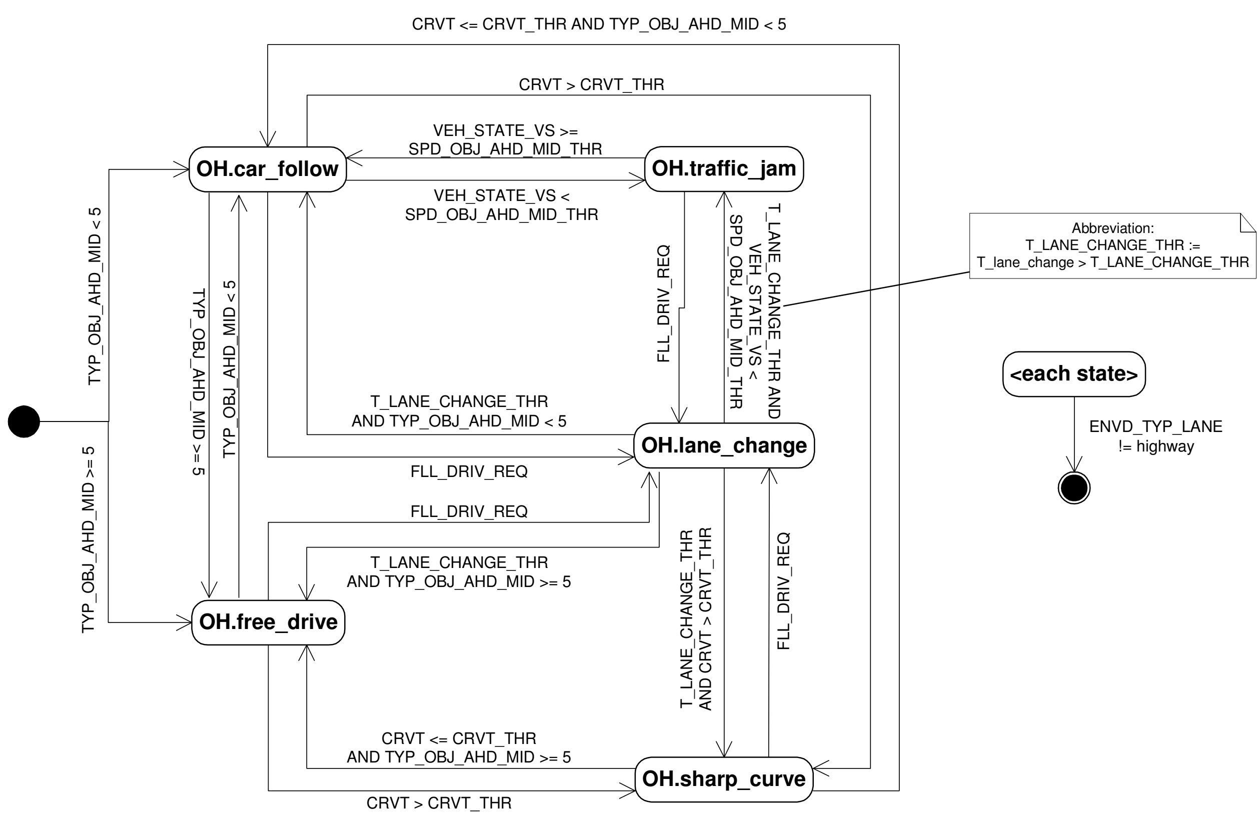


Figure 3: Substates of top-level state "on highway"

3.2.1 OH.car_follow

Within the situation **OH.car_follow** the drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (The drowsiness level detected by the DMS system)
- T_LC
- TD_SWR
- TTC
- T_HANDS_OFF
- T_HANDS_OFF_AFTER_TOR
- N_LC
- N_SW_V
- SDLP_RATE
- AD_SWR_MEAN_RATE

3.2.2 OH.free_drive

Within the situation **OH.free_drive** the drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (The drowsiness level detected by the DMS system)
- T_LC
- TD_SWR
- T_HANDS_OFF
- T_HANDS_OFF_AFTER_TOR
- N_LC
- N_SW_V
- SDLP_RATE
- AD_SWR_MEAN_RATE

3.2.3 OH.traffic_jam

Within the situation **OH.traffic_jam** the drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (the drowsiness level detected by the DMS system)
- TTC
- T_V_EGO_AFTER_STAND_STILL
- T_HANDS_OFF_AFTER_TOR

3.2.4 OH.lane_change

Within the situation **OH.lane_change** the drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (the drowsiness level detected by the DMS system)
- TTC
- T_HANDS_OFF_AFTER_TOR
- T_HANDS_OFF

3.2.5 OH.sharp_curve

Within the situation **OH.sharp_curve** the drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (the drowsiness level detected by the DMS system)
- TD_SWR
- TTC
- T_HANDS_OFF
- T_HANDS_OFF_AFTER_TOR

3.3 Situation classification for state “calibration” (CA)

The following state chart in Figure 4 shows how the situations “car_follow”, “free_drive”, “traffic_jam”, “lane_change” and “sharp_curved” are classified within the top-level state “calibration”. The signals and constants that are used in conditions for transitions are described in chapter 4.

3.3.1 CA.car_follow

Within the situation **CA.carfollow** calibration data for SDLP and AD_SWR_MEAN are collected. The drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (the drowsiness level detected by the DMS system)
- T_LC
- TD_SWR
- TTC
- T_HANDS_OFF
- T_HANDS_OFF_AFTER_TOR
- N_LC
- N_SW_V

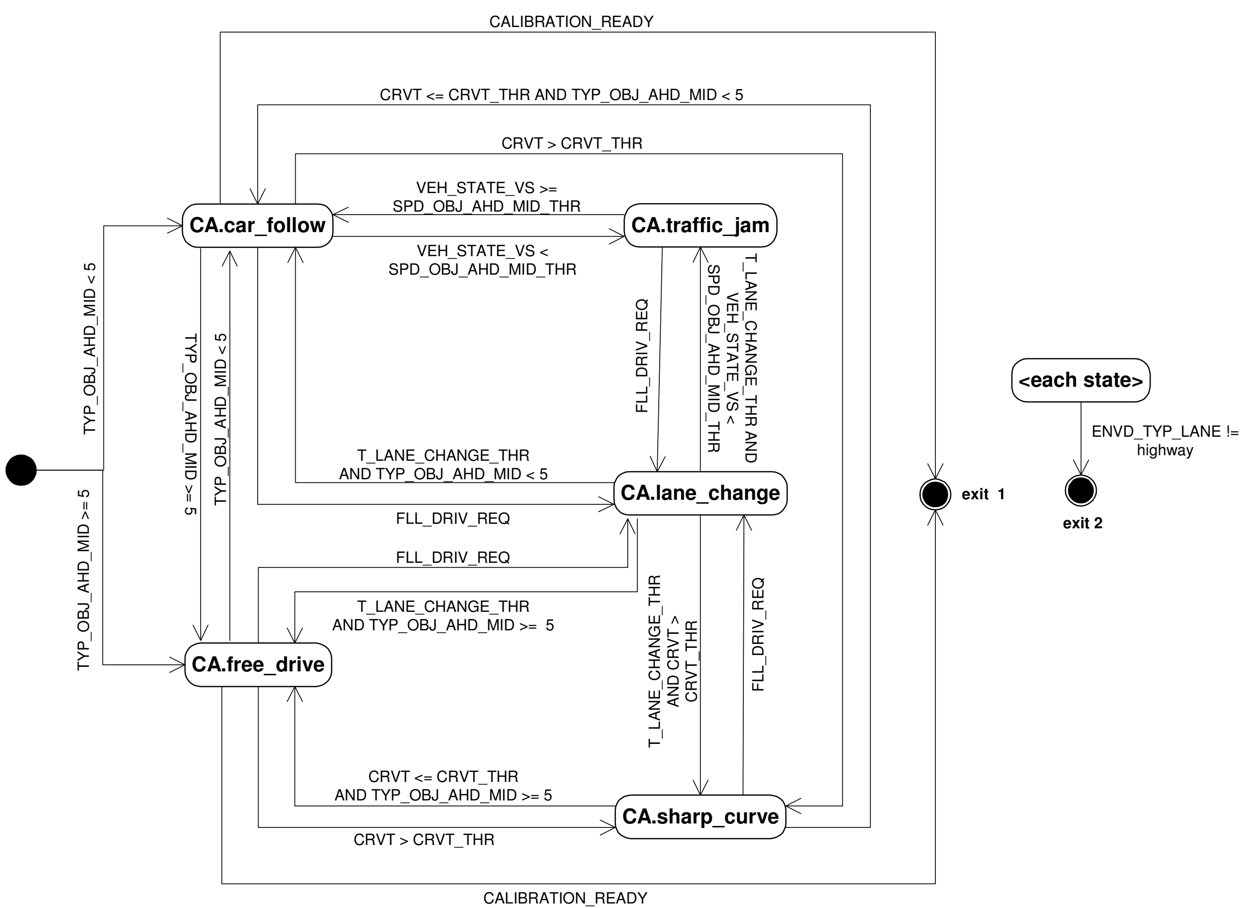


Figure 4: Substates of top-level state “calibration”

3.3.2 CA.free_drive

Within the situation **CA.free_drive** calibration data for SDLP and AD_SWR_MEAN are collected. The drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (the drowsiness level detected by the DMS system)
- T_LC
- TD_SWR
- T_HANDS_OFF
- T_HANDS_OFF_AFTER_TOR
- N_LC
- N_SW_V

3.3.3 CA.traffic_jam

Within the situation **CA.traffic_jam** no calibration data are collected. The drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (the drowsiness level detected by the DMS system)
- TTC
- T_V_EGO_AFTER_STAND_STILL
- T_HANDS_OFF_AFTER_TOR

3.3.4 CA.lane_change

Within the situation **CA.lane_change** no calibration data are collected. The drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (The drowsiness level detected by the DMS system)
- TTC
- T_HANDS_OFF_AFTER_TOR
- T_HANDS_OFF

3.3.5 CA.sharp_curve

Within the situation **CA.sharp_curve** no calibration data are collected. The drowsiness level is calculated based on the following measures (for a description of signals and internal measures see chapter 4), if certain preconditions are fulfilled (e.g. sensor data availability, sufficient confidence level, appropriate automation level):

- DRIV_STATE_DROW_DMS (The drowsiness level detected by the DMS system)
- TD_SWR
- TTC
- T_HANDS_OFF
- T_HANDS_OFF_AFTER_TOR

4 Inputs, outputs, parameters and internal signals

4.1 Inputs

The following table is strictly based on the HAVEit interactor description.

Table 2: Inputs for DSA module according to HAVEit interactor description

signal name	interactor	data_type	enum_type	recurrence (ms)	description
STG_WHL_DRIV_OFF	I_10_10		0 = hands on, 1 = hands off	10	steering wheel hands on/off
FLL_DRIV_REQ	I_10_3		0 = FLL_RI 1 = FLL_OFF 2 = FLL_LE 3 =FLL_BOTH	100	indicators
STG_WHL_ANG_DRIV_REQ	I_10_7	angle_rad		10	steering angle, left positive
STG_WHL_ANG_DRIV_REQ_GRD	I_10_8	angle_rad_rate		10	steering wheel rate, left positive
VEH_STATE_VS	I_11_3	speed_signed_32		40	vehicle speed
DATE_HH	I_37_1	time_hours		1000	time of day: hours
DATE_MM	I_37_2	time_minute		1000	time of day: minutes
T_DC	I_37_4	time_32		1000	driving duration [s]
DRIV_INPUT_ADD_AV	I_38_1		bit 0 = undefined bit 1 = distract_listen bit 2 = distract_SW_controls bit 3 = distract_info bit 4 = distract_add bit 5 = distract_phone bit 6 = distract_eyes bit 7= distract_hands_off	50	driver secondary task command. The values for bit6 (distract_eyes) and bit7 (distract_hands_off) are ignored. The respective inputs are derived internally from the signals DRIV_DST_DIAG and STG_WHL_DRIV_OFF.
DRIV_INPUT_ADD_CONF	I_38_2		bit 0 = undefined bit 1 = distract_listen bit 2 = distract_SW_controls bit 3 = distract_info bit 4 = distract_add bit 5 = distract_phone bit 6 = distract_eyes bit 7= distract_hands_off	50	driver secondary task command configuration. Only inputs with the corresponding bit set in DRIV_INPUT_ADD_CONF are considered for distraction monitoring.

PRST_TRAN	I_43_1	number_8		50	state of the current transition
AUT_LEVEL	I_45_1	number_8	0 = Off 1 = Driver Only 2 = Assisted 3 = ACC 4 = LKS 5 = SemiAutomated 6 = HighlyAutomated 7 = Fully Automated 8 = MinimumRiskState 9 = Failure	50	current automation level
DRIV_STATE_DROW_DMS	I_6_1		0 = DRIV_DROW_UNDEFINED 1 = DRIV_DROW_AWAKE 2 = DRIV_DROW_SLIGHTLY_DROWSY 3 = DRIV_DROW_DROWSY 4 = DRIV_DROW_SLEEPY 5 = DRIV_DROW_UNRESPONDING	200	direct driver drowsiness state
DRIV_DST_T	I_6_17	time_16		20	inattentiveness time [s]
DRIV_DST_DIAG	I_6_22		0=undef 1=on road 2=off road 3 = off road up 4 = off road down 5 = off road left 6 = off road right	200	attentiveness level
DRIV_BLINK_T	I_6_20	time_16		20	blink duration
DRIV_CL_SRC	I_6_19	fraction_8		20	drowsiness confidence
DRIV_DST_CL_DIAG	I_6_23	fraction_8		20	confidence inattentiveness
TYP_OBJ_AHD_MID	I_7_1		0=OBJ_TYP_CAR 1=OBJ_TYP_TRUCK 2=OBJ_TYP_MOTOR_BIKE 3=OBJ_TYP_PEDESTRIAN 4=OBJ_TYP_BICYCLE 5=OBJ_TYP_POLE 6=OBJ_TYP_TREE 7=OBJ_TYP_BARRIER 8=OBJ_TYP_WALL 9=OBJ_TYP_UNCLASSIFIED 10=OBJ_TYP_NO_OBJECT	40	type of object in front on same lane

DIST_OBJ_AHD_MID	I_7_2	length_signed_0.01		40	distance to host vehicle
SPD_OBJ_AHD_MID	I_7_3	speed_signed_16		40	relative speed of object in front on same lane
VEH_DIST_LGT_LIM_LANE	I_7_46	length_signed_0.01		60	lateral distance to middle of the lane
ENVD_TYP_LANE	I_7_47		0=highway 1=rural 2=urban 3=unknown	60	type of lane
CRVT	I_7_49	bending_16		60	curvature
LANE_WIDTH	I_7_51	length_signed_0.01		40	lane width

4.2 Outputs

The following table is strictly based on the HAVEit interactor description.

Table 3: Outputs of the DSA module according to HAVEit interactor description

signal name	interactor	data_type	enum_type	recurrence (ms)	description
DRIV_DROW_LEVEL	I_39_1		0 = DRIV_DROW_UNDEFINED 1 = DRIV_DROW_AWAKE 2 = DRIV_DROW_SLIGHTLY_DROWSY 3 = DRIV_DROW_DROWSY 4 = DRIV_DROW_SLEEPY 5 = DRIV_DROW_UNRESPONDING	500	drowsiness level
DRIV_CL_LEVEL	I_39_2	fraction		500	drowsiness confidence
DRIV_STATE_DST	I_19_1		0 = not distracted, 1 = distracted	200	distraction level
CL_DRIV_STATE_DST	I_19_2	fraction		200	distraction confidence

4.3 Internal signals and derived measures (Debug Outputs)

Table 4: Internal signals and derived measures (Debug outputs) of the DSA module

signal name	data_type	recurrence (ms)	description
STATE	unsgined char	10	STATE 0 = DSA_S_OFF_HIGHWAY 1 = DSA_S_ENTER_HIGHWAY 2 = DSA_S_CALIBRATION 3 = DSA_S_ON_HIGHWAY
SUBSTATE	unsigned char	10	SUBSTATE 0 = DSA_SS_NA 1 = DSA_SS_FREE_DRIVE 2 = DSA_SS_CAR_FOLLOW 3 = DSA_SS_TRAFFIC_JAM 4 = DSA_SS_LANE_CHANGE 5 = DSA_SS_SHARP_CURVE

SDLP	float		standard deviation of lateral position
SDLP_CALIBRATION_STEP	unsigned char	10	during calibration phase: current calibration step
SDLP_RATE	float	10	in top-level state on_highway: current mean sdlp / sdlp from calibration phase
T_LC	float	10	duration of current lane crossing
N_LC	unsigned int	10	number of lane crossings in current time window
T_V_EGO_AFTER_STAND_STILL	float	10	after standstill (traffic jam): time between start of leading vehicle and start of host vehicle
T_HANDS_OFF_AFTER_TOR	float	10	time between a take over request and hands on
AD_SWR_MEAN	float	10	mean difference between amplitudes of Steering wheel reversals
AD_SWR_MEAN_RATE	float	10	ration: current AD_SWR_MEAN / AD_SWR_MEAN from calibration phase
AD_SWR_MEAN_CALIBRATION_STEP	unsigned char	10	during calibration phase: current calibration step
TD_SWR	float	10	time between significant steering wheel reversals
N_SW_V	unsigned int	10	number of significant steering wheel rates in current time window
SW_V	float	10	steering wheel rate
TTC	float	10	time to collision to leading vehicle
T_HANDS_OFF	float	10	duration of hands off driving in current time window
SCORE_SW_CONTROLS	float	10	distraction score for SW_CONTROLS events
SCORE_INFO	float	10	distraction score for INFO events
SCORE_ADD	float	10	distraction score for ADD events
SCORE_PHONE	float	10	distraction score for PHONE events
SCORE_HANDSOFF	float	10	distraction score for HANDSOFF events
SCORE_EYES	float	10	distraction score for EYES

4.4 Constants

The following table lists the constants that are used within the DSA software component:

Table 5: Constants used in the DSA module

signal name	description	usage within DSA
AD_SWR_MEAN_RATE_THR	Threshold for amplitude-differences between SWR compared to the individual calibration phase	If AD_SWR_MEAN increases more than xxx% compared to the individual calibration phase the driver can be defined as drowsy
ADD_WEIGHT	Weight for ADD events	
CRVT_THR	Threshold for defining a curve as a sharp curve	In sharp curves it does not seem to be meaningful to analyze lane keeping performance or steering activity
DRIV_BLINK_T_THR	Critical threshold for blink duration (raw data derived from DMS)	Blink durations above xxx s are defined as microsleep events, indicator for a driver already fallen asleep
DRIV_STATE_DST_DM_THR	Critical threshold for inattentiveness diagnostic (derived from DMS)	Glances away from the road above xxx s are defined as safety-critical, especially if the driver is impending to getting off the road or colliding with the vehicle in front
EYES_WEIGHT	Weight for EYES events	
HANDSOFF_WEIGHT	Weight for HANDSOFF events	
INFO_WEIGHT	Weight for INFO events	
N_LC_THR	Threshold for the number of short lane crossings within the observed time interval	If the driver touches the lane markings very often this is a severe indicator that he is no longer able to maintain a stable driving performance
N_SW_V_THR	Threshold for the number of fast steering corrections > 50°/s²	If very fast steering corrections occur this is a reliable indicator that the driver is no longer able to maintain a stable driving performance
PHONE_WEIGHT	Weight for PHONE events	
SDLP_RATE_THR	Threshold for SDLP compared to the individual calibration phase	If SDLP increases more than xxx% compared to the individual calibration phase the driver can be defined as drowsy
SPD_OBJ_AHD_MID_THR	Threshold for the speed of the target vehicle what should be defined as traffic jam	In lower speed ranges it does not seem to be meaningful to analyze lane keeping performance or steering activity, the non-reaction to the re-acceleration after a stand still can be used as indicator for driver unresponsiveness
SW_CONTROLS_WEIGHT	Weight for SW_CONTROLS events	
T_ENTER_HIGHWAY_THR	Time after entering the highway until calibration is started	It is assumed that after a certain time the entering manoeuvre is finished and the vehicle is driving on the highway

T_HANDS_OFF_AFTER_TOR_THR	Critical threshold for putting the hands back to the steering wheel after a system-initiated Take-over-Request	If the driver has not put his hands back to the steering wheel after a certain period of time, the driver has to be defined as unresponsive
T_HANDS_OFF_THR1	Critical threshold for driving hands_off in straight sections when it is not allowed (meaning automation level lower than highly automated)	Combined with driver state: If the driver has his hands off longer than a certain period of time, when he is driving in automation levels < highly and is additionally detected as already fallen asleep or not having his eyes on the road- the driver has to be defined as unresponsive
T_HANDS_OFF_THR2	Critical threshold for driving hands_off in sharp curves when it is not allowed (meaning automation level lower than highly automated)	Combined with driver state: If the driver has his hands off longer than a certain period of time, when he is driving in automation levels < highly and is additionally detected as already fallen asleep or not having his eyes on the road- the driver has to be defined as unresponsive- threshold has to be lower in curves
T_LANE_CHANGE_THR	Definition of the end of a lane-change manoeuvre	Xx sec after the driver has set the indicators the lane change manoeuvre should be finished
T_LC_THR	Critical threshold for the duration of a non-intended lane-cross (without using the turn-signals)	Above xxx sec duration of a lane-cross one can conclude that it's not simply a short attentional lapse but a critical indicator for driver unresponsiveness, especially when the driver is not looking at the road for several seconds
T_OFF_HIGHWAY_THR	Time since the driver has left the highway	If the driver has left the highway and again enters it within a defined time interval no new calibration phase is needed
T_V_EGO_AFTER_STAND_STILL_THR	Critical threshold for the time it takes that the EGO-vehicle accelerates > 0 after a stand still and the reacceleration of the target vehicle	If the driver doesn't re-accelerate after a stand still in traffic jam and the target vehicle has accelerated again the driver can be defined as unresponsive
TD_SWR_THR1	Threshold for time differences between SWR below 0.5 s, for straight sections	If the driver doesn't execute any steering correction within xx sec and is in addition detected as fallen asleep or not looking at the road, he can be defined as unresponsive
TD_SWR_THR2	Threshold for time differences between SWR below 0.5 s, for curves	If the driver doesn't execute any steering correction within xx sec and is in addition detected as fallen asleep or not looking at the road, he can be defined as unresponsive, should be earlier in curves than on straight sections
TTC_THR	Threshold for a critical TTC to the vehicle in front	Below a TTC minima of xxx sec , situations can be described as safety-critical, especially when the driver has fallen asleep or is looking away from the road; but driver can still avoid the collision if warned
VEHILCE_WIDTH	Width of the host vehicle.	

5 Supported platforms

5.1 Windows (WIN32)

The DSA software for the Windows platform consists of the following files:

- DSAInterface.h: ANSI-C header file containing declarations of structures for data input / output and of functions for initialization, performing a computation step and retrieving outputs.
- DSA.dll: WIN32 dynamic link library that implements the functions declared in DSAInterface.h
- DSA.lib: Library compiled with Microsoft Visual C++ 8.0 for easy integration of the DSA.dll in the Microsoft Visual Studio 2005 development environment. Please note that if another compiler is used, the dll has to be interfaced via the WIN32-API functions `LoadLibrary`, `GetProcAddress` and `FreeLibrary`.

To run the DSA software component, the following steps have to be performed:

1. At start up, call `DSAInit(0)` once.
2. Every 10 ms
   a. Fill a structure of type `sDSAInputs` with input data in the appropriate format. Use hereby the macros that are defined in `DSAInterface.h` (`I2_number_8`, `I2_fraction_8` and so on) to ensure that the resolution of signals conforms to the definitions given in the interactor list.
   b. Call `DSAStep10ms(…)`.
3. At any time (after a call to `DSAStep10ms(…)`) get the “official” outputs by calling `DSAGetOutputs(…)` and the debug outputs by calling `DSAGetDbgOutputs(…)`.

5.2 CSC

The DSA software has been successfully compiled and flashed to the CSC platform using the development environment provided by Continental Automotive. First tests have been performed with the following results:

- The algorithm uses approximately 60% of the available computing power.
- The memory that is provided by the CSC is sufficient.
- When fed with input data recorded in the driving simulator study (s. section 6) the algorithm produces the same outputs as the WIN32 version. There are only insignificant differences that arise from the reduced numerical precision of the input data due to the message format of the CAN-Bus. These differences have no influence on the quality of the output.

Currently, Continental Automotive and WIVW work on the finalization of the CAN-Bus interface and on preparing a first release for vehicle integration.

6 Validation of DSA software version 2.0

For a first technical and empirical validation of the algorithms, the current software version was implemented in the WIVW driving simulation. 2 separate studies were conducted: one for the validation of the drowsiness detection module, one for the validation of the distraction detection module. It has to be noted that the results presented here are based on the software versions of the DMS (Direct Monitoring System) that had been available in summer 2009. Especially, the DIM component for visual inattentiveness detection has been largely improved in the meanwhile.

6.1 Validation of drowsiness detection module

6.1.1 Experimental setup

The empirical tests were conducted with 12 test drivers in the WIVW driving simulator. They were all familiar with simulator driving. Mean age was 32 years (standard deviation 10 years), the oldest driver was 59 years old, the youngest 23, 7 were male, 5 female. They all had a normal non-corrected vision and did not require glasses or lenses for driving.

They were randomly assigned to 2 experimental groups: 6 drivers drove the test course in the Driver Assisted mode of the HAVEit system (DA group). This means that they were slightly assisted by a lane keeping assistance system which only intervened in critical situations when the driver tended to get off the road by providing a slight force on the steering wheel towards the opposite direction. The other 6 drivers drove in the Highly Automated mode of the HAVEit system (see Figure 5 left). On this level, lateral and longitudinal control is performed automatically by the system up to a speed of 130 km/h. The driver can drive hands-off. In case of a situation the system can not manage (e.g. if a lead vehicle is decelerating and the relative speed between ego and lead vehicle is too large) a take-over request is given. The driver then has to take-over the steering wheel and the pedals and a transition towards the Driver Assisted mode is executed. Lane changes have to be performed manually by the drivers.

Figure 5: The HMI of the HAVEit system showing the state “Highly Automated mode” (left) and one of the night-time scenarios “traffic jam” (right) in the validation study.

The driving task consisted of driving on a 2 lane motorway with mainly straight and slightly curvy sections. The valid speed limit was set to 120 km/h over the whole track. The track contained free driving scenarios (without any lead vehicle), car follow scenarios with a lead vehicle driving around 110 km/h, traffic jams, forced lane changes at road works and heavy braking manoeuvres of the lead vehicle in random intervals (resulting in a take-over request when driving in Highly Automated mode). The drivers were instructed to always stay on the right lane even when the lead vehicle drives slower than allowed, stick to the valid speed limit and only execute a lane change when they are forced to at road works. Furthermore, driving in night time was simulated by a very realistic illumination of the surrounding environment and traffic (see Figure 5 right). The drivers started the drive after lunch at about 1.30 pm and after having performed another 2 hours lasting study with a distracting task (reported in chapter 6.2). The duration of the drive was determined by the time it took the drivers really get drowsy or even sleepy. Due to the very realistic night-time environment, the time of day and the heavy load of the previous study for most of the drivers it took not longer than 2.5 hours. For the low minority of drivers who showed no tendency to really fall asleep the drive was stopped after 2.5 hours.

The measurements for the validation of the DSA module were:

- The outputs of the direct driver monitoring (DMS system by CAF) - providing different drowsiness states: alert, slightly drowsy, drowsy, sleepy.
- The outputs of indirect driver monitoring as described by the parameters in section 2 (only for Driver Assisted group as for Highly Automated group no data are available): alert, drowsy, sleepy and unresponsive. Please note that the indirect monitoring provides no “slightly drowsy” output.
- Driver’s subjective drowsiness rating every 20 minutes online by using the Karolinska Sleepiness Scale KSS.
- Test leader’s expert drowsiness rating every 20 minutes online by using the KSS.
- Observation of other drowsiness indicators by the test leader (e.g. yawning, scratching, head nodding, micro-sleep events)

The Karolinska Sleepiness Scale is a 9 point rating scale from 1 = ”extremely alert” up to 9 = “very sleepy with great effort to stay awake” (Akerstedt & Gilberg, 1990).

6.1.2 Results

6.1.2.1 Induction of drowsiness

The first important question was if it is possible to induce drowsiness at all by driving in the driving simulator. As it gets obvious from rows 1 and 2 in Table 6 drowsiness induction was very successful in the study - nearly all drivers really got drowsy or even sleepy within a very short time of usually less than 2 hours. 10 of 12 drivers rated themselves with maximum values of 8 or 9 on the KSS (see row 1).

Table 6: Drowsiness detection quality provided by DSA module.

	assisted						Highly automated					
	D1	D2	D3	D6	D9	D11	D4	D5	D7	D8	D10	D12
Max. drowsiness rating by driver	9	8	9	9	9	9	7	9	9	7	8	8
Max. drowsiness rating by expert	9	9	9	9	9	9	8	9	9	8	9	9
Drowsy events detected by direct monitoring?	yes	no	yes	no	yes	yes	yes	yes	yes	yes	yes	yes
Sleepy events detected by direct monitoring?	yes	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Drowsy events detected by indirect monitoring?	yes	yes	yes	yes	yes	yes	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Sleepy events detected by indirect monitoring?	yes	yes	yes	yes	no	yes	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Drowsy/sleepy events detected by test leader?	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Two drivers (marked in yellow) reached only a value of 7 according to their opinion which means that they perceived beginning drowsiness but without having problems to stay awake. In most cases this is in agreement with the expert judgment of the test leader (see row 2). Some drivers slightly underestimated their drowsiness level.

6.1.2.2 Detectability of drowsy and sleepy events by direct and indirect driver monitoring

The second question was whether the current DSA algorithm could reliably detect the different stages of drowsiness. When looking at rows 3 to 6 in Table 6 it can be seen that drowsiness was very well detected by both measures in the DSA module. Rows 3 and 4 reveal that the camera reliably detected drowsy and sleepy events for all except 2 drivers: For driver D2 the camera had tracking problems over the whole drive. One explanation could be that the driver had very bright eye brows so that the detection of relevant facial features was impeded. Driver D6 had sleepy blinks without having drowsiness blinks before. This is unusual, however, but not impossible. Indirect driver monitoring was only available for the Driver Assisted condition (see row 5 and 6). Here it gets obvious that for all 6 drivers drowsy events could be reliably detected by the respective parameters. For 5 of the 6 drivers also sleepy events were detected. The last row shows that at least one of the measures should have indicated drowsy or sleepy events as this was observed by the test leader. So, if one of the measures did not fire this could be definitely defined as a missing. Please note that the table is useful for a first overall evaluation of the sensitivity of the measures. Statements on the specificity will be made later on in chapter 6.1.2.5.

6.1.2.3 Occurrence and plausibility of single outputs

<u>Direct monitoring (DMS output):</u>

Table 7 shows the distribution of DMS drowsiness outputs across all drivers and driving time. As can be seen, most of the time the drivers were detected as “alert” (85.9%). In 9.6% of the time drivers were detected as “slightly drowsy” by the camera, in 2.8% of the time as “drowsy” and 1.7% as “sleepy”. The number of false alarms was quite low and mainly due to incorrect classification of display glances or due to the driver speaking (might get a greater problem in real driving). Some specific algorithms were already implemented in the meanwhile to cope with the display glances and to discard them. This is running generally quite well but it depends a lot on the correct implementation of the camera into the vehicle. Further improvements can be made by a connection between distraction and drowsiness detection algorithms.

Cases of extreme sleepiness, when the driver has already fallen asleep and has closed his eyes longer than 2 sec, are not longer detected by the camera. The threshold of the measured eye blink durations up to 2 sec was deliberately implemented in order to limit false alarm rate. Normally it should not be critical because information about a sleepy situation should have been displayed before. This had been also the case in the presented validation study.

Table 7: Distribution of DMS drowsiness states in validation study.

Parameter DRIV_STATE_DROW_DMS	% of total time
0 („alert“)	85.9 %
1 (“slightly drowsy”)	9.6 % (9502 sec)
2 (“drowsy)	2.8 % (2805 sec)
3 (“sleepy”)	1.7 % (1737 sec)

It should also be noticed that in real driving situations more than 2 sec with eye closed would lead to dramatic situations at least if the driver is driving on automation levels lower than Highly Automated (in real driving studies by CAF with manual driving conditions those events have never been reached). Better the detection is earlier. So the evaluation of the detection performance of sleepy situations when eyelid closure time greater than 2 sec is not very relevant. Much more important is the fact that the system was able to detect the occurrence of sleepy events before.

The internally computed confidence level of the DMS output (see Table 8) is in 32.8% of total time below 0.3 (not reliable); in 8.6% of the time between 0.3 and 0.6 (acceptable) and in 58.6% of total time above 0.6 (good). Overall, the tracking quality can be defined as quite good.

Table 8: Distribution of DMS drowsiness confidence level in validation study.

Parameter DRIV_CL_SRC	% of total time
<0.3 (low)	32.8 %
0.3-0.6 (acceptable)	8.6 %
>0.6 (high)	58.6 %

A low drowsiness confidence level can have different reasons:

- Either the face recognition is lost
    - temporarily because the driver is changing his position on the seat or is occluding parts of the face with his hands etc. or
    - permanently due to specific characteristics of the driver’s face (e.g. very bright eye brows),
- or too less eye lid closure events occurred within the observed time interval.

The first reason might lead to a higher number of missings as especially if the driver starts getting drowsy, he tries to activate himself by moving on the seat or grasping in the face. The second reason is less problematic as this occurs very often when the driver is extremely alert. During the drives it could be observed that despite a temporarily low confidence level “drowsy” and “sleepy” events that are classified by the camera are still reliable.

Indirect monitoring (parameters from driving behaviour):

From Table 9 it can be seen how often the defined criteria for the classification of the various drowsiness states based on indirect monitoring were triggered in the validation study. A criterion is fulfilled if the respective threshold of the parameter is exceeded. An overview of constants used in the DSA module can be found in chapter 4.4. Please remember, that the indirect monitoring provides no output for the “slightly drowsy” state.

The following aspects can be summarized:

- Most often the “drowsy” state was triggered by the indirect parameters. Especially sensitive was the criterion CRT_AD_SWR_MEAN_RATE: this event occurred in all 6 drivers of the DA condition. The other criterion for the “drowsy” state, CRT_SDLP_RATE, occurred only with three drivers and always after the other threshold for AD_SWR_MEAN_RATE had been exceeded. This result indicates that parameters from steering behaviour are more sensitive than parameters from the resulting lane keeping performance in order to detect the “drowsy” state.
- The “sleepy” state (initiated by CRT_N_SW_V and CRT_N_LC) was classified less often.
- Events that are classified on state 5 “unresponsive” (for example: hands-off driving in Driver Assisted mode or too late reaction after a standstill) were extremely seldom (except critical TTCs that occurred very often due to the included critical braking event). This result is in full accordance with the expectations, that such events happen only when the driver had really fallen asleep (this could be verified by the online observation during driving).
- For some criteria (CRT_N_SW_V, CRT_AD_SWR_MEAN_RATE, CRT_N_LC and CRT_T_LC) a higher number of false alarms occurred due to an avoidance manoeuvre at the critical braking event. As they are not directly correlated with an increased drowsiness but instead with a critical interaction with another road user these events should be not included in the drowsiness classification. To identify these specific events the classification of a new situation “critical interaction with another road user” is required.
- Some parameters exceeded the defined thresholds also in cases of extreme distraction. In the present study this was the case for one driver who had extreme problems with reactivating the Highly Automated mode and therefore had heavy steering and lane keeping problems. By a connection between distraction and drowsiness algorithms these events could be clearly attributed to distraction.

Table 9: Criteria for drowsiness-related abnormal driving behaviour used for indirect drowsiness monitoring

Criteria	% of total time	Number of events clearly attributable to drowsiness	notes
CRT_AD_SWR_MEAN_RATE	8.6 (8169 sec)	69	Occurred in all 6 drivers of DA-condition; false alarms due to avoidance manoeuvre in critical braking situation
CRT_SDLP_RATE	2.0 (1852 sec)	22	Occurred in 3 drivers of DA-condition, but always after CRT_AD_SWR_MEAN_RATE; 100% w.r.t. driver state
CRT_N_SW_V	5.5 (5196 sec)	6	False alarms occurred due to avoidance manoeuvre in critical braking situation or due to strong distraction
CRT_N_LC	1.4 (1307 sec)	7	Occurred in 3 drivers; FA due to avoidance manoeuvre in critical braking situation or due to strong distraction
CRT_T_LC	0,01 (63 sec)	7	False alarms occurred due to avoidance manoeuvre in critical braking situation or due to strong distraction
CRT_TTC	1,4 (1364 sec)	34	Always in critical braking situation
CRT_HANDS_OFF	0,9 (883 sec)	1	FA in traffic jam
CRT_HANDSOFF_AFTER_TOR	0,0 (12 sec)	0	FA due to a loss of mode awareness
CRT_V_EGO_AFTER_STANDSTILL	0 (2 sec)	1	

6.1.2.4 Analysis of timely correlations between direct and indirect monitoring

Another analysis was the observation of the timely correlation between the direct and indirect monitoring:

- When are the criteria triggered?
- Which criteria react earlier?
- Are there correlations between DSA outputs and the subjective rating of drowsiness?.

Figure 6 shows an example of the time plot for Driver D11 after 120 minutes of driving. The driver had several “slightly drowsy” events detected by the camera before. At the beginning of the 6th 20-minute-loop the criterion CRT_AD_SWR_MEAN_RATE is shortly triggered the first time (classified as “drowsy”), followed by a “drowsy” event detected by the camera. 5 minutes later again CRT_AD_SWR_MEAN_RATE fires, followed by the first “sleepy” event detected by the camera two minutes later. While CRT_AD_SWR_MEAN_RATE stays activated until the end of the loop, several drowsy and again one sleepy event are detected by the DMS. This analysis was done for all drivers over the whole drive. The following results can be summarized:

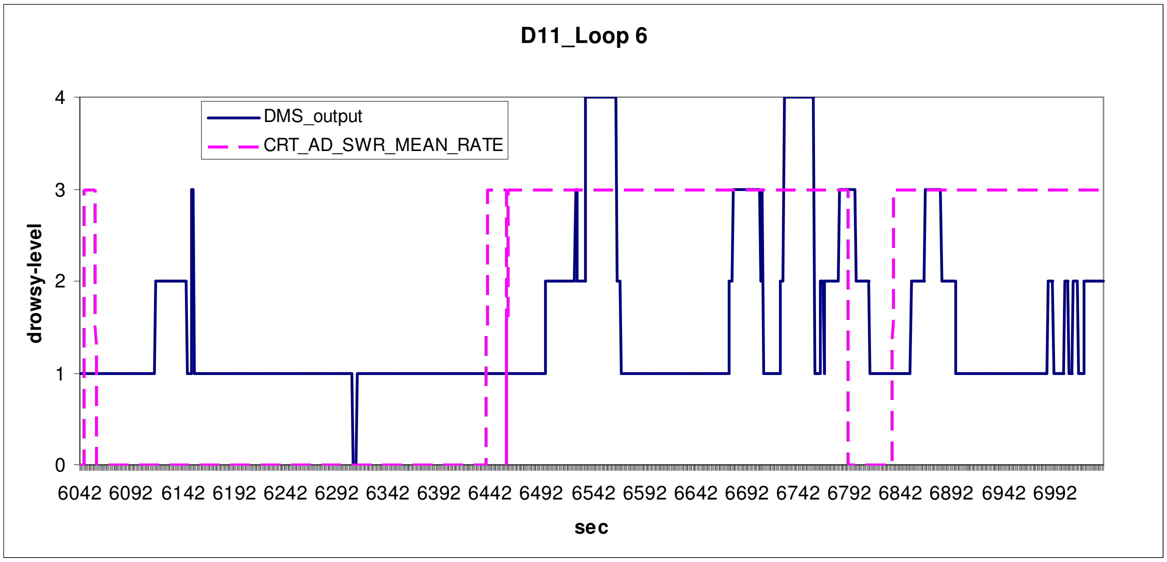


Figure 6: Example for time line of single outputs – Driver D11- loop 6 (after 1 hour 20 minutes driving)

- The outputs of the DSA are highly correlated with the subjective KSS drowsiness ratings by the drivers. Typically, first "slightly drowsy" events classified by the DMS occur in loops where the driver rated his drowsiness at level 7 of the KSS ("sleepy, but no effort to stay awake"). Drowsy and sleepy events either detected by direct or indirect monitoring usually do not occur before a KSS-level of 8 ("sleepy, some effort to stay awake") and 9 ("very sleepy, great effort to stay awake").
- "Drowsy" events classified by indirect monitoring usually occur before "drowsy" events classified by direct monitoring, but after the occurrence of first "slightly drowsy" events classified by direct monitoring.
- For direct monitoring it could be observed that "drowsy" events sometimes did not occur until first sleepy events already have been detected. This leads the driver's state sometimes directly jumping from "slightly drowsy" to "sleepy". This result corresponds to a choice that was made for the setup of the algorithms. There is a specific process for the detection of the sleepy state that can prevail on the normal strategy. Furthermore, the DMS system provides several modes (demo mode vs. robust mode) with different underlying algorithms for slightly drowsy and drowsy classification.

6.1.2.5 Sensitivity and specificity

For the computation of sensitivity and specificity of the measures the subjective drowsiness rating by the drivers (rated every 20 minutes) was used as criterion. Therefore, KSS-ratings up to 6 were classified as "awake", ratings of 7 were classified as "slightly drowsy", ratings of 8 as "drowsy" and ratings of 9 as "sleepy". Then the concordance between observed drowsiness (KSS self-rating over 20 minutes) and predicted drowsiness (highest state classified by the DSA software within the 20 minute interval) was analyzed. This was done separately for DMS outputs (direct monitoring, see Table 10) and driving related parameters (indirect monitoring; see Table 11). For the computation of sensitivity and specificity, a dichotomisation in two categories was made: "awake"/"slightly drowsy" vs. "drowsy"/"sleepy". Sensitivity is then calculated by the number of true positives ("drowsy"/"sleepy" drivers correctly identified as such) compared to all observed “drowsy”/”sleepy” events. Specificity is calculated by the number of true negatives (“alert”/”slightly drowsy” drivers correctly identified as such) compared to all observed “awake” / ”slightly drowsy” events. The total number of observations is lower for indirect outputs as they are only available when driving on the Driver Assisted level.

The analysis reveals a sensitivity of 64.7% and a specificity of 76.3% for the classification of drowsiness by direct monitoring. For indirect monitoring, sensitivity is 100% and specificity is 57.7%. These first results can be interpreted as quite satisfying - especially if one considers that this analysis currently includes all the events that were clearly defined as false alarms and that can be filtered out in the next version of the software. Especially specificity of both measures will benefit from that.

What gets obvious is that direct monitoring tends to produce a higher missing rate but a lower false alarm rate. In contrast, indirect monitoring tends to produce a higher false alarm rate (at least in the current version) but a low missing rate, as it reliably detects all drowsy and sleepy events. Therefore, the two measures seem to complement each other.

Table 10: Drowsiness states as observed by the KSS-selfrating and predicted by the direct monitoring (DMS drowsiness output)

		observed (KSS-selfrating)				total
		awake	**slightly d.**	**drowsy**	**sleepy**	
predicted (DSM-output)	**awake**	14	3	3	0	20
	slightly dr.	11	17	5	4	37
	drowsy	1	2	2	3	8
	sleepy	6	5	6	11	28
		32	27	16	18	**93**

Table 11: Drowsiness states as observed by the KSS-selfrating and predicted by the indirect monitoring- please note that the indirect monitoring does not provide a classification of the state “slightly drowsy”)

		observed (KSS-selfrating)				total
		awake	**slightly d.**	**drowsy**	**sleepy**	
predicted (ind.output)	**awake**	10	5	0	0	15
	slightly dr.	0	0	0	0	0
	drowsy	2	4	3	9	18
	sleepy	2	3	7	5	17
		14	12	10	14	**50**

6.2 Validation of distraction detection module

6.2.1 Experimental setup

The study was conducted with N=12 test drivers in the WIVW driving simulator (mean age: 32 years; SD=10 years, 7 male, 5 female). They were the same as in study 1 (see chapter 6.1). The test drivers were randomly assigned to 2 experimental groups: 6 drivers drove the test course in the Driver Assisted mode of the HAVEit system (DA group, description see chapter 6.1.1). The other 6 drivers drove in the Highly Automated mode of the HAVEit system (HA-group; description see chapter 6.1.1).

The driving task consisted of driving in a 2 lane motorway of about 20 min length which was repeated 3 times in 3 experimental conditions and with varying sequence of the driving scenarios. The valid speed limit was set to 120 km/h over the whole track. It contained free driving scenarios without any lead vehicle, car follow scenarios with a lead vehicle driving around 110 km/h, traffic jams, forced lane changes at road works and one heavy braking manoeuvre of the lead vehicle (resulting in a take-over request when driving in Highly Automated mode). The drivers were instructed to always stay on the right lane even when the lead vehicle drives slower than allowed, stick to the valid speed limit and only execute lane changes when they are forced to at road works.

In addition, the drivers were instructed to perform a secondary task while driving. It was a hierarchical menu navigation task comparable to a modern in-vehicle information system (IVIS) that can be used for several functionalities (e.g. navigation system, vehicle data, entertainment functions and telephone) by one single display and one single controller.

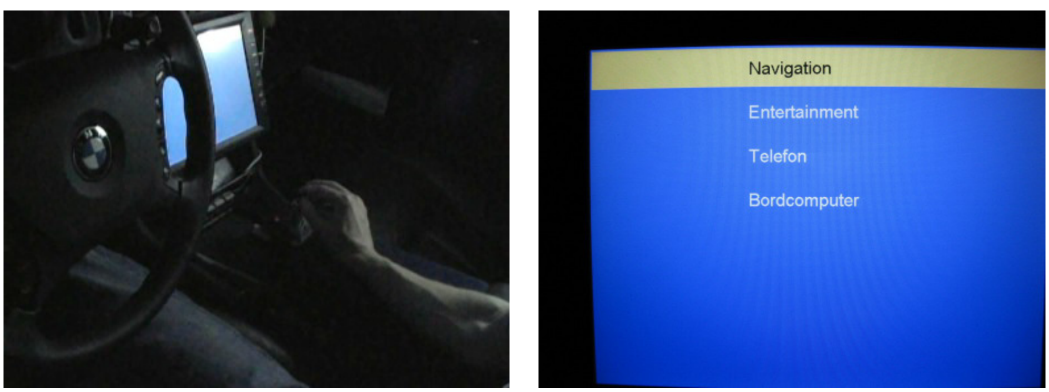


Figure 7: Display of secondary task presentation in the middle console with joystick (left) and contents of the hierarchical menu (right).

The menu system was presented on a visual display at a lower position in the central console (approximately 34° to the right; 23° down, depending on the driver's seat position). To navigate within the menu, a commercially available joystick was used. The driver was instructed to navigate to a specific menu function (e.g. control average fuel resumption). The task was completely self-paced and interruptible. As soon as the driver confirmed the correct option, a new task could be started. Figure 7 shows an extract from the menu system and the positioning of the secondary task inside the vehicle. The drivers were instructed to prioritize the primary driving task and to perform the menu task only when the situation allowed it.

For a first test of suitable interventions in case of distraction a so called Attention Monitor was implemented. The interventions of the Attention Monitor are based on the calculation of a continuous distraction score that depends on the type of the distraction and the time the driver is engaged in the secondary task (for a detailed description of the algorithm see deliverable D32.1). As soon as a certain threshold is exceeded the Attention Monitor starts the escalation and gives respective feedback to the driver (starting with mere information, followed by more urgent warning if the driver does not react and giving a take-over request in the Highly Automated mode if also the warning was ignored). For a more detailed description of the intervention strategy, see Deliverable D33.3.

In the present study two variants of the Attention Monitor were implemented:

- AM 10: Attention Monitor with a threshold of distraction score = 10 (meaning after 5 sec uninterrupted menu navigation)
- AM 20: Attention Monitor with a threshold of distraction score = 20 (meaning after 10 sec uninterrupted menu navigation)

In order to evaluate the effects of the Attention Monitor a control condition without any interventions was introduced as a baseline. Each driver performs 3 drives of 20 minutes with each of the 3 AM variants in fully counterbalanced sequence.

6.2.2 Results

6.2.2.1 Direct monitoring (DMS output)

Identifying visual distraction caused by the secondary task used in the present study seemed to be somewhat problematic for the DMS system:

- As the inattentiveness diagnostic is based on driver's head/face positions >20° to the left or the right the system is not able to detect glances to the display when the face is not moved or only slightly moved towards the same direction - this varies individually for each driver. In the present study 3 of the drivers did not move their head towards the display at all. 4 others moved it only slightly with the result that detection rate was also very low. However, this seems to be problematic as the display of the secondary task was located on a position in the central console that is typically for an IVIS (in-vehicle information system). For later application in the vehicle it might be that especially the interaction with these devices will get undetected by the camera system.
- Head movements to the mirrors are detected quite good - however, especially in lane changes this is more an indicator of high attention instead of distraction. Therefore, the output of the inattentiveness diagnostic might be ignored in this special situation. However, one has to handle that case carefully because even if the driver is performing a manoeuvre he can for example spend too much time looking to the lateral rear view mirror and this can lead to a critical situation.
- The face recognition for the inattentiveness diagnostic seems to be very susceptible to driver's seat position and body movements. As soon as the driver starts to move on his seat tracking gets instable. One explanation is that face recognition detection and tracking is very sensitive to the position of the camera. Therefore, an optimum position of the camera must be found for each in-vehicle implementation. Experience has proven that such optimum position exists for all vehicles.

- In case of tracking problems the default value “distracted” is triggered: this leads to a high number and a long duration of false alarm events for some drivers - in extreme cases the driver is identified as distracted over nearly the whole drive - it is recommend-ded to include a kind of plausibility check in the algorithm in order to define an additional state “undefined”.

It has to be noted that the version of the inattentiveness diagnostic used in that evaluation was a very primary one. The new version that will be distributed to the project partners soon presents some strong evolutions. This new version is described in detail in deliverable D32.1 edited in May 2009 and some upgrades are also presented in this report (see section 6.3). Basically, the principles used for this new version are based on a head pose learning approach (ON/OFF-road poses). Poses are learnt off line, with a large variety of drivers, through the acquisition of some specific face components to train the poses detector. The approach that was used within the prototype of the version tested here was based on feature detection and real time tracking of these features which can generate false detection when tracking doesn't perform well. The new approach solves this issue by complementary analysis of the face appearances. In addition, it is more robust to face variability, including illuminations and glasses.

6.2.2.2 Indirect monitoring (parameters from driver’s interaction with secondary tasks)

Driver’s interactions with secondary tasks were restricted to the interaction with the HAVEit system (operation of the ACC lever) and the interaction with the IVIS (operations with the joystick). The operations with the ACC lever were assigned to the distraction group distract_SW_control defined in the input signal DRIV_INPUT_ADD_AV. The operations with the joystick were assigned to the distraction group distract_add defined in the input signal DRIV_INPUT_ADD_AV. All inputs were reliably detected and computed by the DSA software. The internal signals computed from that signals were SCORE_SW_CONTROLS and SCORE_ADD (see table 4.3 for a more detailed description of the internal signals).

Driver D02 - 20 minutes baseline drive

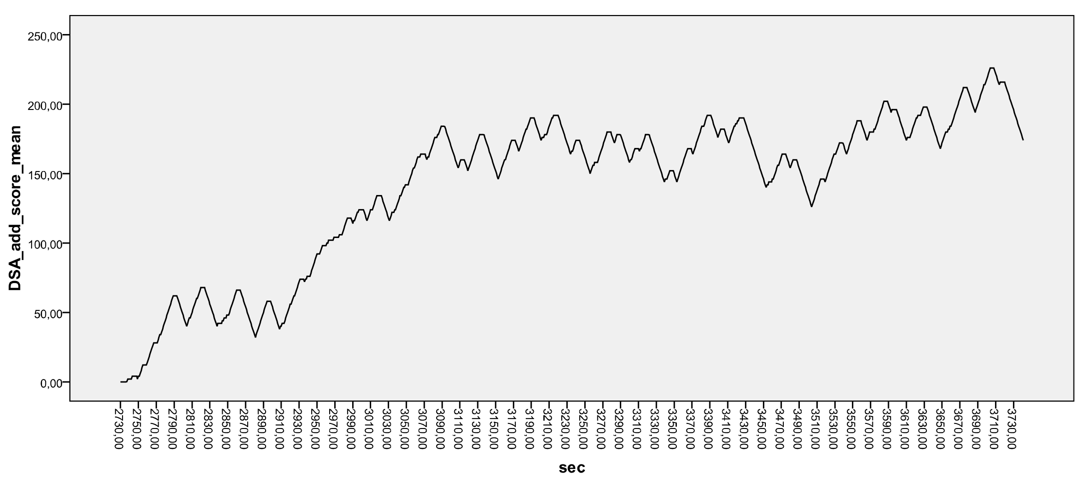


Figure 8: Internal signal SCORE_ADD over a 20 minutes baseline drive with the performance of a secondary task for Driver D02

Maximum value of internally computed signal SCORE_SW_CONTROLS in the validation study was 23. Maximum values of SCORE_ADD heavily varied between the drivers. Figure 9 and Figure 9 show an example of the SCORE_ADD over time for two drivers in the baseline drive. For driver D02 (Figure 8), it can be seen that the score increased very rapidly up to values of 225. This driver was highly motivated to perform the secondary task and did this nearly all the time. As he did not interrupt the task for meaningful times the score never reached a lower level but permanently increased till the end of the drive. Driver D03 however, operated the system less often and with more pauses in between. His score reached maximum values of 62. In between the score again reached a level of zero before it rose again (see Figure 9).

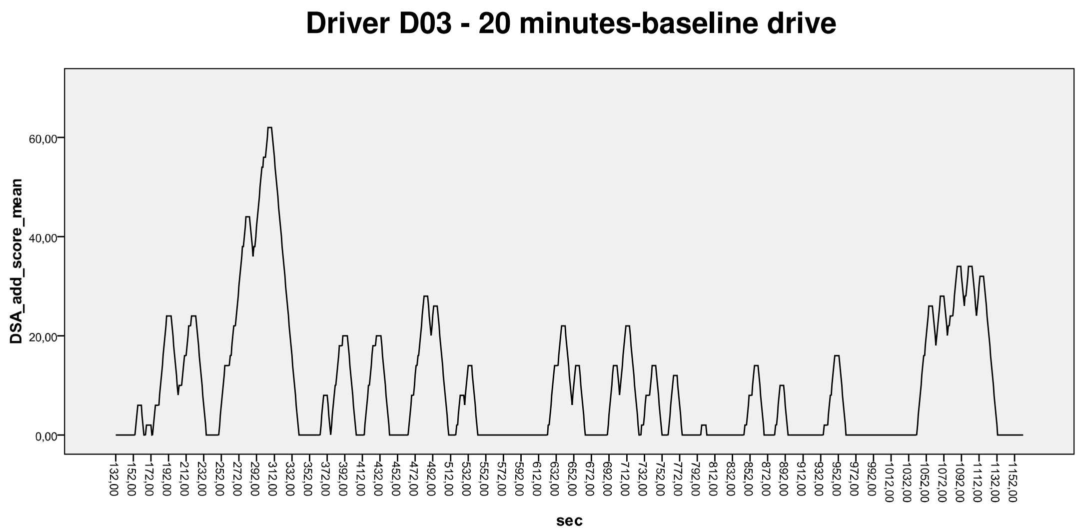


Figure 9: Internal signal SCORE_ADD over a 20 minutes baseline drive with the performance of a secondary task for Driver D03.

In the validation study it was also analysed how driver's would accept interventions (mainly information and warnings to make the driver attentive again) that are triggered at thresholds of a global distraction score of 10 respectively 20. Due to the instability of the inattentiveness diagnostic it was decided to refer the computation of this global distraction score only to the signal SCORE_ADD. First analysis (for a more detailed description see deliverable D33.3) revealed that the current algorithms and the chosen thresholds (both threshold of 10 and 20) would lead to a very high number of interventions of an Attention Monitor that reached only low acceptance by the drivers. In addition, in many cases the interventions were perceived as unjustified as the drivers were still visually attending the road.

Proposed solutions are:

- Raise thresholds for interventions (and with it the discrimination between distracted and not-distracted).
- Slow down the increase of the continuous distraction score, e.g. do not reduce it successively but reset the score to zero after a meaningful time or decrease the acceptable time for interruptions between single inputs.

Further results from the study showed that drivers expected the thresholds to be adapted to the current driving situation (e.g. higher threshold in situations with low demands as traffic jams, lower threshold in situations with high demands as sharp curves). Also the automation level might be considered in the classification of thresholds at least for reaching a higher acceptance by the drivers. This adaptation of thresholds is already intended in the DSA software but not yet included.

From the study on drowsiness it got obvious that also extreme distraction leads to conspicuous driving behaviour - these events should be extracted from the drowsiness algorithm and included in the distraction algorithms. If distraction is linked with a critical driving situation a separate output should be generated that leads to an immediate intervention of the HAVEit system despite triggering distraction warning messages. This application is already considered in the state “unresponsive” but should be further optimised.

6.3 Required modifications of the DSA algorithms

The conducted validation studies reveal a set of required modifications that will further increase the overall reliability of the DSA outputs with regard to drowsiness and distraction detection. They will be included in the next software version. The recommendations are summarized in the following chapter.

6.3.1 Distraction detection module

6.3.1.1 Direct monitoring

The presented results of the validation studies on the distraction detection are based on a very primary version of the DIM module. In the meanwhile, additional functionalities have been added. Some of them are already described in chapter 6.2.2.1. The most important improvements are described in the following section.

Basically, the DIM module provides general information about the head position: **On road /off road**[3]. The algorithm principle is based in a pose learning approach. Two categories of poses are distinguished: On-road poses (driver is attentive) and off-road poses (driver is inattentive or

[3] *On/Road information is characterized by the following scenario*

Head in direction of the road
Head is turned left or light less than 20°
Head is bended downward less than 20°
No limit upward as the driver can still easily look at the road

Off road information is characterized by the following scenario

Head is turned left or right more than 20°
Head is bended down more than 20°
Head is turned toward the radio/central console
Head is turned toward the central rear view mirror
Head is turned toward the right or left rear view mirror
Head is turned toward the passenger seat
Head is turned backward (e.g. looks at a children seated at the back)
Head bended downward

distracted). Poses are learnt off-line to train the pose detector. The learning is based on the acquisition of some specific face components like left and right eyes, mouth etc. so to cover a wide range of face morphologies, glasses, head poses and scenarios. This approach allows high robustness to environmental conditions, partial occlusion and glasses. Additionally, the real time tracking of the components provides supplementary information about the general direction of the head when off-road:

- Off Road + left
- Off Road + right
- Off Road + up
- Off Road + down

The assessment of the head orientation information is based on the tracking of the components trajectories previous to the off-road situation. If component movement amplitude is above a given threshold then rotation of the component is detected. The head rotation is achieved by majority vote. In order to guarantee a robust detection of the rotation 2 consecutive same head rotations are necessary to validate a head rotation or 1 head rotation followed by not-measurable image (lack of components). The following Figure 10 is presenting a typical situation of head rotation to the right side.

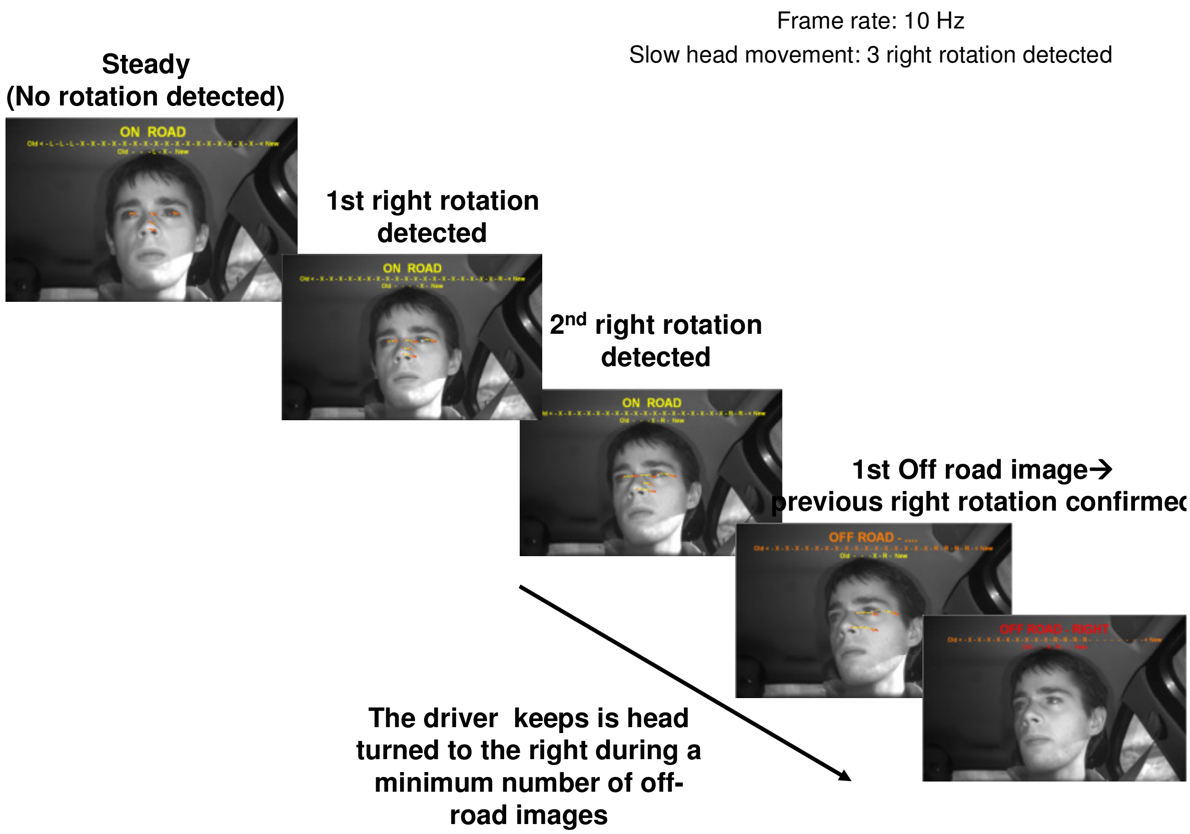
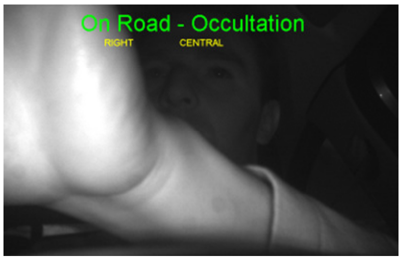


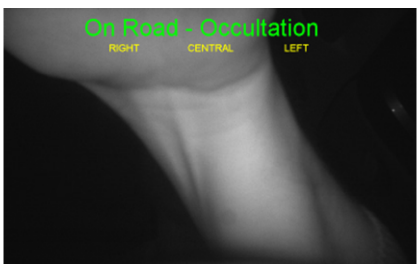
Figure 10: Typical sequence of head rotation detection and classification

The DIM is also capable to avoid false alarms in case of camera occultation by detecting objects in front, hand on top of steering wheel, driver's arm etc. Three binary occultation outputs can be provided: left, central and right. Occultation is mainly characterized by a local increase of the image brightness. The corresponding occultation detection algorithms are measuring the image brightness parameters and specific Region of Interest (ROI). Then rule based detectors take occultation decision on the basis of the number and location of bright ROIs (see Figure 11).



Right and central occultation

Left occultation



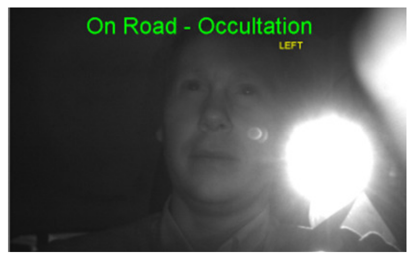


Figure 11: Example of occultation

The evaluation of the capacity of the system to detect occultation has been performed on a real driving data base. An occultation considered there is either a left, right or central occultation. Table 12 below is presenting the results achieved on this data base. It demonstrates very good efficiency of these algorithms.

Table 12: Evaluation of the performances of the DIM occultation algorithms

		Ground Truth	
		Positive	Negative
Occultation diagnostic	Positive	True positive: 6895	False positive: 7782
	Negative	False negative: 37	True negative: 103220
		Sensitivity: 99,47 %	**Specificity: 92,99 %**

6.3.1.2 Indirect monitoring

In the next software version the following modifications will be made with reference to the indirect monitoring of distraction:

- The computation of the continuous global distraction score will be modified with reference to a slower increase of the values.
- The distinguished states and sub-states that were mainly designed for the drowsiness algorithms will be also considered in the distraction algorithms (e.g. exclusion of inattentiveness diagnostic in lane changes).
- First proposals for the adaptation of the classification thresholds of distracted / not distracted to the driving situation and the automation level will be made.
- The state “unresponsive” attributed to distraction will be further explored.

6.3.2 Drowsiness detection module

6.3.2.1 Indirect monitoring

In the next software version the following modifications will be made with reference to the indirect monitoring of drowsiness:

- Detected minor problems in signal processing or parameter computation will be removed.
- An additional sub-state “critical interaction with other road users” will be included to reduce the false alarm rate for indirect monitoring.
- In the current version the parameters “time of day” and “trip duration” are not considered. They will be included in the next software version as weighting factors for the overall output of the module.

6.3.3 Fusion of direct and indirect monitoring

The following proposals are made for the fusion of direct and indirect monitoring

- Several analyses revealed that direct und indirect monitoring seem to complement each other - currently there are no indicators that one method is in general better than the other and should therefore be prioritized. However, there will be situations where the camera will provide more reliable outputs than the indirect monitoring and vice versa. This will heavily depend on the signal qualities on which the outputs can rely on. The signal qualities are already considered in the software architecture by including the confidence levels of the single outputs. Only if the confidence has been high enough within the last observed time window the measures are included in the algorithms. A further look will be made into more sophisticated fusion algorithms if they provide better results as the currently proposed disjunction.
- The proposed conjunction of direct and indirect measures for the „unresponsive“ state should be skipped. The camera will not be able to detect the driver for example, suddenly getting unconscious, and therefore not longer be able to react at all. Really critical events

resulting from an unresponsive driver can be reliably classified by indirect parameters. However, it must get clear that this might be too late to make any useful interventions despite to execute a minimum risk manoeuvre. In the optimum case the DSA had detected a critical driver state before that “unresponsive” level.

6.3.4 Fusion of distraction and drowsiness detection

For a reduction of false alarms both in distraction and drowsiness detection the algorithms should be fused. This is also partly done within the DMS and will be further pursued in the DSA development:

- In order to reduce false alarms in distraction detection, it should be thought of excluding glances to the mirrors detected by the inattentiveness diagnostic if the driver is currently performing a lane change manoeuvre.
- If abnormal driving behaviour (e.g. worse lane keeping performance) detected by indirect drowsiness monitoring occurs simultaneously with the detection of distraction (either by driver inputs or by the camera) the driver should not be identified as “drowsy” or “sleepy” but as “distracted”.
- In order to reduce false alarms in drowsiness detection, DMS drowsiness outputs should be ignored if the driver is detected as engaged with a secondary task by indirect distraction monitoring. This should make the decisions more robust. All external information that can be complementary to the monitoring is well suited for plausibility checks of the single DSA outputs.

7 Summary and Conclusion

To sum up, the present deliverable gives an overview about the current state of the DSA algorithm and software development. A documentation of the first software version that is already running on PC as well as on the CSC is given. Furthermore, validation studies of the drowsiness and distraction detection components conducted in the driving simulator are described.

Analyses of sensitivity and specificity of the single measures provide already quite good results with much potential for further improvements.

The recommended modifications for a second improved software version refer on the one hand to the single outputs alone, where modifications of the algorithms will clearly reduce false alarm rates. For direct monitoring this can be reached by e.g. inclusion of an undefined state for the inattentiveness diagnostic in case of tracking problems or by exclusion of display glances in lane change situations. For indirect monitoring this can be reached by e.g. the inclusion of a further sub-state “critical interaction with other road users” and the adaptation of the distraction diagnostic to the current driving situation and automation level. Furthermore, the quality of the final output can be increased by fusing not only direct and indirect monitoring but also closer linking distraction and drowsiness detection with each other.

From the analysis of the single outputs and the timely correlations between them it seems that the two measures could complement each other. Currently there are no indicators that one method is in general better than the other and should therefore be prioritized. However, there will be situations where the camera will provide more reliable outputs than the indirect monitoring and vice versa. The signal qualities are already taken into account in the software architecture by considering the confidence levels of the single outputs. Only if the confidence has been high enough within the last observed time window the measures are included in the algorithms. It will be interesting especially for the indirect monitoring, how these confidence levels and with them the weighting of direct vs. indirect methods will change when data from real driving are gathered (where e.g. lane detection quality might be not always 100% reliable).

Maybe more sophisticated fusion algorithms than the currently proposed solution will be helpful to further improve the reliability of the final DSA output. However, the first step now would be to improve the reliability of the single outputs before looking into more detail on the fusion of them. This will require a deeper look into the complex process of drowsiness development including for example specific timely correlations between direct and indirect measures (different criteria are triggered earlier or later in the drowsiness process) as well as their different timely resolutions (direct monitoring will provide very short drowsy and sleepy events of few seconds while indirect monitoring will provide more persisting outputs of several minutes).

8 Outlook/next steps

The required modifications will be included in the next software version. This version will again be validated by using a specially developed test environment that allows to offline replay the already collected simulator data. Also data from testing the software in the demonstrator vehicles will be used to improve the software. In addition, the new version will again be tested with a small subset of drivers in the driving simulation. The second release of the software will be made available for the two platforms Windows and CSC. Support for the vehicle owners for the CSC integration will be provided.

9 References

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Annex 1 Abbreviations

AM	Attention Monitor
CAF	Continental Automotive France
CSC	Chassis and Safety Controller
DA	Driver Assisted
DDM	Driver Drowsiness Monitoring
DIM	Driver Inattention Monitoring
DM	Driver Monitoring
DMS	Driver Monitoring System
DSA	Driver State Assessment
FA	False Alarm
HA	Highly Automated
HAVEit	Highly Automated Vehicles for intelligent transportation
IVIS	In-Vehicle-Information-System
KSS	Karolinska Sleepiness Scale
ROI	Region of Interest
SD	Standard Deviation
SDLP	Standard deviation of lateral Position
TTC	Time-to-Collision
WIVW	Würzburg Institute for Traffic Sciences

Annex 2 Glossary

Attention Monitor	Fictitious system (outputs triggered by the experimenter) in the DSA validation studies that gives the driver respective feedback on his current drowsiness and/or distraction level, e.g. by displaying information and warning messages.
Confidence rate	Reliability of the current drowsiness or distraction score
Co-system	A vehicle automation including the human machine interface that has the technical ability, at least in certain situations, to drive the vehicle by itself, but is used a complement for the driver for highly automated driving.
Current automation level	The automation level which the human-machine system has or is in, objectively and at the moment.
Direct driver monitoring	Driver related psycho-physiological measures of driver state; in HAVEit referred to direct observation of driver's eye movements and gaze/face direction via camera
Distraction monitoring	Component of DSA module; analyzes parameters related to distraction monitoring. A distraction level (and a respective confidence level) is derived from these parameters.
Distraction Score	Internally computed continuous level for describing the current distraction of the driver
Distraction	Impaired state of the driver defined if his/her attention is not directed towards relevant driving related targets but to other stimuli inside or outside the vehicle
Driver	Driver of the subject vehicle
Driver Assisted	A level of the automation spectrum between driver only and semi automated. Can be further classified as assisted by feedback and active support.
Driver Drowsiness Monitoring	DDM; component of the DMS, provided by CAF; algorithms for drowsiness detection based on analysis of blinking behaviour
Driver in the loop	Confirms that the driver state is active; e.g. awake, focused on the road, etc.
Driver Inattention Monitoring (DIM)	Component of the DMS, provided by CAF, algorithms for distraction detection based on analysis of driver's head and gaze direction, detection of eyes on/off the road
Driver Monitoring System (DMS)	vision based system analyzing the face of the Driver in order to provide information about his/her state degradation, provided by CAF
Driver State Assessment (DSA)	Software module within HAVEit for the online assessment of driver' state - fuses direct and indirect monitoring techniques to assess driver's drowsiness and distraction level

Drowsiness diagnostic	Diagnostic output by the DMS system by CAF; fuzzy rule based algorithm using the number and duration of the blinks observed on the given time window
Drowsiness monitoring	Component of DSA module; analyzes parameters related to drowsiness monitoring. They derive a drowsiness state (and a confidence level for the state) that is based on the parameters the unit is responsible for.
Drowsiness	Impaired state of the driver either caused by reduced vigilance, sleep loss or fatigue, resulting in decreased activation and arousal
False Alarms	Synonym for false positive classification in a binary classification test. Healthy (or here: awake) people incorrectly identified as sick (or here: drowsy)
Hands on/off	Driver has his/her hands on/off the steering wheel
Highly Automated	The highest automated level of the HAVEit system, where automation for longitudinal and lateral vehicle guidance is combined, but where the driver is still involved in the driving task most of the time.
Indirect driver monitoring	Indirect driving related measures; assessing driver's activity and performance measures which can be used to draw conclusions about the driver's state (e.g. reduced steering activity or decreased lane keeping performance)
Interactor	Information that has to be transferred between functional blocks of the HAVEit system – for a detailed description of the interactors see Deliverable D12.1
Karolinska Sleepiness Scale	Frequently used measure for evaluating subjective sleepiness; developed by Åkerstedt & Gilberg, 1990
Minimum Risk Maneuver	The maneuver that is most appropriate in a certain situation to reach a Minimum Risk State of the vehicle-driver system. An example for a Minimum Risk Maneuver could be a safe stopping of the vehicle.
Missing	Synonym for false negative classification in a binary classification test. Sick (or here: drowsy) people incorrectly identified as healthy (or here: awake).
Off road	Output of the DIM, Head is turned left or right more than 20°, head is bended down more than 20°.
On road	Output of the DIM; head is in direction of the road, is turned left or right less than 20°.
Sensitivity	Statistical measure of the performance of a binary classification test. Sensitivity measures the proportion of actual positives which are correctly identified as such.
Specificity	Statistical measure of the performance of a binary classification test. Specificity measures the proportion of negatives which are correctly identified as such.

True positive	Output of a binary classification test. Sick (or here: drowsy) people correctly identified as sick (or here: drowsy).
True negative	Output of a binary classification test: healthy (or here: awake) people correctly identified as healthy (or here: awake).