ARTEMIS	**HoliDes** **Holi**stic Human Factors **Des**ign of Adaptive Cooperative Human-Machine Systems	HoliDes

D 3.2 - Plan for Integration of Adaptation Techniques and Tools

Project Number:	332933
Classification:	Public with Confidential Annexes
Work Package(s):	WP3
Milestone:	M1
Document Version:	V1.0
Issue Date:	04.07.2014
Document Timescale:	Project Start Date: October 1, 2013
Start of the Document:	Month 7
Final version due:	Month 8
Deliverable Overview:	**Main document:** D3.1 - public **Annex I:** WP3 Partners Materials v3 - confidential **Annex II:** WP3 Partners Materials Tools Specs v3 - confidential
Compiled by:	Dlugosch, Carsten - ERG
Authors:	Eilers, Mark – OFF Borchers, Svenja – TWT Moravek, Zdenek - OFF Bellet, Thierry - IFS Dlugosch, Carsten - ERG
Reviewers:	Tango, Fabio - CRF Kolrep-Rometsch, Harald - HFC
Technical Approval:	Gärtner, Jens, Airbus Group Innovations
Issue Authorisation:	Feuerstack, Sebastian - OFF

DISTRIBUTION LIST		
Copy type[1]	Company and Location	Recipient
T	HoliDes Consortium	all HoliDes Partners

[1] Copy types: E=Email, C=Controlled copy (paper), D=electronic copy on Disk or other medium, T=Team site (AjaXplorer)

RECORD OF REVISION		
Date (DD.MM.JJ)	Status Description	Author
23.06.2014	Initial version	Dlugosch, Carsten - ERG
26.06.2014	Added another contribution	Dlugosch, Carsten - ERG
04.07.2014	Incorporated reviewer's comments	Dlugosch, Carsten - ERG

Table of Contents

1 Introduction

This document describes the adaptation techniques and tools and how they could be adapted to the RTP if desired.

Therefor the project partners created a list of tools and techniques (see appendix). Exemplary some of these are described in this document. In the overall project, more tools will be used e.g.

- HGRAPH, a hierarchical and functional modeling tool
- COSMODRIVE, a driver simulation model
- IFSTTAR driving simulator
- AEON, a framework for cloud message management
- APA for Advanced Patterns Assessment
- GreatSPN for Petri nets, Markov Decision Processes, model checking.
- PRISM for probabilistic verification
- A data visualisation simulation environment
- Dikablis Eyetracker
- FITMAN, a framework for validation
- And many more

This list shows how different the used tools are and gives an impression of the challenge to create a collaboration platform for all of them.

The following chapters will describe some different tools and techniques, which are currently in the focus of the project. For possible use cases the inputs and outputs are described. Furthermore, if it is planned to adapt the tool to RTP, they will mention which benefit is expected from the integration and describe the use cases and informal explain the interfaces for interchanging data. If there should be any preconditions necessary for a successful adaptation into the RTP, they are also mentioned.

2 Bayesian Autonomous Driver Mixture-of-Behavior (BAD MoB) models

2.1 Purpose

The Human Centered Design of intelligent transportation systems requires computational models of human behaviour and cognition. Especially for potentially adaptive and anticipatory onboard driving systems, the integration of internal predictive models of the human driver is a necessity in order to

- allow the automated re-configuration and adaption of assistance functionalities and/or the human machine interfaces based on the hidden intentions and cognitive states of the human driver,
- allow the early detection of non-normative driving behavior for recognizing and preventing safety and performance critical situations and events,
- while at the same time allow the reduction, delay, or suppression of assistance functionalities in non-critical situations, in order to prevent unreasonable interventions and warnings of assistance systems that lead to problems of acceptance.

A Bayesian Autonomous Driver Mixture-of-Behavior (BAD MoB) model is a probabilistic model that intends to predict the driving behaviour and intentions of a human driver. As such, it can be seen as a tool that supports the adaption within an AdCoS application. The techniques and methods for developing BAD MoB models will be developed in WP2. Within WP3, the use of BAD MoB models to support adaption within an AdCoS will be investigated.

BAD MoB models implement the complex sensorimotor system of human drivers in a modular and hierarchical probabilistic architecture. Based on a skill hierarchy (an example is shown in Figure 1) that recursively decomposes complex human driving behaviour into easier to model basic driving skills, a BAD MoB model combines multiple Dynamic Bayesian Networks (DBNs) with distinct purposes: Each basic skills in the skill hierarchy is realized by a distinct *action*-model that implements the isolated sensorimotor schema of the corresponding driving skill. The appropriateness of a pure or a mixture of basic skills in a given situation is inferred by a *behavior-classification*-model. The functional interaction of action- and behavior-classification-models then allows the context-dependent generation, prediction, and assessment of complex human driving behavior.

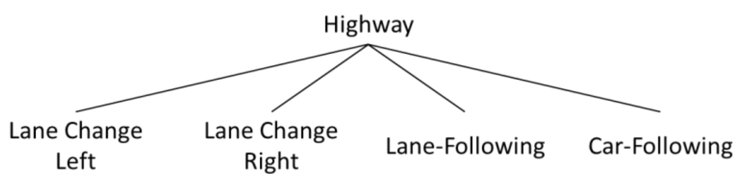

Figure 1: Skill-hierarchy for a BAD MoB model defining discriminable maneuver intentions.

2.2 Use Cases

In the context of HoliDes, BAD MoB models shall be used to provide an AdCoS application with predictions about the intentions and actions of the human user in real-time and in a non-intrusive manner.

2.3 AdCoS Use-Cases

BAD MoB models will be used for human behaviour and intention prediction/recognition in the CRF demonstrator vehicle developed for the primary WP9 Automotive use-case for lane-change assistance.

2.4 Input

During runtime, at each time step *t*, a BAD MoB model expects a multivariate data sample of synchronized and pre-processed information about the environment. This includes but is not limited to:

- Sensor information about the surrounding traffic participants, like e.g., time-headway, time-to-contact/collision, distance, bearing,
- Sensor information about the future path of the road,
- Sensor information about current speed limits,
- Information about the current state of the car, like e.g., velocity, distance from lane edges,
- Information about the current state of the actuators, like e.g., steering wheel angle, acceleration- and braking-pedal position.

Information may be provided by real sensors or via simulation.
For design and development of BAD MoB models, a library of time-series of data samples in the same format is required in order to learn the structure and parameters of the model.

2.5 Output

The primary output of BAD MoB models are *conditional probability distributions* (CPDs) over driving actions, denoted by *A* (we assume steering wheel angles for lateral control and acceleration-/braking-pedal positions for longitudinal control) and maneuver intentions, denoted by *B*, given the current environmental perception, denoted by *P*. The maneuver intentions a BAD MoB model shall be able to infer or discriminate between are defined via a skill-hierarchy and are yet to be defined for the CRF onboard system. Figure 1 shows an exemplary skill-hierarchy for a BAD MoB model, where the complex driving behaviour for driving on highways can be represented by the four maneuvers for performing lane changes to the left lane, lane changes to the right lane, lane-following, and car-following. In the following, the planned outputs the BAD MoB model will provide to the AdCoS shall be briefly described.

2.5.1 Maneuver Intention Classification / Prediction

At each time-step *t*, the BAD MoB model will provide a maneuver intention prediction via the CPD P(b^{t+n}|$a^{1:t}$,$p^{1:t}$), where *n* is a desired anticipatory horizon. The CPDs in the bottom right of Figure 2 to Figure 4 show some examples for such a maneuver intention prediction in different contexts.

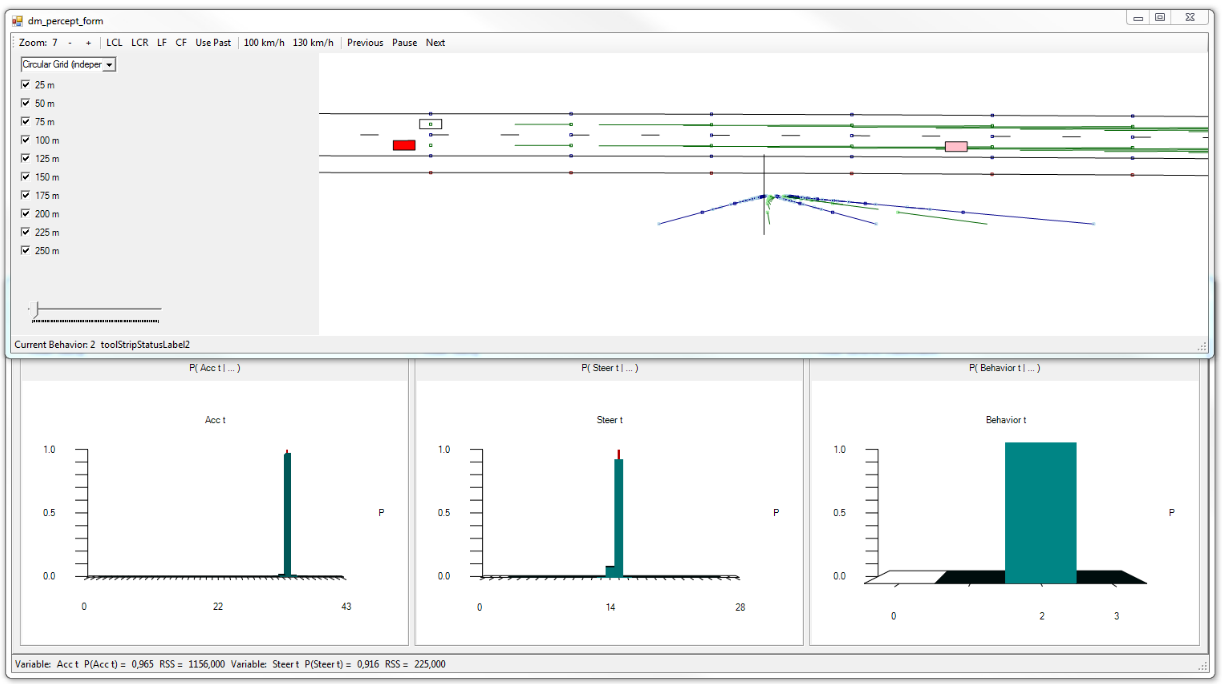

Figure 2: Exemplary maneuver intention prediction of a BAD MoB model for an unknown test dataset. The model correctly (compared to an earlier expert annotation) infers that the driver currently performs a lane-following behaviour (Behaviour = {lane change to the left lane (0), lane change to the right lane (1), lane following (2), car-following (3)}).

2.5.2 Lateral and Longitudinal Driving Action Prediction

At each time-step t, the BAD MoB model will provide an action prediction via the CPD P(a^{t+n}|$a^{1:t-1}$,$p^{1:t}$), where *n* is a desired anticipatory horizon. The CPDs (bottom left = longitudinal control, bottom middle = lateral control) in

Figure 2 to Figure 4 show some examples for such driving action prediction in different contexts.

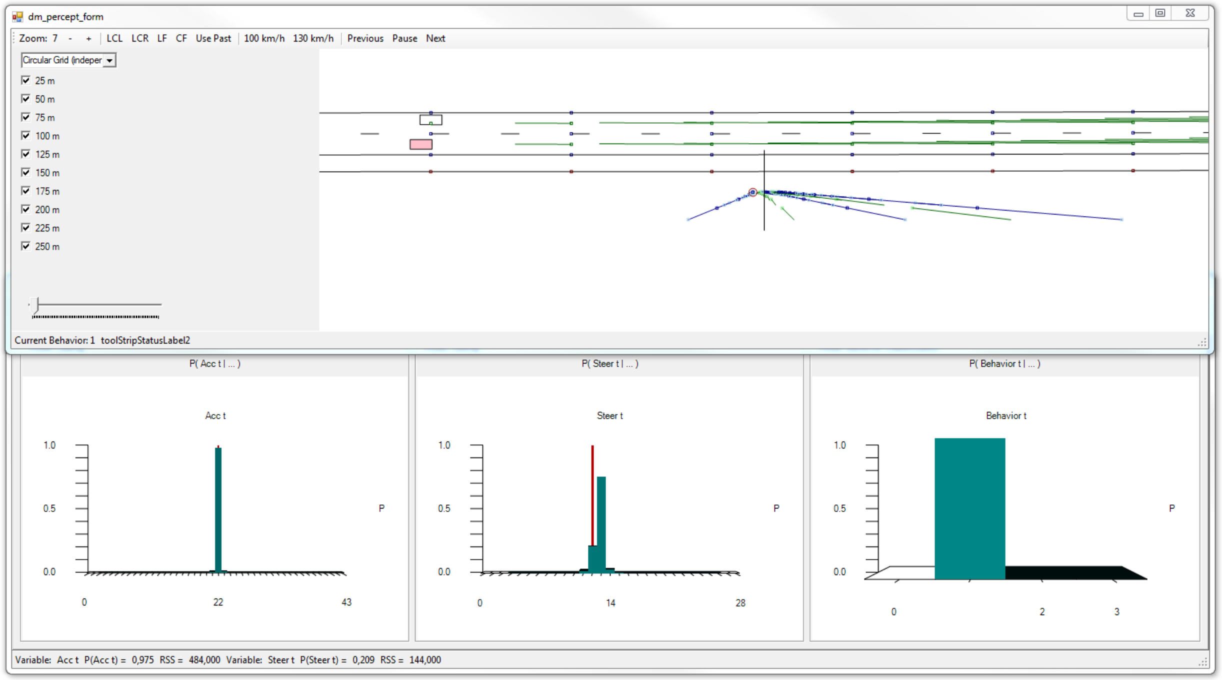

Figure 3: Exemplary maneuver intention prediction of a BAD MoB model for an unknown test dataset. The model correctly (compared to an earlier expert annotation) infers that the driver currently performs a lane change to the right lane (Behaviour = {lane change to the left lane (0), lane change to the right lane (1), lane following (2), car-following (3)}).

2.5.3 Likelihood of the current driving actions

The BAD MoB model will provide the log-likelihood of the last *n* chosen driving actions log $P(a^{t-n:t}|a^{1:t-(n-1)},p^{1:t})$. Under the assumption that the model represents normative driving, this can be used as a measure of normative driving. Low values or sudden drops (under the assumption that certain thresholds are defined) indicate that the driver does not show normative driving behavior and can be used to adapt the HMI or the influence/alertness of the assistance systems.

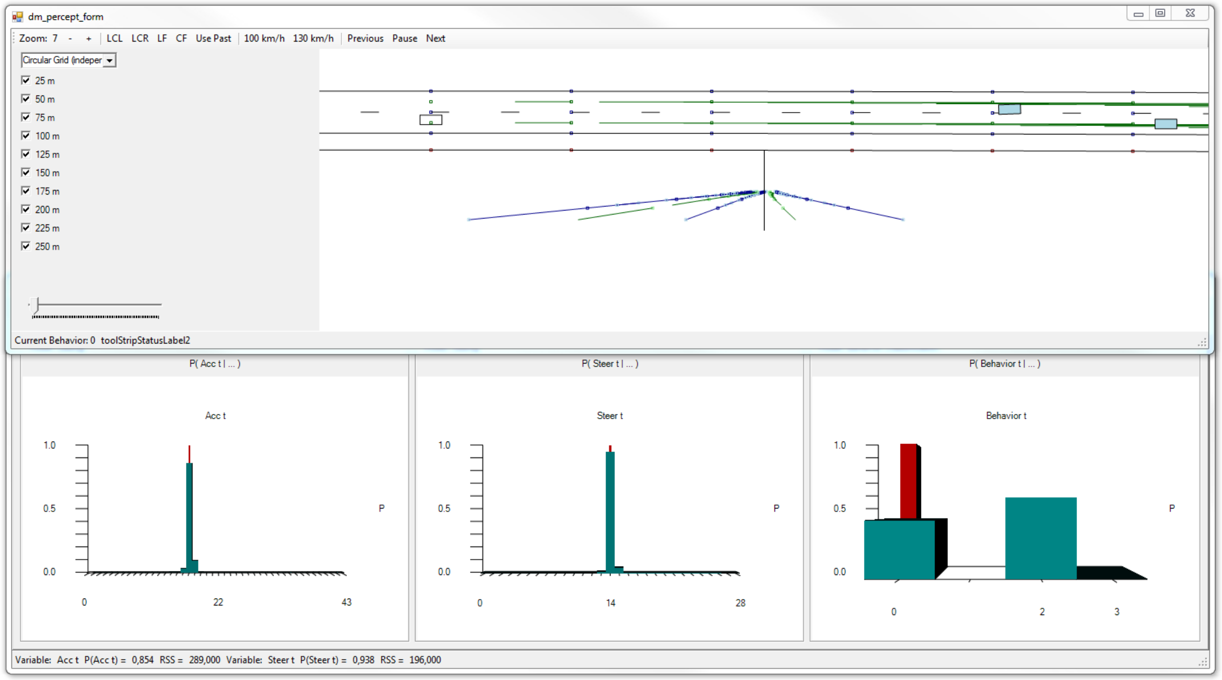

Figure 4: Exemplary maneuver intention prediction of a BAD MoB model for an unknown test dataset. Although the driver does not show corresponding steering actions, the model gradually (compared to an earlier expert annotation) infers that the driver performs a lane change to the left (Behaviour = {lane change to the left lane (0), lane change to the right lane (1), lane following (2), car-following (3)}).

2.5.4 Confidence

At each time step *t*, for each provided CPD, the BAD MoB model will provide an assessment of its confidence in the inferred CPD. Note that this confidence does not relate to the probabilities itself (which are obvious from the CPD) but takes into account the confidence in the estimated parameters used for the inference. Higher confidence values indicate the confidence of the BAD MoB model in the correctness of the inference and should rise in the presence of more available data.

3 Detection of driver distraction based on in-car measures

This tool will be developed by TWT.

3.1 Description

Distraction during driving leads to a delay in recognition of information that is necessary to safely perform the driving task (Regan und Young 2003). Thus, distraction is one of the most frequent causes for car accidents (Artho et al., Horberry et al. 2006). Four different forms of distraction are distinguished, although not mutually exclusive: visual, auditory, bio-mechanical (physical), and cognitive. Human attention is selective and not all sensory information is processed (consciously). When people perform two complex tasks simultaneously, such as driving and having a demanding conversation, there is an attention shift. This kind of attention shifting might also occur unconsciously. Driving performance can thus be impaired when filtered information is not encoded into working memory and so critical warnings and safety hazards can be missed (Trick et al. 2004). Sources for distraction of the driver can be located within and outside of the car.

An acoustic analysis including the detection of the number of speakers, the degree of emotional content, information about the driver's involvement in the conversation (e.g., whether the driver himself is speaking), is used for the prediction of the driver's degree of distraction. In addition, eye-tracking signals, such as temporal measures of eye movements, and face movement information, such as mouth movements, can be exploited to increase the reliability of distraction prediction. A computational and empirical cognitive distraction model is used for analysing the different signals, with the aim of computing a "distraction degree" of the driver. The effect of cognitive distraction, based on different audio scenarios, on driving performance will be empirically tested in a parallel task in order to assess the impact of auditory stimuli on distraction.

3.2 Use Cases

Deriving knowledge about the human operator can be very valuable in the system validation phase. While interacting with a prototype or some modules of the AdCoS, the operator's degree of distraction can be evaluated. The tool provides feedback whether or not a new system (module) increases or decreases the operator's degree of distraction.

In addition, this tool bears the potential to be used online to classify the driver's distraction not only during testing of a prototype, but also during everyday interaction with the AdCoS. This online measure of distraction could in turn be used to adapt the degree of automation of the AdCoS to the driver's state.

A combination with the tools developed by BUT (Detection of operators' head orientation) and UTO (Detection of driver distraction based on data on vehicle dynamics) is possible to increase the tool's predictive power.

This method will be either applied to the frontal collision use case or to the overtaking use case of WP9.

3.3 Input

In-vehicle information is needed. This includes, but it is not limited to, in-car audio recordings and eye-tracking data from the driver. These data need to be stored in a way that enables linking them to certain system states, e.g., inputs from the user to the system. Thus multimodal data integration and synchronization is mandatory for the tool to produce meaningful results.

3.4 Output

The tool provides a temporal description of the driver's degree of distraction. The metrics used to quantify the driver's distraction based on in-car information are developed in T5.2. The different measurements will be integrated in RTMaps provided by INTEMPORA. Personal components of the cognitive model and computations are intended to be mobile, e.g., via a Smartphone App. The core of the App, the personal model, should be exchangeable between the mobile device and an on-board system.

3.5 Adaptation to RTP

This tool may be integrated as part of the RTP and thus can be used by one or more RTP instances.

3.6 Benefit

This tool is mainly developed in the context of an automotive AdCoS. However, it can be relevant for other AdCoS environments, where auditory input may lead to distraction of a human performing any critical task.

3.7 RTP Use Case

The tool can directly be used for the WP9 use cases. Other use cases may include control rooms (where the human operator plays an essential role), or in aeroplanes (where distraction of pilots can be estimated).

3.8 Interfaces

The format of the respective input/output data remains yet to be determined. While continuous sensorial information may be exchanged as data samples (such as head pose or audio samples), the model which is adapted to the human driver can result in a rather large set of parameters.

4 Honeywell preliminary plans

The following ideas are planned to be addressed in WP7 use-case (DivA – Diversion Assistant) with respect to WP3 activities.

4.1 Framework for adaptation

WP7 use-case considers adaptation being invoked by detecting the deterioration of operator, system or external conditions. We are interested in determining the thresholds to invoke the adaptation and the modeling of the adaptive behaviour. The thresholds are related to

1. Machine failure – specifying the severity of failure, its impact on pilot's tasks and possible counter-actions
2. External conditions
    a. Weather
    b. Aerial traffic and ground conditions
3. Internal environment and operator state
    a. Information perception/recognition due to noise, illumination and direct light, turbulence
    b. Human state due to workload, temperature, humidity, pressure and oxygenation

The architecture should consider fusion of these various data channels. The fusion is based on algorithms that can on one hand select the best combination of data channels and on the other on identifying relevant patterns in the data. We plan to cooperate with partners to build and evaluate the tools.

4.2 AdCoS Context

In WP7 we want to address the state of the pilot as the pilot is the major cause of accidents/incidents in aviation. The workload created by machine failure (and thus reallocation of tasks to pilots) can be investigated from the procedure modelling (WP2). The pilot state is more related to internal environment (T3.2 3a) and physiological conditions (T3.2 3b). The theoretical concepts from T3.2 will be practically investigated by physiological measurements, video recording and analysis.

1. Machine failure should be modelled to compare the reallocation of tasks, new tasks or task priorities. The result should be related to the change in workload of pilots and performance of the aircraft (range, maneuverability, altitude restrictions)
2. External conditions can influence the path of the aircraft, flight time and its landing performance.
3. With respect to turbulence and illumination, there may be perceptions levels in contrast/readability that could be detected and when compared to thresholds they may be the basis for starting the adaptation.

4.3 Techniques and tools for adaptation

Task allocation should be done based on evaluation of task list, situation and transferability of tasks/information. For our use-case it implies that pilot can control strategies of the calculation and extent of information to use and to produce, while machine calculates all and considers the context to produce relevant information presentation. Machine may also disable some strategies so that pilots cannot use them.

4.4 Communication of reasons for adaptation

We need to define specific approaches to communicate information that is difficult to perceive by the pilot – the physiological state, workload, adverse conditions (oxygenation, noise level etc), especially when performance is affected. The critical aspect is that pilot

- understands the reasons immediately
- does not need to search the information usually provided
- has no feeling of random display

We should be able to decide when the adaption is to be communicated at all – some situations can be solved by alternative algorithms (adaptation) without a need to inform the operator.

5 COSMO-SIVIC & COSMODRIVE

5.1 Techniques and Tools

In the HOLIDES project as a whole, IFSTTAR will develop, in partnership with Intempora and CIVITEC, a Human Centred Design Platform (named COSMO-SIVIC) integrating a driver model (COSMODRIVE) in charge to pilot a virtual car equipped with an AdCoS (to be simulated with pro-SIVIC and RT-MAPS tools), in a virtual road environment.
In the specific frame of WP3, IFSTTAR will design and develop a set of Monitoring Functions to be integrated in the AdCoS for automotive domain, aiming to assess road accident risk due to drivers' visual distraction (to be simulated with COSMODRIVE model), and then to adapt the Human-Machine Cooperation functionalities of the AdCoS, according to this situational risk.

5.2 Use Cases

Uses cases investigated by IFSTTAR in WP3 will be primarily focused on car drivers' visual strategies simulation and analysis. The challenge will be to use COSMODRIVE model to simulate, in a realistic way, visual scanning as implemented by real drivers when driving their car. In this perspective, it will be necessary to defined with ERGONEERS a shared format of datafile generated by COSMODRIVE's virtual eye, in order to monitor COSMODRIVE's visual scanning in a similar way of a real driver equipped with an Eye tracking system. Then, the monitoring function will be in charge to diagnose visual distraction risks in the frame of the driving scenarios (already defined in WP9), for virtual design and test of AdCos, for automotive domain.

5.3 Interfaces

The inputs of the Monitoring Functions to be developed by IFSTTAR in WP3 will come from the "virtual eye" of the COSMODRIVE model and/or by a real driver equipped with an Eye Tracking system.
The outputs of these Monitoring Functions will take the form of "a diagnosis of situational risk", due to "visual distractions" of the car driver. Such a diagnosis will be then used in virtual AdCos (to be developed in WP9 for automotive application) in order to monitor the car drivers and to adapt the driving aids according their visual scanning and/or distraction state.

5.4 Adaptation to RTP

All the interactions between the Monitoring Functions to be developed by IFSTTAR in WP3 and the HF-RTP will be supported through the RT-MPAS tool of INTEMPRA. Requirements towards this tool (and others like Pro-SIVIC) where already done in other WP (WP2, WP4, WP9). Not any additional requirement is proposed by IFSTTAR in this WP3, except the general requirement that RT-MAPS should be connected / interfaced / integrated into the HF-RTP as a whole.

6 Adaptation Plans

At the present time, the tools are gathered, which to be linked. Furthermore, the input and output parameters were described informal.

The next steps will be:

- Formal Description of the parameters of the tools used. This includes number, length and type of the parameters and a syntax description.
- Choosing one or more techniques and protocols for data transfer, e.g. REST, UDP-Server Client, RDF, CSV, XML,… .
- The definition of the network points and a description of the overall network structure.
- Finally the implementation of adapters to link individual tools.

7 Conclusion

In the field of Human Factors, many different tools and techniques are used. The combination and linking of these tools is very challenging and laborious. The overall idea of adapting these tools to one platform is to simplify this process. The following deliverables will address this in more detail.

8 References

Artho, J.; Schneider, S.; Boss, C.: Unaufmerksamkeit und Ablenkung: Was macht der Mensch am Steuer? - Transport Research International Documentation - TRID. Online verfügbar unter http://trid.trb.org/view.aspx?id=1244037, zuletzt geprüft am 21.05.2014.

Horberry, Tim; Anderson, Janet; Regan, Michael A.; Triggs, Thomas J.; Brown, John (2006): Driver distraction: the effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. In: Accid Anal Prev 38 (1), S. 185–191. DOI: 10.1016/j.aap.2005.09.007.

Regan, M. A.; Young, K. L. (2003): Driver distraction: a review of the literature and recommendations for countermeasure development. In: Proc. Australas. Road Safety Res. Policing Educ. Conf. 7 (v1), S. 220–227.

Trick, Lana M.; Enns, James T.; Mills, Jessica; Vavrik, John (2004): Paying attention behind the wheel: a framework for studying the role of attention in driving. In: Theoretical Issues in Ergonomics Science 5 (5), S. 385–424. DOI: 10.1080/14639220412331298938.

A Annex

This Annex contains two excel sheets:

- "WP3 Partners Materials v3.xlsx" present an overview of the potential contributions of the WP3 partners, including references to contact persons, tools, etc.
- "WP3 Partners Materials Tools Specs v3.xlsx" provides an overview of the tools inputs and outputs.