

AN INTELLIGENT DECISION SUPPORT SYSTEM FOR DRIVER ASSISTANCE BASED ON VEHICLE, DRIVER AND ROAD ENVIRONMENT MONITORING

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ABSTRACT

This paper describes an intelligent decision support system, a part of the I-WAY platform, which uses internal (vehicle parameters) and external (road infrastructure messages) information to provide drivers with useful warnings about potential road hazards. One of the novel aspects of this study is that the psycho-physiological state of the driver is assessed and is taken into account in a twofold way: i) as additional parameter of the overall driving risk estimation and ii) as parameter for the selection of the best warning strategy. We propose a framework based on Dynamic Influence Diagrams for the optimal driver assistance.

KEYWORDS

ADAS, Decision Support Systems, Dynamic Influence Diagrams, driver state, optimal warning strategy

INTRODUCTION

A variety of driver support and information management systems have been designed and implemented with the objective of improving road safety. Many solutions for this problem have been proposed through the development and demonstration of road safety applications such as a lateral and rear monitoring systems, lane change assistants, collision warning systems and several telematic applications on the road infrastructure that communicate direct and up to date traffic information between infrastructure and motorised vehicles [1, 2, 3]. These approaches deal with individually considered road events and produce warnings only under specific driving situations. Other systems introduce hypo vigilance detection in real time, based on multiple measuring parameters, in order to warn safely and on time the driver about his decreased alertness.

Although the crucial issues at a technical level have been mostly solved, their consequences on driver activity remain open. In particular, the conditions of use of these new systems, their effects on driver response and their impact on the operation and safety of the traffic system are of paramount concern amongst researchers and safety analysts [4, 5]. The current Advanced Driver Assistant Systems (ADAS) are designed to support drivers in maintaining some safety thresholds or ensuring compliance with some formal driving rules, such as maintaining safe time headways in car-following situations or adhering to legal speed limits, independently of the driver' current state, the current weather conditions or the road situations

(infrastructure and traffic related), however the diversity of the driver psycho-physiological conditions are not taken into account.

In this work, we propose an intelligent Decision Support System (DSS), called I-WAY DSS, able to provide information to the driver and reduce the possibility of car accidents. The key feature of I-WAY DSS is the “proactive risk assessment”; its aim is to preview an event/situation taking place and inform the driver well in advance with supportive suggestions to the driving task when necessary. In order to achieve that goal, the proposed system focuses on the integration of different data sources for risk assessment, the creation of individual alert levels and the generation of dedicated and tailored messages to the driver. More specifically, the decision support system receives information about i) driver stress and fatigue level from a dedicated driver monitoring module, ii) vehicle position, speed and heading via GPS, iii) information about local weather, traffic, road constructions and blocks via road infrastructure and produces an enhanced situation assessment that generates integrated, high level information from the aforementioned data sources. The supportive outputs of the DSS are divided into three main categories based on the overall situation, its severity and the level of the involved risk. Those are: i) notification (text message), ii) warning (low intensity vocal message with recommendation on driving task), iii) alert (high intensity vocal message urging for particular driving action). Figure 1 presents the I-WAY functionality, illustrating the central part of I-WAY system DSS.

One of the main innovations of I-WAY DSS lies on the fusion of the driving environment (weather, traffic etc.) and the driver’s psycho-physiological state (stress, fatigue) for the overall risk estimation. Moreover, the driver’s state implies (among with the overall risk estimation) the type and intensity of the provided messages. The importance of the driver’s state in the decision process is illustrated through the following example: Consider information reporting road constructions in a few kilometres is received from the road infrastructure; in a smooth driving case (normal driver state and environmental conditions) the overall risk estimation is low and therefore this information is forwarded to the driver in the form of a notification message (e.g. “Road constructions in 2 km distance”); in a driving scenario with the same environmental conditions but different driver state (e.g. fatigue), the overall risk increases (due to reduced driver reactions) and the system’s feedback to the driver becomes a warning indicating the presence of a road hazard (e.g. “Slow down. Road works ahead”).

Furthermore, an important feature of our proposed methodology is the *personalizing* ability. Each driver has different reactions to specific events and recommendations from the system. The I-WAY DSS will be fully adapted using as feedback the drivers states and responses to specific recommendations.

We present a probabilistic framework for the I-WAY’s DSS based on Dynamic Influence Diagrams (DID). In this initial implementation stage, only information from road infrastructure, vehicle data and driver state are considered in order to calculate the overall risk.

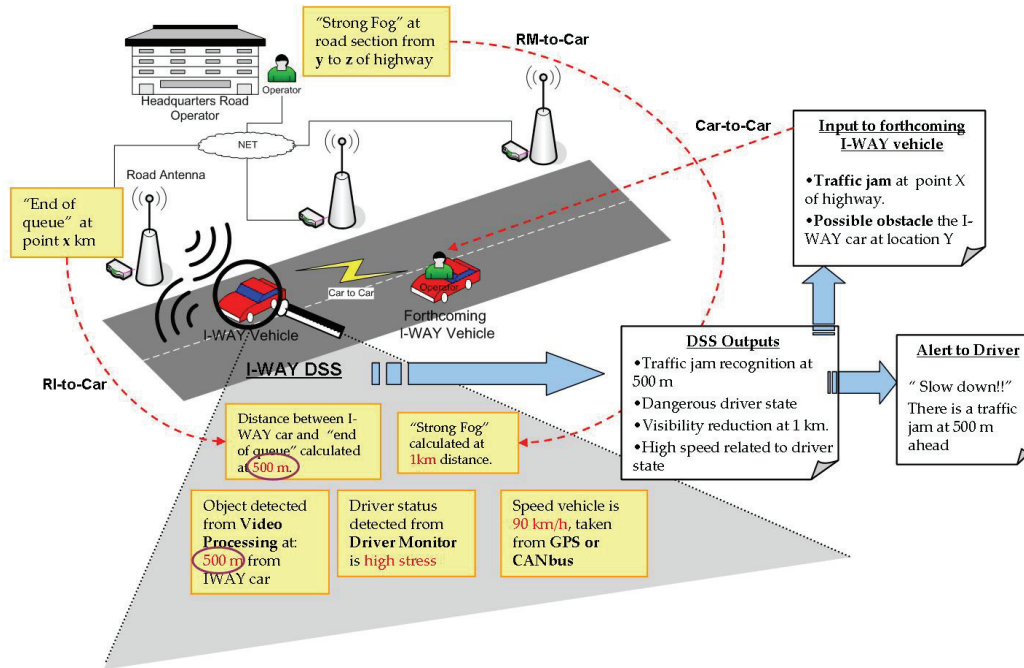


Figure 1 - I-WAY DSS showcase introducing drivers to an effective coupling of knowledge with decisions

MATERIALS AND METHODS

During a pre-research study, in which more than three hundred drivers participated, a set of situations identified as the most critical for them, has been selected. These situations are summarised in Table 1

Domain	Example of risky events
Driver State	Stress, Fatigue
Obstacles	Queue/ traffic jam, static obstacle, slowing down traffic, road constructions
Visibility	Fast reduction (fog bank), visibility level
Roadbed	Uneven road surface, slippery surface (water on road), start of narrow road
Weather	Ice, Snow, Rainfall, Wind

Table 1 - Critical Events/ situations evaluated by the I-WAY DSS

Based on the available observations (user's and car status) and the relevant contextual information (messages from road infrastructure), the proposed methodology fulfils the challenging task of driver support through the following 4-level procedure:

Level 1: Combination of heterogeneous information provided by different sources (data-level fusion)

Level 2: Conversion of multimodal input data into features with standard format comprehended and handled by the DSS in a similar way.

Level 3: Correlation of features from different domains (weather, visibility, roadbed conditions, driver psycho-physiological state) in order to produce an overall risk assessment (feature-level fusion)

Level 4: Generation of high-level information and useful suggestions tailored to specific driving scenarios (decision-level fusion).

These levels are depicted in Figure 2.

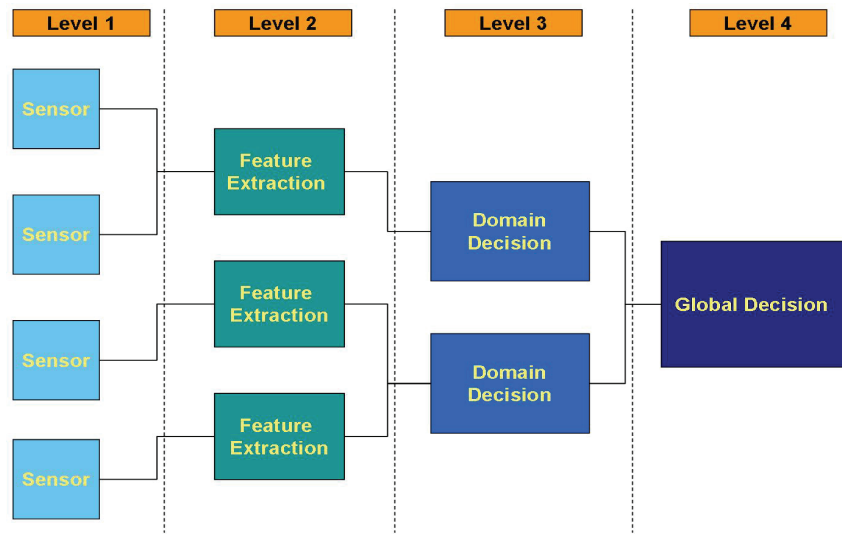


Figure 2 - Functional decomposition of I-WAY DSS

Thus, the decision making process is decomposed in two layers: *Domain Decision* (Level 3) and *Global Decision* (Level 4). The first, handles individually the classes of interest, while the second provides decision fusion on the outputs of the previous level. The individual classes of interest handled by Domain decision are:

- i) The *Biometric class*, which provides driver state classification (normal, stress, fatigue)
- ii) The *Car-Status class*, which checks vehicle parameters (position, heading, velocity, acceleration) and inferences about vehicle behaviour (high-medium-low speed etc).
- iii) The *Road-Status class*, which considers roadbed surface conditions (dry/slippery), road narrowness or damages.
- iv) The *Proximity class*, which collects external incident information (traffic, queue, accident, obstacle) from road infrastructure and provides meaningful indications for possible collisions.
- v) The *Weather class*, which collects environmental data from the vehicle (external temperature, wipers) and from the Road Infrastructure (fog, rain, snow, wind) and provides classification for visibility level (poor/ normal) and for weather conditions

All the aforementioned classes are combined to provide an overall assessment of the driving environment, therefore the Global Decision deals with the *overall risk minimization* and the *unobtrusive driver assistance*. In this initial approach, the dominant risk indicator is the *braking effort*, which models the deceleration rate required to reach obstacle's speed, given the current speed and distance from the obstacle [6]. Next, the braking effort, calculated in the previous stage is combined with road conditions (e.g ice, aquaplaning) and driver state in order to estimate the risk. On the other hand, the proposed I-WAY DSS will provide *unobtrusive driver assistance*. This is accomplished by distracting the driver as less as possible and only if it is considered necessary. Our aim is to achieve an optimal strategy compromising between two contradictory goals: safety and unobtrusive function.

The problem of optimal decision-action strategies is usually confronted by minimizing a cost function. Methods handling both minimum cost decisions and uncertainty (induced by the probabilistic nature of the variables) include Decision Trees and Influence Diagrams. In this work we are going to construct a Dynamic Influence Diagram (DID). DIDs are temporal extensions of Influence Diagrams which are in turn extensions of Bayesian Networks. We selected DIDs for their probabilistic framework and the temporal representation ability

implied by the problem nature (e.g driver's action taken influences risk in the next time slice). In the next section we briefly introduce Bayesian and Dynamic Bayesian Networks as well as Influence and Dynamic Influence Diagrams.

Bayesian and Dynamic Bayesian Networks

Bayesian Networks, are widely used for knowledge representation and reasoning under uncertainty in intelligent systems [7]. In a general form, the structure of a BN is a directed acyclic graph (DAG) in which nodes correspond to random variables of interest and directed arcs represent direct causal or influential relation between nodes. The uncertainty of the interdependence of the variables is represented locally by the conditional probability table (CPT) $\Pr(x_i | \pi_i)$ associated with each node x_i , given its parents π_i , is independent of any other variables excepts its descendents. The graphical structure of BN allows an unambiguous representation of interdependency between variables. This, together with an independence assumption, leads to one of the most important features of BN: the joint probability distribution of

$X = \{x_1, x_2, \dots, x_n\}$ can be factored out as a product of the conditional distributions in the network,

$$\Pr(X) = \prod_{i=1}^n \Pr(x_i | \pi_i), \quad (1)$$

where n the number of variables.

BNs do not explicitly model temporal relationships between variables. The only way to model the relationship between the current value of a variable, and its past or future value, is by adding another variable with a different name. When constructing a DBN for modeling changes over time, we include one node for each $X = \{x_1, x_2, \dots, x_n\}$, for each time step. If the current time step is represented by t , the previous time step by $t-1$, and the next step by $t+1$.

Influence and Dynamic Influence Diagrams

Influence diagrams for solving decision problems extend BN with two additional types of nodes, namely decision nodes and utility nodes. Nodes for the random variables in the BN are called chance nodes in ID. A decision node defines the action alternatives considered by the system. Every decision node has a finite number of alternatives standing for the actions that the decision system can take to achieve the desired outcome. A decision node is connected to those chance nodes whose probability distributions are directly affected by the decision. A utility node is a random variable whose value is the utility of the outcome. Like other random variables, a utility node holds a table of utility values for all value configurations of its parent nodes. In an influence diagram, the value of each decision variable is not determined probabilistically by its predecessors, but rather is imposed from the outside by the position maker to meet some optimization objective [8].

In an ID, let $A = \{a_1, a_2, \dots, a_n\}$ be a set of mutually exclusive actions, and X the set of determining variables. A utility table $U(A, X)$ is needed to yield the utility for each configuration of action determining variable in order to assess the action in A . The problem is solved by calculating the action that maximizes the expected utility:

$$EU(a) = \prod_H U(a, X)P(X | a), \quad (2)$$

where $U(a, X)$ are the entries of the utility table in value node U . The conditional probability $P(X | a)$ can be computed from CPT of the variable $x_i \in X$ given that action a is fired [9]. Just as Bayesian Networks can be extended with a temporal dimension to give

Dynamic Bayesian Networks, in a similar way influence diagrams can be extended to Dynamic Influence Diagrams (DIDs). DIDs represent explicitly how information changes over time and they model general sequential decision making.

The Proposed Framework

As described above, the influence diagrams are extensions of Bayesian Networks. To construct an influence diagram we must define the structure of the graph, the dependency of the variables and the parameters of the conditional probability distributions. The variables for our problem Domain are presented in Table 2. The parameters and the connections between the infrastructure variables (concerning weather and obstacle) are defined using the data and expert knowledge with Bayesian Network learning [10]. The next step is to define the dependencies between decision (GIVE MESSAGE variable) and chance nodes as well as the values of the utility costs. The variables depending on the GIVE MESSAGE DECISION are IGNORE MESSAGE in the same time slice, as well as DRIVER ACTION and DRIVER STATE in the next time slice. The external variables are obviously independent on the decisions; the internal variables (SPEED, DISTANCE) are conditionally independent on the GIVE MESSAGE decision, given the driver action. In Figures 3, 4 we present the intra-connections (for legibility purposes, the environmental variables are summarized to WEATHER) and inter-connections of the proposed DID, respectively.

Parameters	Configurations
Driver State	Normal, Stress, Fatigue
Obstacle Risk	Normal, Low, High
Braking Effort	0-5 m/s ²
Visibility	0-2000 m
See Obstacle	Yes/No
Ice	Yes/No
Rain	1-3 (Levels of rain fall)
Fog	No, Light, Heavy
Give Message (Decision Node)	No Message, Display Message, Low Intense Message, High Intense Message
Ignore Message	Yes/No
Driver Action	Maintain Speed, Accelerate, Slow Down
Speed	0-250 km/h
Distance from Obstacle	>0 m

Table 2 - The Variables of the Influence Diagram

The values of utility nodes are computed in order to minimize the overall cost of the cases in the dataset described in the next section.

DATASET

We gathered data from the Autostrada Brescia Padova infrastructure. The data consist of XML files with two kinds of reports. The first one concerns the environmental conditions taken from 18 different stations. The environmental state for the vehicle is taken from the weighted average from the two nearest stations. The second type of information is events occurred in the Highway.

From the infrastructure data we constructed a Bayesian Network (BN) using combination of prior expert knowledge and data [10]. To produce a complete dataset and cover extreme cases we sampled the BN until no more new samples were available. The next step is to get a dataset with cases and corresponding desired decisions in order to train the decision making

system. In order to obtain a desired action for each case we considered two different approaches. The first one is the use of an expert who could propose the optimal action for each case. This approach has two major disadvantages. (i) the decision is biased by the expert's opinion and (ii) the expert should annotate a large number of cases. The second approach is to distribute the cases among different drivers. Unlike medical decision problems where the experts are few, in our case, any driver can be considered as an expert. Drivers were asked to propose/define a desired action from the decision system, through an interface which produces different driving scenarios. The recommended actions were gathered and used for training the decision system.

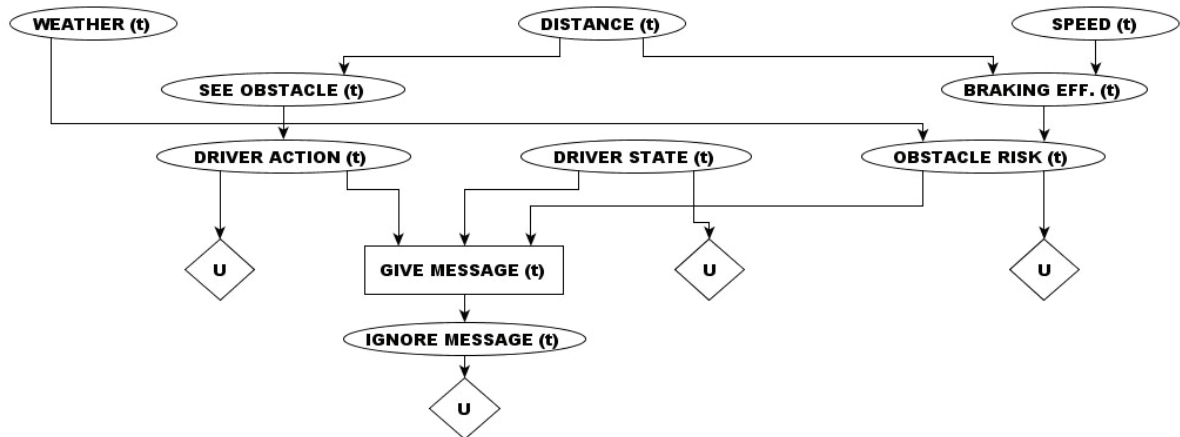


Figure 3 - The Intra Dependencies in the DID

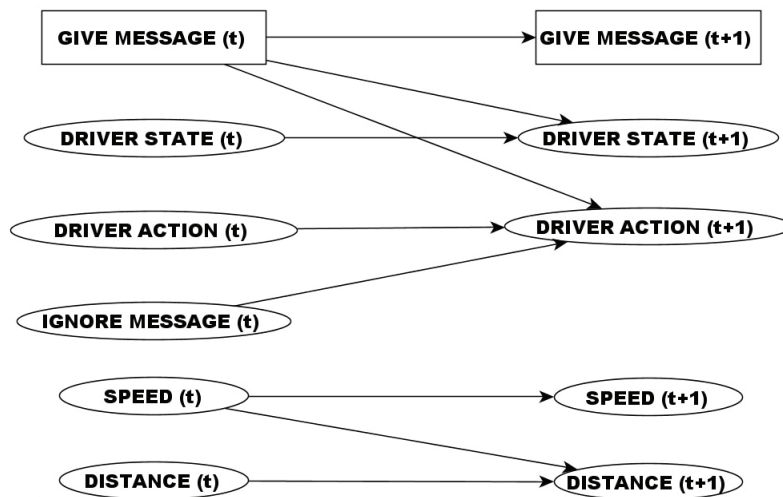


Figure 4 - The Inter Dependencies in the DID

EXPERIMENTS AND RESULTS

We have conducted a series of experiments to examine the performance of the decision system. We tested the decision system under different scenarios with different driver states, weather conditions and different driver's response patterns to the system outputs.

We present below the implemented DSS strategy under four different conditions combining the following driver and weather conditions:

- (a) Weather conditions: Good, Driver state: Normal
- (b) Weather conditions: Good, Driver state: Fatigue
- (c) Weather conditions: Heavy rain, Driver state: Normal
- (d) Weather conditions: Heavy rain, Driver state: Fatigue

Obstacle reported by the Road Infrastructure is illustrated as a black box in some distance from I-WAY car. Different types of messages provided by DSS are shown in different colours, namely: blue text box represents *notification* (text message), yellow text box represents *warning* (light vocal message) and red text box represents *alert* (intense vocal message)

The recommendation part of the message is not displayed here – we assume it is “slow down-obstacle ahead” in all cases. The dynamic content of message which refers to the distance from the obstacle is displayed as indicator of when the driver is informed about the forthcoming event. The car speed is not part of the message given to the driver but it is displayed here as an indicator of the driver’s response (compliance or not with system’s recommendation). According to the driver’s reactions (sufficient deceleration) and if considered necessary, DSS generates updated warning messages to keep the driver informed about the overall risk.

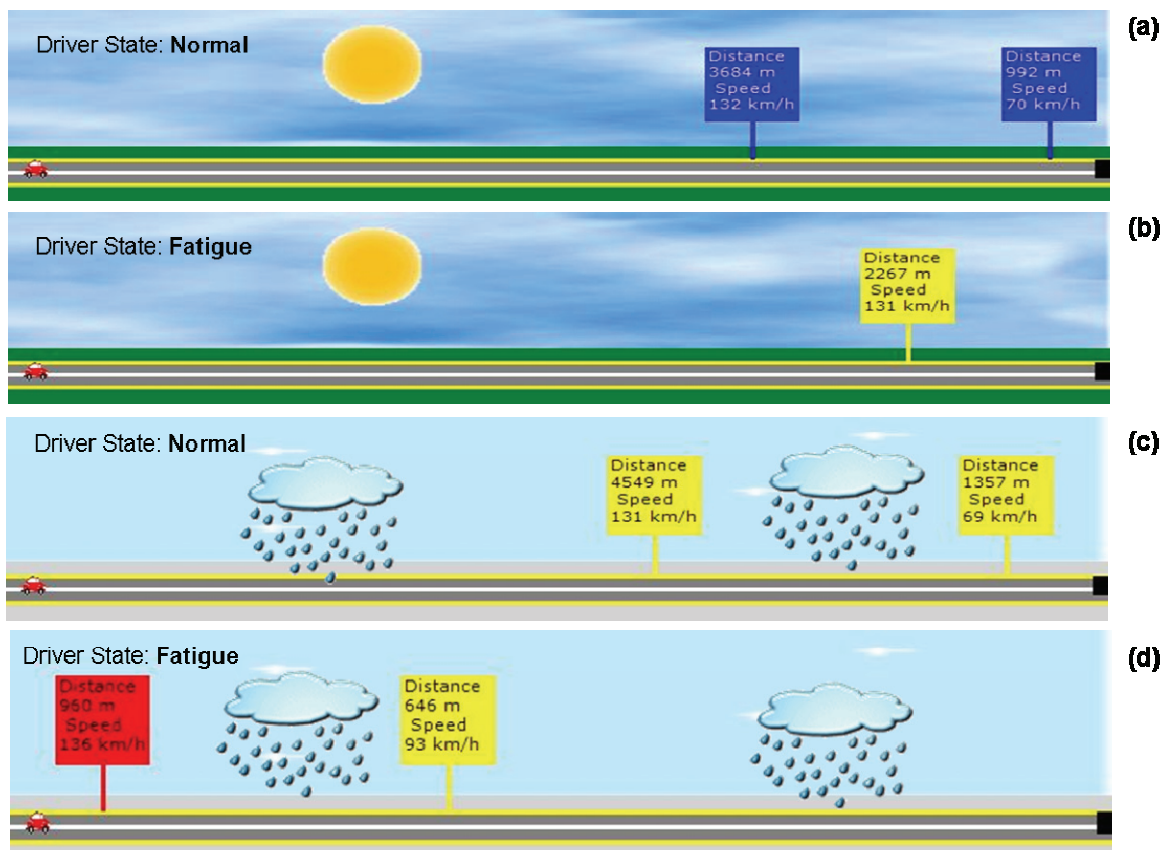


Figure 5 – DSS outputs during different driving cases

DISCUSSION

In this work, we propose an intelligent Decision Support System (DSS) based on Dynamic Influence Diagrams. We described the DIDs primitives, the proposed framework, the dataset and the experimental results. The innovation lies on the fusion of the driving environment

(weather, obstacles, etc.) and the driver's psycho-physiological state (normal, stress, fatigue) for the overall risk estimation, as well as the DSS adaptation to the driver's specific reactions. We discussed the importance of driver's state inclusion in the decision process. The system can adapt to the specific driver responses using an influence diagrams personalizing approach, as described in [11]. According to this work, each action is granted a certain reward depending on the driver's response. The adaptation is accomplished using reinforcement learning. The Bayesian Q-learning approach [12] (reported to achieve promising results by [11]) will be incorporated in our future work.

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