The Design of Preventive Safety Systems: a Cognitive Engineering Problem

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Abstract

In this paper a design framework for preventive safety systems (ADAS) is proposed. The design framework takes into account risk mitigation strategies, advanced driver's model, based on modern approaches and algorithms (machine learning and add-on functionalities), able to capture key aspects of human behavior, such as distraction, and to retain the fundamental characteristics of cognition and decision making.

Introduction

Driver modeling is a scientific area involving several disciplines, such as psychology, physics, computer science, etc. The importance of adding the learning capability to information systems, in order to make them more effective and smarter, is confirmed by the variety of areas in which user's modeling has already been applied: information retrieval, filtering and extraction systems, adaptive user interfaces, educational software, etc.

In relation to the problem formulated above, the aim of this paper is to deeply understand the problem of ADAS (Advanced Driver Assistance System Design) design, the problem of developing an effective driver's and driving model supporting distraction mitigation. Such systems would mitigate the effects of distraction and tolerate the consequences of distraction thanks to a better road and vehicle design (Regan, Lee & Young 2009).

A feasible and promising solution is the use of Add-On functionalities, able to detect driving maneuvers that are indication of distraction, placing them in the framework of a cognitive model of human behavior.

In this paper a design framework for preventive safety systems is proposed, following three main building blocks:

1. **new knowledge about driver behavior**: extensive empirical studies about the sources of accidents and potential counter measures as a basis for the driver model development.
2. **risk mitigation strategies**: implementation of a human error risk based approach;
3. **advanced driver modeling**: development of models for predicting correct and erroneous driver behavior, based on modern approaches and algorithms (machine learning), able to capture key aspects of human behavior, and to retain the fundamental characteristics of cognition and decision making.

The precondition analysis

Accidents occur because multiple factors combine to create the necessary conditions for them. Over the past 30 years, the literature shows a consistent trend in trying to understand accidents in aviation, nuclear power generation, telecommunications, unmanned and manned spaceflight, railroad transport, shipping, healthcare and many other fields (Catino 2002). Regardless of the domain of investigation, there are some crucial questions to which the research is trying to find an answer (Cook & O'Connor 2005):

- *How do accidents happen and what do they mean?*
- *Are accidents foreseeable?*
- *If so, are they preventable?*
- *What role does technology play in accidents?*
- *What role does human performance play?*
- *Are accidents evidence of systemic problems or are they isolated failures?*
- *If accidents are systemic, how can the system be fixed to prevent future accidents?*

What it may be interesting to study is the detection of an accident pre-conditions and which may be the conditions combination (circumstances) that may lead toward an accident. For each combination (that we may label *risk layouts*) a mitigation strategy will be applied in order to avoid a possible accident. "What was lacking was the ability to foresee that circumstances would conspire to create the conditions needed to make these technical features active and lethal" (Cook & O'Connor 2005).

An adaptive system should be able to detect risk layouts and dynamically adapt its behavior in order to avoid accident, but the failure factor in this scheme is *change*. In a complex system formed by a context, a predictable system (including automatic applications) and the human being, the unpredictable factor is the human being behavior and its combination to a certain context.

Although information technology can defend against some types of accidents and failures, the impact of automation on human-machine system performance is a mixture of desirable and undesirable effects (Perry, Wears & Cook 2005).

Systems like ADAS (Advanced Driver Assistance Systems) have great potential for enhancing road safety, but on the other hand the safety benefits of ADAS may be significantly reduced by unexpected behavioral responses to the technologies, e.g. system over-reliance, safety margin compensation and distraction, leading toward an automation failure. The automation failure is a side effect of an effort to produce ‘‘safety’’(Catino 2002).

ADAS: existing applications

In addition to the safety issues associated with the driving task, the proliferation of complex in-vehicle functions itself poses a further challenge for the design of the driver-vehicle interface: one of the current research area in automotive is the development of preventive warning systems, also called ADAS (i.e. Advanced Driver Assistance Systems) adopted with the aim of improving driving safety. These systems are able to detect an incoming dangerous in advance, allowing a time to perform a repairing manoeuvre.

ADAS are aimed at “partly supporting and/or taking over the driver’s tasks” (Berghout, Versteegt, van Arem 2003) so to generally provide safer driving conditions. Several functions can be mentioned within ADAS set. In the following, a list of the main relevant ones is reported (Ehmanns & Spannheimer 2004):

- **Lane departure warning**: If certain thresholds (like distance, time to lane crossing) allow a prediction of a lane departure this system warns the driver by means of acoustic, optic or haptic feedback. The detection of the lane markings results from e.g. video image processing. In order to have a robust lane marking detection two needs can be absolved: (i) good visible lane markings have to be provided by the infrastructure and (ii) a robust lane detection sensing system has to be implemented in the vehicles. Both aspects are influencing the complexity of the system on the roadside and the technical level.
- **Near field collision warning**: The near field collision warning includes the detection of especially vehicles in the near field like in the blind spot area. The detection area is very close limited to the vehicle. Suitable sensor systems for the detection of other cars are radar or vision based sensors.
- **Curve & speed limit info**: These systems inform the driver about speed limits and the recommended speed in curves. Possibly the necessary information can be taken from digital maps, image processing communication systems between vehicles and infrastructure.
- **Adaptive Cruise Control (ACC) /Stop & Go:** The ACC and Stop & Go establish a virtual link with the frontal vehicle via a radar-based technology and keep booth vehicle within a safe distance. The main innovation of this systems, that is derived from the well-known cruise-control, is that the distance can be adapted both to the driver’s preferences (as in ACC) and to the specific requirements of the urban environment (as in the Stop & Go). In traffic condition as in a queue, the Stop & Go automatically drive the vehicle timely providing vehicles’ stops and small movements.
- **Lane Keeping Assistant**: The function of a lane keeping assistant system includes the lane detection and the feedback to the driver if he/she is leaving a defined trajectory within the lane. An active steering wheel can help the driver with a force feedback to keep on this trajectory. The lane is detected by a video image processing system.
- **Local Hazard Warning** : If a hazard occurs far away in front of the vehicle, so that the driver cannot see it, this system will warn him/her. By the means of communication it is possible, to transfer this information over long distances
- **Lane Change Assistant**: Before and during a dangerous lane change process, the lane change assistant will warn the driver. Several stages of such a system are possible from pure warning systems to even haptic feedback at the steering wheel to help the driver following a lane change trajectory.
- **Blind Sport Monitoring:** This function detects if a vehicle is present in the so called “blind spot” area when the vehicle is starting a lane change and/or overtaking maneuvers. A camera is placed into the left rear-mirror and once the incoming vehicle is recognized, a warning is issued to the driver.
- **Obstacle & Collision Warning**: The driver will be warned if a potential collision is detected via radar-based technology (e.g. another car or obstacle). The functional limits of these systems have to be clearly pointed out. The liability problem of these systems grows with the complexity of the detecting scenarios.
- **Obstacle and Collision Avoidance**: This system has an extended functionality compared to the Obstacle and Collision Warning. An autonomous intervention takes over the control of the vehicle in critical situations in order to avoid an accident. Longitudinal and lateral control will be done by the system during the defined time while the dangerous event takes place.
- **Night Vision**: Based on camera techniques like near or far infrared, it allows enhancing the perception of the driver in dark light conditions. The picture of the camera will be shown to the driver by monitors or head up displays.
- **Platooning**: Several cars are connected electronically (e.g. by the means of communication) and follow one after the other in a platoon. An example is the connection of trucks in order to save space, fuel and to increase the traffic flow. As the following vehicles are driven automatically, the system is complex concerning all aspects. The

takeover of the driver at e.g. gateways has to be taken into account as well as the behavior in mixed traffic at driveways.

Designing the trustiness: ADAS research issues

Interaction with these devices is one of the many activities that constitutes driving and so it can represent an additional source of driving-related distraction (Regan, Lee & Young 2009). For example poorly designed collision warning systems may be even more likely to distract drivers; navigation represents a driving-related task with substantial potential to distract (Neale et al 2005), (Dingus et al 1989).

The analysis of ADAS working conditions, architectures and performances leads towards the definition of a proper theoretical framework that is not yet present in current projects.

The reasoning behind is the following: Advanced Driver Assistance Systems, or ADAS, are systems that help the driver in its driving process: they detect a dangerous situation and gives a warning. We can define *analytical* (Andreone et al 2005), the ADAS type that warns the driver suggesting accident-avoiding maneuvers. The ADAS is *behavioral* if it acts in place of the driver, partially taking over a certain driving task (Andreone et al 2005) (Hoch et al 2007)0.

In the case of analytical ADAS we can consider there are two actors playing a role:

- The driver
- The warning system

In the case of behavioral ADAS we can consider there are three actors playing a role:

- The driver
- The *horse* (the artificial system able to drive in place of the driver, see Flemisch et al 2003)
- The warning system

In both cases, analytical and behavioral ADAS, there is a warning systems that detects the dangerous situation and then provides the driver, as safety warning, accident-avoiding maneuvers.

The purpose of these systems is to foresee and detect possible driver's errors and mistakes, due to a misbehavior such as distraction, or resulting from too high workload, missing perception, wrong action/execution or poor operator skills.

The ADAS design is aimed at enhancing the driver's perception of hazards and critical situations (in some cases, by partly automating the driving task as well). Of course the potential of such systems in reducing accidents depends on the effectiveness of their interaction with the driver. For example, in the case of an anti-collision systems it is safety-critical that the collision warning is able to generate the appropriate feedback (e.g. an avoidance maneuver).

Since ADAS can be actually considered recommending systems, the use of an appropriate driver's or/and driving model will improve their effectiveness and consequently, human safety.

Risk mitigation strategies: recommending the accident avoiding actions

ADAS can be considered an application of recommending systems that recommends the driver repairing maneuvers in order to avoid an accident. The most advanced systems are able to directly take part in the driving task, whether the driver doesn't react on time. Also in this case, the systems follows a recommendation formulated by the system itself.

Recommender systems have become a promising research area since the appearance of the first papers on collaborative filtering in the mid 1990s (Hill et al1995), (Resnick et al 1994), (Shardanand & Maes 1995)

Shortly, the recommendation problem is formally represented as a space *S* of possible items that may be very big, ranging in hundreds of thousands or even millions of items in some applications, such as recommending books. An utility function measures the usefulness of each item for a certain user.

In recommender systems, the utility of an item is usually represented by a rating, which indicates how a particular user likes a particular item or how a particular item is appropriate for a certain user, taking care of a set of context conditions. Generally speaking , utility can be an arbitrary function, including a profit function. Depending on the application, the utility can either be specified by the user, as is often done for the user-defined ratings, or is computed by the application, as can be the case for a profit-based utility function (Adomavicius, Tuzhilin 2005).

To each element of the user space *C* can be associated a profile that includes the user characteristics that are relevant for the current application. Similarly each element of the item space S is defined by a set of relevant characteristics.

In recommender systems, utility is typically represented by ratings, therefore, the recommendation engine should be able to estimate (predict) the ratings of the nonrated user/item combinations and issue appropriate recommendations based on these predictions. Extrapolations from known to unknown ratings are usually done by:

- specifying heuristics that define the utility function and empirically validating its performance
- estimating the utility function that optimizes certain performance criterion, such as the mean square error.

Despite of the results nowadays achieved, the existing generation of recommender systems still requires further improvements including better methods for representing user behavior and the information about the items to be recommended, more advanced recommendation modeling methods, incorporation of various contextual information into the recommendation process, utilization of multicriteria ratings, development of less intrusive and more flexible recommendation methods that also rely on the measures that more effectively determine performance of recommender systems (Adomavicius, Tuzhilin 2005).

In the case of services provided on board a car, we can notice that they are rapidly growing. Almost all car manufactures are offering systems that add functionality to route planners, possibly integrated with internet and web access or that support driver in high demanding tasks, in order to increase safety and avoiding accidents. The availability of these add-ons is an interesting opportunity, considering that nowadays the amount of time spent in the car (e.g., for commuting or for work and vacation trips) is very high (Console et al 2003).

If on one hand the driver and the other vehicle occupants can actively use the time spent on the car, on the other hand the use of these services can be distracting and can create serious safety problems (Green 200) (Console et al 2003), contracting societal goals of increasing safety, reducing the number of accidents. As a consequence it is necessary to find a proper compromise between the increasing number and complexity of the services and the need of making the services compatible with the fact the user is driving.

Starting from this consideration, the introduction of personalization and adaptation strategies and techniques should be a feasible solution in the case of services in the car. In fact, by considering the characteristics of the user and the context of interaction, a personalized and adaptive system may tailor the interaction to the way which is most appropriate to avoid distractions, and as a direct consequence, to avoid an accident (Console et al 2003).

In the case of safety-critical systems which should recommend accident avoiding maneuvers, the adaptation of the recommendations to the specific user is crucial, according to the psychophysical parameters that are taken into account (i.e. mental workload, distraction, arousal level, situation awareness). In the case of advanced driving assistance systems one of the most important psychophysical parameter to be taken into account is distraction. The system should be able to assess driver's distraction in order to estimate accident precondition (risk layout) and recommend driver appropriate actions, or in the case of adaptive automatic systems to perform a proper risk mitigation strategy.

If the recommending engine has not at its disposal a user behavior model, it can formulate recommendation that may lead towards no decisions or wrong decisions.

Whether the system prediction capability is augmented through a user behavior model it is possible to reduce errors and then the risk of accidents. This consideration is of paramount importance in complex safety critical systems as avionic and automotive, that commonly use different kind of recommending services.

The design of cognitive preventive safety systems

Driving is considered as a complex and multitasking cognitive activity that can be summarized by four main sub-processes: perception, analysis, decision and action. To be performed, each phase presumes the achievement of the previous one. That said, it is likely that the demands of one element of driving will interfere with another element.

ADAS new technologies have great potential for enhancing road safety, however, when an ADAS or an In-Vehicle information system (IVIS) is activated and the driver is asked to interact with it, the driver him/herself is distracted from the driving task, that is, his/her attention is moved from the driving task to the secondary task. A relevant part of vehicle crashes are estimated to

The Driver Assistance Systems have to be able to adapt their action to the context and to the driver and vehicle status. Thereby, they need a model of human behaviour that takes into account the model of the system performance and that is able to detect and classify driver's intention and distraction, in order is essential to facilitate operating mode transition between users and driver assistance systems.

The need of an effective user model is a requirement for any recommending system, as faced and confirmed by the domain literature on user modeling and automatic recommending systems. This requirements is crucial for any recommending system that has to cope with time-criticality, that directly affects safety.

ADAS applications are examples of such systems and they represent a challenging test bed for the implementation and validation of user behavioral modeling systems realized by means of Machine Learning techniques.

Basically, the human behavior is characterized by the interactions between driver-vehicle and driver environment.

The first interaction is related to how the driver interacts with the vehicle and all systems and sub-systems on-board.

The second interaction is related to how drivers perceive and process the data coming out from the surrounding scenario.

Hence, the driver model should be adaptive to different drivers' style and preferences as well as to the external environment (including learning both from the driving experience and from the surrounding conditions), but overall it should allow to assess and foresee distraction.

Preventing distraction permit to prevent driving errors and accident risk, as a consequence, a risk based design approach (that follows a risk mitigation strategy) is crucial for the design of vehicles and transport systems in order to guarantee safety and efficiency of human mobility.

User modeling (UM) aims at improving system effectiveness and reliability by adapting the behavior of the system to the needs of the individual.

The importance of adding this capability to information systems is proven by the variety of areas in which user modeling has already been applied: information retrieval, filtering and extraction systems, adaptive user interfaces, educational software, safety-critical systems .

Machine learning (ML) techniques have been applied to user modeling problems for acquiring models of individual users interacting with an information system and grouping them into communities or stereotypes with common interests. This functionality is essential in order to have a useful and usable system that can modify its behavior over time and for different users (Langley 1999). As elicited from literature (Tango Botta 2009), (Tango et al 2009) (Tango et al 2010) there is a trend in choosing machine learning techniques in the study of modeling of human behaviors, that is non-deterministic and highly non-linear.

Driver Assistance Systems have to handle crucial aspects like timing and warning, therefore the development of an algorithm for the personalization of such aspects that takes into account for example is needed.

Regarding the drivers' intention prediction, several models have been proposed aiming at reproducing in a virtual environment how the drivers could behave according to specific Driver, Vehicle or Environment conditions , that is DVE model (Tango et al. 2010) . In the domain literature there are different approaches like:

- the IPS (Information Processing System), which has been applied in almost all technological fields to describe human interaction with control systems, at different levels of automation (Neisser 1967)
- the PIPE (Perception, Interpretation, Planning and finally Execution) based on a very simple approach that assumes that behaviour derives from a cyclical sequence of four cognitive functions in brackets. (Cacciabue 1998)

The development of a model of the human machine system is driven by the model of the Driver, which is the most complex element of the system.

Concerning the design of algorithms used to represent the Driver behaviour, previous and ongoing studies propose different approaches based on the real-time monitoring of the drivers' performance (Lolli et al 2009) (e.g. variation of the position on the road, speed, steering wheel movements) or the drivers' physiological status performing primary and secondary tasks (e.g. eye gaze, eye movements, heart frequency variation, galvanic skin response, etc.) (Ji & Yang 2002).0

Basing on these information, these approaches allow to predict specific drivers' profiles (e.g. stressed, aggressive, tired, distracted, high workload etc.) and are developed following machine learning approaches. Thanks to machine learning, information on drivers' profile can be automatically extracted from data, by computational and statistical methods applied to observable information (e.g. drivers' performance data).

On one hand the assessment of the driver's status and consequentially the prediction of his/her next behaviour is easier and most successful using driver's physiological data, as for example the eye gaze and the eye movements measured by means of eye tracker. On the other hand eye-tracking is an intrusive measurement system of distraction, it represents a further equipment and a further cost that stand in the way of a next future mass-marketing. What is really interesting and challenging is to obtain a driver index analysing driving performance data, realising what it may be considered an ADD-On Functionalities.

Understanding driver's maneuvers by the use of Add-On Functionalities

Research in driver comfort and performance improvement understanding driver's maneuvers is very active. Usually, these targets are achieved through the installation of further in-vehicle sensors and devices (Lolli et al. 2009) .

An alternative is the use of the so-called Add-On Functionalities (AOF). They do not require new sensors but only information coming from the on-board network and sub-systems (e.g. the elements of chassis, suspensions, steering angle, etc.). This information is computed in a well tuned algorithm and the results provide some added-value supports to the drivers as AOFs for pre-crash detection. They prepare the vehicle to the impact in critical situation which can not be avoided, for example, by pre-tensioning the seat belt (Lolli et al. 2009). They can be used also to indirectly infer form the driving & driver data crucial information about driver's behavior like distraction, workload and arousal.

Add-On Functionalities can in fact be divided in two main categories:

- **Driving Behaviour**: i.e. Add-On Functionalities related to driving performance. Main objective of these AOF is to estimate driving conditions concerning road, dynamics and current manoeuvre.
- **Driver Behaviour**: these AOF deal with driver current state, mainly intended as mental effort (or workload) related to the driving task.

In order to be implemented, an Add-On function has to satisfy two conditions:

- All Add-On inputs must be available and shareable.
- At least one Add-On output can be received as input by a vehicle device.

An Add-On Function with m inputs and n outputs is defined as:

$$(x_1, x_2, \dots\ x_n) = F\ (y_1, y_2, \dots\ y_m)$$

or in a concise form:

$$\bar{x} = F\ (\bar{y})$$

If Y is set from available device output and X is set from available device inputs, the two aforementioned conditions can be expressed as follows:

In order to be implementable, an add-on functionality F, defined as

$$\bar{x} = F\ (\bar{y}),$$

with $\bar{x} = (x_1, x_2, \dots\ x_n)$ and $\bar{y} = (y_1, y_2, \dots\ y_m)$ must satisfy the following conditions:

1. $\bar{y} = (y_1, y_2, \dots\ y_m) \in Y^m$
2. $\exists\ x_i \in \bar{x}, i = 1, \dots, n | x_1 \in X$

where X and Y are respectively set of devices inputs and outputs.

In the study presented in (Lolli et al. 2009) the efforts are focused on the use of AOF in order to collect useful data that will be employed to fill in the driver's profile and status and to log his/her performance. All this information will be used as a trigger for the adaptive automation applied to the in-vehicle information systems (IVIS) or to the Advanced Driver Assistance Systems (ADAS). The development of AOFs has been tested for tuning in a simulated environment using data Matlab/Simulink vehicle model. Identified AOF outputs to improve driver performance and safety are the following:

Driver Stress (DS). From previous studies (Gulian et al. 1989), stress can be related to lateral vehicle control. Then, it could be derived by the steering activity: several indexes for lateral control monitoring were provided, in particular: HFS (High Frequency Steering) (McDonald Hoffman 1980), RR (Reversal Rate) (McLean Hoffman 1975) and SAR (Steering Action Rate) (Verwey 1991).

According to the level of stress it is possible to find strategies to assist the driver in particularly demanding maneuvers by modifying the steering force feedback, braking behavior and inhibition of secondary task to avoid possible safety-risk situations.

Particularly, modifying the steering force feedback or the braking behavior has an interesting impact in the human-machine interaction, because the feedback to the driver is haptic Empirical test confirmed that driving performance significantly improved when the system activated the force feedback models.

These results compared with data arose from other studies in the literature (Steel Gillespie 2001) suggested that, using an intelligent, haptic steering wheel rather than a traditional passive steering wheel, drivers are better able to closely follow a reference path while requiring fewer visual cues (Minin et al. 2009)

For a decade researchers (Bertollini Hogan 1999) have been finding that the presence of haptic feedback on the steering wheel could help drivers to perform a visually-guided task by providing relevant information like vehicle speed and trajectory. Referring to the augmented cognition field, we can assess that when using a haptic assist steering wheel rather than a traditional passive steering wheel, drivers are better able to follow a reference path and at the same time, they required fewer visual cues (Griffiths Gillespie 2004).

Traffic congestion (TC). Through the monitoring of longitudinal vehicle parameters (e.g. brakes and speed behavior) it is possible to state whether drivers are driving in a heavy traffic situation or not. In this case, strategies could be elaborated by optimizing both the engine-fuel management at a low speed and the driver comfort aiming at reduces the level of stress (Lolli et al. 2009).

Road Conditions (RC). The knowledge of road profile characteristics through information coming from specific sensors (i.e. suspensions, Roll Rate Sensor, Pitch Rate Sensor, Sound Sensor Cluster, ESP intervention) allows alerting active suspension system to smooth the impact of obstacles, helping drivers to reduce the effect of this critical situation (Lolli et al. 2009).

The table below (Lolli et al. 2009) reports inputs coming from the vehicle chassis and used to compute AOFs.

Table 1 AOF inputs, parameters and outputs (Lolli et al. 2009).

AOF inputs from chassis	AOF parameters	AOF outputs
Steering Angle	HFS, SAR, RR	DS
Speed	Deceleration Jerks (DJ)	TC
Brake Pressure	Braking Frequency (BF)	TC
Accelerator Displacement	Accelerator Frequency (AF)	TC
Gear number	Gear Index (GI)	TC
Z acceleration	Frontal Obstacle Preview (FR)	RC
Roll rate	Roll Index (RI)	RC
Pitch rate	Pitch Index (PI)	RC
Suspensions Displacement	Frontal Obstacle Preview (FR)	RC

Inputs were selected to compute specific AOF parameters with the aim to describe driver stress, traffic congestion and road conditions. AOF outputs are the result of the balanced sum among parameters; for instance, the Driver Stress (DS) index (2) was developed as follow 0:

$$DS = (RR \times c_{RR}) + (HFS \times c_{HFS}) + (SAR \times c_{SAR}) \qquad (2)$$

Where $c_{RR} + c_{HFS} + c_{SAR} = 1$ are the coefficients to be tuned in order to define the final value of the AOF output. Each AOF outputs (TC, DS and RC) and their related computed parameters (see “AOF parameters” in Table 1) were developed in a simulated environment using Matlab/Simulink (www.mathworks.com).

In order to test and tune these parameters, AOF models were interfaced with a Matlab/Simulink simulated vehicle. The whole model (AOF and simulated vehicle) is fed by real driving data coming from a professional driving simulator. Specific tests were carried out, aiming to provide driving situation where each parameter varies significantly; then, their effectiveness was assessed.

According to the result, information monitored by AOF outputs (DS, TC and RC) will be used as a basis for the development of strategies aiming at improve driving performance, safety and comfort.

AOF test and tuning: Driver Stress

In the following, test and tune of Driver Stress (DS) parameters are described. The DS index is the balanced sum of steering angle based parameters, in particular: SAR (Steering Action Rate), HFS (High Frequency Steering), RR (Reversal Rate). A default tuning of coefficients related to these parameters has been applied (C_{RR} = 0,4; C_{HFS} = 0,2; C_{SAR} = 0,4). The effect of the tuning was assessed by comparing the expected stress profile in certain pre-determined conditions (i.e., the points numbered from 1 to 5 in Figure 1) with the drivers’ steering activity (Lolli et al. 2009).

Two tests were conducted on a driving simulator where 12 subjects, each of them was asked to drive for 10 minutes. Test environments were characterized by roads with different curve radius, variable visibility (from 100 to 4500 m) reproduced with fog and variable traffic (from 10 to 50 vehicle/km) (Lolli et al. 2009).

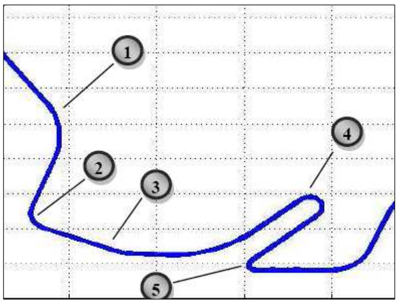

Figure 1 Driving scenario (track) (Lolli et al. 2009).

In order to increase the steering activity, subjects were also expected to complete a secondary visual task, which consisted in pressing the left/right side of a touch-screen on the left side of the vehicle cabin, according to the position of a circle displayed among smaller ones. Data regarding DS parameters were collected and compared with the steering activity in a specific point of the road (the number from 1…5 circled in Figure 2) (Lolli et al. 2009).

Due to the large amount of information, the comparison focused on a sub-sample of 3 subjects; mean values of steering activity and DS parameters are then depicted. An example of steering angle activity is showed in the top side of Figure 2, while Driver Stress index in the bottom. Both are related to scenario coordinates (x-axis). As foreseen, an increased steering activity leads to higher Driving Stress values 0. These peaks are pointed out in particularly critical situations (due to curves, high traffic, low visibility), highlighted in the circled number of the figures.

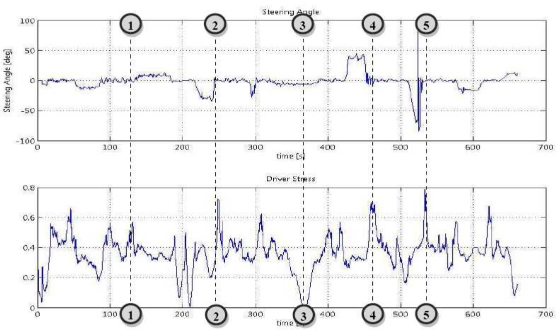

Figure 2 DS compared with steering angle (Lolli et al. 2009)

Results show that the first DS parameters' tuning produced an index able to detect driver stress status. Since the analysis was carried out on a small sample of subjects, in order to increase the significance of the tuning the above deployed comparison will be extended to all subjects (Lolli et al. 2009).

Driving Stress Index appears to be a good starting point for developing a parameter able to detect driver status in real-time even if a deeper test and tuning activity is needed. Furthermore, together with the other AOFs (Traffic Congestion and Road Conditions) can be easily implemented on a vehicle ECU (Electronic Control Unit) or a DSP (Digital Signal Processor) (Lolli et al. 2009).

Conducted simulations are just preliminary tests to find out the most promising indexes. It is very important to improve techniques aimed at monitoring of the status and the performance of both the driver and the vehicle in order to gather all data useful to customize the information provision strategies of the in-vehicle devices. In this way the vehicle may adapt his status, improving comfort or modifying driving performances.

This proactive behaviour paves the way to mechanisms able to infer the driver's distraction and situation awareness, allowing the triggering of adaptive automation strategies. The information provided by AOFs are real-time and allows at dynamically implementing such adaptive strategies and referring them both to the path changes and to the driver's status. The AOFs added-value is the prospect to obtain information in a not intrusive way (Lolli et al. 2009).

The framework for the design of preventive safety systems

The aim of preventive safety system is to support drivers, especially in risky and critical situations, or whenever distraction may occur. The first step for the design of a vehicle able to assess the driver status and intentions is the development a model able to explain and reproduce driver's characteristics. Based on the empirical results presented in the previous chapters, this research work aims at developing a little missing piece of the puzzle of the future intelligent vehicles: namely to identify the main elements for a feasible architecture of a "cognitive driving assistance system" which will substantially advance both integrated safety/assistance systems and the cooperation between human beings and highly automated vehicles.

The feasibility of such an architecture has been investigated analyzing:

- The problem of accident precondition analysis
- ADAS existing applications and research issues
- Risk mitigation strategies for the accident avoiding
- Design issues of cognitive preventive safety systems
- The understanding of driver behavior from driving maneuvers by means of add-on functionalities

Hence the framework to develop an effective model of driver's perception will be include four major functional areas:

1. The **core application**, where motion-planning tools including enhanced personalisation, will be used to explore the maneuver space and to ultimately understand the driver, and if needed, to produce maneuvers compatible to human motion.
2. **Improved sensing of driver input**, where the control input ("input" in control theory sense) produced by the driver, both in longitudinal and lateral directions will be measured. The scope is

to better discriminate between different motion alternatives. The representation of driver input will be given in abstract, vehicle independent way; preferably in terms of the longitudinal and lateral jerk (Nakazawa Ishihara Inooka 2003).

3. A **model for driver perception**, which is an ambitious additional function of the system. The scope of this module is to maintain a representation of the items the driver is aware of, which do not necessarily coincide with the real world. For this module, the feasibility to the expected accuracy is not sure (see risks section), but it does not cost much (here) and if it works it may provide additional very useful information (e.g., understanding that a mistake comes form a missing entity in driver world). The function combines eye gaze observations with information from the perception layer to determine which objects and points the driver watched. The gazed features are introduced into an alternative representation of the world (the driver mental model of the world) and then evolve according to rules that plausibly reproduce the assumptions a driver do about objects he is no longer looking at.
4. An **interaction manager** in the form of a variable plug-in. It will show how a variety of interactions, suited for different types of vehicles and different types of support, can all be built above the same unified situation assessment produced by the core application.

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