Agent-Based Driver Abnormality Estimation

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Abstract. For enhancing current driver assistance and information systems with regard to the capability to recognize an individual driver's needs, we conceive a system based on fuzzy logic and a multi-agent-framework. We investigate how it is possible to gain useful information about the driver from typical vehicle data and apply the knowledge on our system. In a pre-stage, the system learns the driver's regular steering manner with the help of fuzzy inference models. By comparing his regular and current manner, the system recognizes whether the driver is possibly impaired and betakes in a risky situation. Furthermore, the steering behavior and traffical situation are continuously observed for similar pattern. According to the obtained information, the system tries to conform its assistance functionalities to the driver's needs.

1 Introduction and Motivation

Nowadays, customers of automobiles are often confronted with new systems, which shall provide more comfort and safety. However, such complex assistance and information systems have a significant impact in car accidents. To ensure a higher safety for all traffic participants, modern systems have to involve the human state and behavior as essential factors.

Driving is a complex interaction process between driver, vehicle and environment. However, engineers included the human factor in the design of such systems not yet, e.g., current assistance systems as the anti-lock brake system ABS, only consider vehicle information. Current systems analyze the environment to warn the driver about risky situations, e.g., lane departure warning. This system tracks the road markings and calculates the course of the vehicle using wheel angle and velocity. Further, the system just considers the usage of the turn signal to differ an intended lane leaving from a drive mistake. In reality, the driver often librates inside of the lane or sometimes carries out a lane change without setting a turn signal. As a result, the driver suffers from unnecessary interventions and warnings from the system. Further, every user receives the same level of support regardless of his regular driving characteristics, experience, skills or age. The desired modality or grade of assistance varies according to the driving behavior. For optimal assistance, it is desirable to create systems with high considerateness of driver state and behavior.

J.A. Jacko (Ed.): Human-Computer Interaction, Part III, HCII 2009, LNCS 5612, pp. 189–198, 2009.

2 Driver State Parameters

The general driver state can be regarded as an information tuple comprising all drive-relevant information about the person who is currently engaged in a driving task. The consideration of the driver's state includes physical as well as psychological aspects. According to [9], all information parameters affecting the driver's actual condition can be distinguished in regard to their time possibility in changing: *non or long-term variable* (driving experience and skills, personality, etc.), *mid-term variable* (fatigue, circadian rhythm, individual driving strategy, restriction due to current health, influence of alcohol and drugs, etc.), and *short-term variable* (emotion, vigilance, intention, situation awareness, etc.).

Distraction denotes the disturbance of the ability to maintain the focus on the essential object due to lack of concentration, lack of interest or attraction by another object. Sources of distractions can be both, internal and external. Physical urges, own thoughts or even emotions are some internal factors that can effect distraction. In contrast, possible external influences are physical stimuli for any human senses. If the focus of the driver is attracted by some visual stimulus, e.g., a blinking light within his sight area or rather a dominant stimulus averts the percipience of the essential stimulus in the effective field of view, then it can be assumed that the driver is distracted. Here, attention should be paid to the differentiation between external directed attentiveness and self-directed attentiveness. The reassignment of resources from the primary and secondary driving tasks to diverse tertiary tasks is not distraction but rather turning away. The assignation, what resources are assigned to what tasks at which time, is done deliberately by the driver himself.

2.1 Acquisition of Driver State Factors

Determining driver state factors for proper safety-relevant assistance presents a problematic challenge. Due to the mental nature of most factors, a direct access for measurement is in principle not possible. Thus, most studies and approaches use specific manifestations as metrics for inference on the current level of the respective parameter. Therefore, it is necessary to have indicators which can be determined continuously during a drive. In this work, we are engaged in investigating the representativeness of various typical vehicle data as basis to imply individual behaviors or attentiveness of drivers and reducing the mentioned handicaps of current assistance systems with the help of that information. Hence, only the relevant metric types and their relevance for a reliable acquisition of mid- and short-term variable driver state factors are presented in the following.

2.1.1 Longitudinal Control Parameters

Longitudinal control parameters represent all variables relating to the longitudinal vehicle steering such as acceleration, velocity, headway distance, brake, throttle position, etc. Their relevance for a driver's state was investigated in numerous studies. A very common assumption in most studies is that the driver tries to reduce the main task load, i.e. stress from driving, while he is engaged in other tasks at the same time. This was primarily noticeable in the driver's speed regulation. In general, the test persons in [16] slowed down while performing auxiliary tasks. The essential indicator was the throttle position. About 80% of the subjects showed an alternate behavior in fine throttle corrections during secondary activities. While focused on multiple tasks, drivers could not maintain all activities continuously and tend to pause temporarily the speed adjustments. Furthermore, [7,16] stated that longitudinal control measures as indicator for diversions are more appropriate than lateral variables. It should be noted that the tests were performed both, on straight roads and curves. Similar results could previously be seen in [1,4]. Moreover, [5] observed that before such compensatory behavior occurred, there was an increase of headway variation and speed that already hint at higher demand of the driver. In [6] it was also noticed that during concurrent mobile phone use and cognitive tasks a driver's stop behavior is significantly affected. In addition to more intense brakings, the stopping distance – i.e. the headway distance to stop lines or intersections – is shorter. The results of the study regarding the relation between longitudinal steering performance and strain – as representative for all driver state factors – could be summarized by following points: (a) additional workload mainly reduces the driver's capability of interaction with traffic environment, (b) increasing task complexity and cognitive demands induce a reduced speed control, (c) typical indicators: increased speed variation, increased distance variation, harder decelerations, and (d) compensatory behavior in form of speed decrease.

2.1.2 Lateral Control Parameters

Lateral control parameters are all variables relating to a vehicle's lateral movement such as steering wheel angle, steering frequency, lateral position, lateral deviation, lateral acceleration, etc. [15] showed that the additional strain due to several visual auxiliary tasks caused an increase in the steering wheel reversal rate. The number of steering motions in the higher frequency range increased significantly. According to [10], the percentage of high frequent steering motions can be interpreted as an objective metric of strain. Based on this knowledge, a steering entropy was introduced to quantify a driver's effort to maintain a lateral safety clearance [11]. A significant alteration in the lateral driving behavior in terms of phone usage could be seen in [14]. In addition, according to the statistical analysis in [13], lateral position standard deviation and steering wheel angle seem to represent two of the most important variables for driver's impairment detection. Following points are essential findings from the surveys: (a) additional workload during driving can induce variations in lateral steering behavior, and (b) steering frequency presents an adequate objective metric for strain.

3 Concept and Implementation

Our system acts as a virtual fellow passenger in a purely advisory capacity. It informs the driver about potential traffical conflicts depending on the driver's current performance and recommends suitable behaviors to handle different situations. Therefore, this system shall be able to dynamically model the driver's steering behavior and detect abnormality in regard to the driving style.

The basic idea is the direct usage of regular vehicle information to build up knowledge about the relation between environment and driver. All relevant information (e.g., present steering behavior and traffic conditions) are logged continuously in the history database. Significant discrepancy between the current and previous steering behavior are determined by a widespread agent network to estimate safety relevant impairment of the driver's state.

3.1 Architecture

Information Acquisition. The estimation of the current driver condition is based on ordinary vehicle steering data. Changes of a driver's state are noticeable in his manner of steering. Essential is the fact if the driver is actually impaired and to what extent this disturbance is currently affecting his driving performance. The availability of an inter-vehicle communication infrastructure is assumed for more information about the present traffic state. The structural conditions are given by the driving simulator.

Modular Design. Base of the entire system is the software agent platform *Java Agent Development Framework JADE* [2]. This provides basic agent and behavior structures, communication functions, management tools and a respective agent runtime environment. The information processing is done by various agents.

Functional Structure. The entire system is divided in several functional parts primary in the form of software agents. The system comprises a total of seven agents, each of them assigned with different behaviors. Five agents are responsible for the processing and analysis of the raw data with regard to following scopes:

Drive Behavior: This agent continuously gathers all relevant steering data and models the driver's present steering style, primarily longitudinal steering. Significant unusual variations in the manner of driving are detected and reported to other relevant agents as an indicator for impairment. *Driver Type:* This agent rates the driver's steering manner, and classifies the driver in three different groups according to his headway distance and approaching behavior (careful, normal, and aggressive). All agent units are controlled and supervised by a *Chief Executive Agent* (CEA). This agent is the last instance of the entire system. All information provided by the processing agents is transmitted to the CEA for the final decision. The last agent presents the user interface agent. This includes the timing as well as the scheduling to an appropriate displaying area. The warning is implemented using the known metaphor of a traffic light (i.e. a red, orange or green light; depending on the current risk level) in the central information display. A further essential component of the system is the database in which all raw information and results from agents are stored.

3.2 Drive Behavior Modeling

The relation between traffic situation and the driver's operations is an essential knowledge to determine whether the driver is currently deviating from his usual driving manner or not. Generally, human processes information in the form of vague statement, e.g., *the distance is too short*. He decides his further acts according to his knowledge and experience, such as *If the headway vehicle is closing too fast, I should slow down*. Such uncertain mind processes of a human driver are represented by fuzzy inference systems (FIS). The implementation is based to the approach introduced in [8]. For the detection of a driver's impairments, especially due to additional tasks during driving, the agents primarily focus on the longitudinal steering behavior during car-following and lane-keeping. Reason for this is the assumption that a driver tends to counter additional loads and would not increase it further by changing lanes. The longitudinal steering model is separated in two parts, each represented by an adaptive FIS. Both rule bases are formed as follows:

$$R_l: IF\ x_1 = F_1^l\ AND\ \dots AND\ x_n = F_n^l\ THEN\ y = G^l \quad (l = 1, \dots, k)$$

where k and n is the number of rules and input variables. The fuzzy set F_i^l for input variable x is given by following Gaussian membership function:

$$\mu_{F_i^l}(x_i) = \exp\left[-\left(\frac{x_i - c_i^l}{\sigma_i^l}\right)^2\right]$$

where σ_i^l is the standard deviation and c_i^l is the mean. To simplify the optimization process, singleton membership functions are used for the output. The output value v is computed according to the center of singletons method (COS/COGS) where s_{Gl} is the position of singleton G^l:

$$v = \frac{\sum_{l=1}^{k}\left[\left(\prod_{i=1}^{n}\mu_{F_i^l}(x_i)\right)\cdot s_{G^l}\right]}{\sum_{l=1}^{k}\left(\prod_{i=1}^{n}\mu_{F_i^l}(x_i)\right)}$$

Each output membership function is optimized at run time by applying gradient descent algorithm with a small learning rate η.

$$\Delta s_{G^l} = -\eta\frac{\partial \mathrm{E}^2}{\partial s_{\mathrm{G}^l}}$$

$E=[v_{act}-v]$ is the model error determined by comparison of the model output v and actual value v_{act}. The optimization is paused if E falls below a certain threshold. Following sub behaviors are modeled by the two fuzzy inference systems:

Headway control behavior: Primary aim of steady car-following is to maintain an *adequate* distance to the headway vehicle. The distance is usually decided by the driver with regard to the current speed and his own understanding of *adequate*. The first FIS reflects this assumption by using the current speed v of the ego vehicle to estimate the steady-state distance d_e. The agent determines the estimation error by comparing the estimated value with the actual distance d. The error $E_d=d-d_e$ is interpreted as the deviation of the regular headway control manner. Furthermore, the error e_d is used by the agent to calibrate the output membership functions of the FIS. Therefore, the agent observes the incoming velocity and distance measures.

Acceleration behavior: During car-following, a driver generally controls his car depending on his sense of distance to the vehicle ahead d, his own speed v and the relative speed $v_{rel}=v_{hw}-v$. The driver tries to adapt to the situation by accelerating or braking. In cases of no external influences, e.g. if there is no vehicle ahead, a person normally drives only according to a self-chosen speed v_{des}. This is modeled by the second FIS. The estimated acceleration a_e is described as a function of d, v, v_{rel} and v_{des}. The error $E_a=a-a_e$ is calculated and used for model calibration. Here, v_{des} is an average value based on empirical data from previous periods of the run.

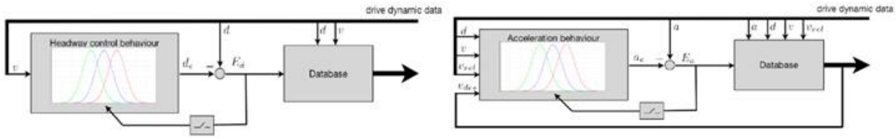

Fig. 1. Behavior models; the left part shows the headway control behavior model, and the right part shows the acceleration behavior model

3.3 Drive Abnormality Rating

Through the modeling process described above, the software agent gains two essential information from the driver. By using small learning rates (here, values $\eta \leq 0.5$), the agent is able to determine a driver's mean longitudinal steering behavior of a certain period. With the comparison of the mean behavior and the actual measures, the system acquires the present deviation. Since the human is not a high-precision sensor and actuator, there will be always some deviation. The variations in the steering actions could be treated as noise for the modeling process. However, exactly these variations characterize a driver's natural steering manner. Basically, the extent of those variations reflects a driver's capability to maintain steady driving. A driver's performance changes due to physical and mental influences. Especially in case of influences due to additional tasks, the effects become manifest in increased variations of velocity, distance and acceleration. Hence, changes of a driver's regular steering variations denote also changes of its state. The agent models the natural steering deviation by accumulating all estimation errors of a certain period, in which the driver is following a car without any disturbance and steady driving is given. From these data, a corresponding frequency distribution is generated for each FIS. For determining the level of performance deviation and impairment, the responsible agent uses an additional FIS which is tuned periodically according to the distribution. By comparing the actual deviation with attributes of the distributions, this rates the current longitudinal steering behavior in the range between no and extreme abnormality. Therefore, the inputs of the system are the scaled distance estimation error $e_d=(d-d_e)/d_e$ and scaled acceleration estimation error $e=(a-a_e)/a_e$. The input spaces are partitioned as shown in fig. 2. The partition parameters are given by the error frequency distribution and some constraints of the ego vehicle. The value $e_{d,P0}$ represents the positive border of the driver's regular headway control deviation. It is defined by the interval $[0,e_{d,P0}]$ of the corresponding distribution in which 90% of the positive smallest values are located, provided that the limits $0.05 \leq e_{d,P0} \leq 0.20$ will not exceed otherwise the respective limit is used. The positive space boundary $e_{d,P2}=1.0$ corresponds to double regular headway range. $e_{d,P1}$ is the midpoint between $e_{d,P0}$ and $e_{d,P2}$. In contrast, $e_{d,N0}$ is the negative border of driver's regular headway control deviation and is defined in a similar way as $e_{d,P0}$ but by the negative half of the distribution and with $-0.15 \leq e_{d,N0} \leq -0.05$ as limitation. The negative space boundary describes the error in the critical distance at which immediate full braking is necessary to avoid collision and is defined as follows

$$e_{d,N2} = \frac{1}{d_{e,avg}}\left(\frac{v_{avg}^2}{2 \cdot a_{max-}} - d_{e,avg}\right)$$

where v_{avg} and $d_{e,avg}$ are the average velocity and the average distance estimate in the regarded period of the run.

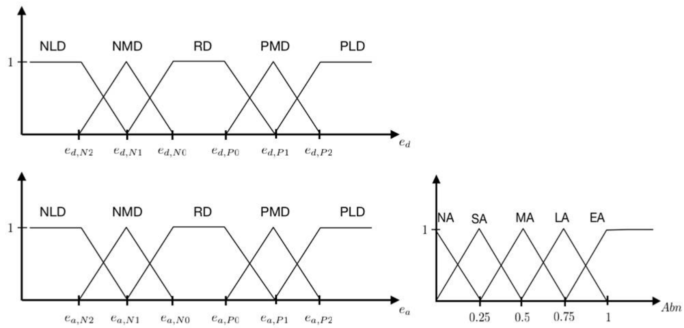

Fig. 2. Abnormality rating. The left part of the figure shows the partition of the input spaces and the right part shows the partition of the output space.

The value a_{max-} corresponds to the vehicle's maximum brake power. $e_{d,N1}$ is the midpoint between $e_{d,N0}$ and $e_{d,N2}$. The range of the driver's regular acceleration deviation is defined by $e_{a,N0}$ and $e_{a,P0}$. Both values are determined similar like $e_{d,P0}$ but without any limitation. The values $e_{a,N1}$ and $e_{a,P1}$ correspond to the driver's average maximum braking and acceleration. $e_{a,N2}$ is the midpoint between $e_{a,N1}$ and the error value corresponding to the maximum brake power a_{max-}. The value $e_{a,P2}$ is the midpoint between $e_{a,P1}$ and the error value corresponding to the maximum acceleration a_{max+}. The fixed partition of the output space can be seen in fig. 2.

3.4 ChiefExecutiveAgent

The ChiefExecutiveAgent (CEA) evaluates the results of all the other agents. According to the linguistic rules, the CEA calculates the risk levels for the longitudinal and lateral steering behavior and displays them in the user interface. The assistance functionality is designed in a way that at the end of the entire processing the output recommendation bases solely on the recommended acceleration from the CEA. All other relevant information has already been taken into account in advance. In critical situations, this acceleration amount is unusually large.

4 System Evaluation

The evaluation of the system was carried out in a driving simulator experiment. The simulator is equipped with several freely configurable displays. The simulation software platform is based on computer game Unreal Tournament 2004 [13].

A total of 20 test persons (TP) participated. The average age was 25 years. About 80% of the TPs rated themselves at least as experienced drivers. All TPs were very interested in technical innovations, and the majority favors a discharge of the driver by assistance systems.

The test course was composed of a freeway section and an urban section. As the freeway section possesses mainly straight road segments with two lanes per direction, the urban section contained straight and crossroad segments with one lane. External vehicles (EV) are positioned on the course and move on ideal trajectories. Their speed was mostly constant and set to a low value to provoke the TPs to overtake. Also, their speed varies only at several periods to induce desired traffic situations. At the start, the TP is instructed to follow an EV on the freeway. The range-clearance and speed are chosen by the TP. At a certain period, variations of the headway vehicle' driving velocity are abruptly induced to observe the TP's regular performance. Such scenario is repeated later while the driver is performing auxiliary tasks. The driver is instructed to enter a navigation destination. Afterwards, the test person is allowed to drive freely. The whole sequence is repeated in the urban section.

4.1 Experimental Results: Abnormality Rating

During the experiment, it could be observed that the used modeling procedure can sufficiently approximate the TP's mean longitudinal steering behavior. The usage of the abnormality rating system could indicate whether a TP was changing his driving style. Especially high abnormality values of long duration occurred while the driver was performing an auxiliary task. The detected periods of abnormality were mainly concordant with the subjective impressions of the TPs. Fig. 3 shows an output sequence. The upper part shows the distance between the ego and headway vehicle.

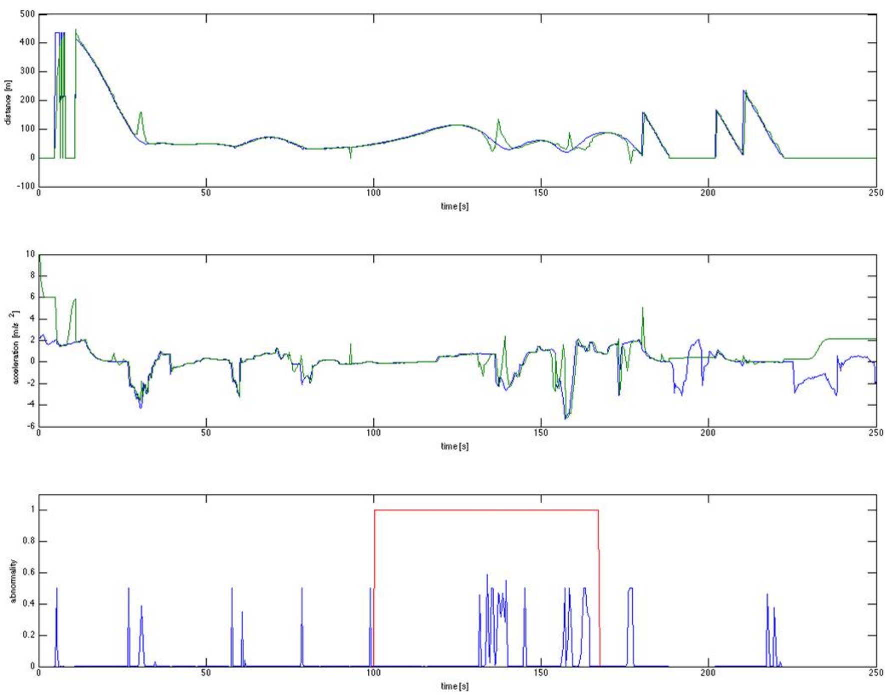

Fig. 3. Example sequence: Abnormality rating raw outputs

The progress of acceleration is shown in the mid part. The blue and green graphs represent the actual and estimated mean steering values. The plot at the bottom shows the trend of abnormality. Fig. 3 shows raw output values which are further processed before they are used for any decisions. The sequences comprise three periods. The first part represents the car-following in which the TP approached and followed an EV with a self-chosen range-clearance. In this period, the agent analyzed the incoming data and learned the regular steering manner.

In the second phase, the TP was instructed to input a navigation destination while following the headway vehicle. This period is marked by a red box in the abnormality part. Afterwards, the TP was allowed to drive as desired. Here, a higher and denser abnormality signal is conspicuous while performing the auxiliary task. This was caused by an increased variation in the TP's steering manner compared to the previous periods. This phenomenon could be seen in 70% of all valid experimental runs. It seemed that most TPs could not maintain their regular driving manner due to the auxiliary task. The reactions of the system in the last phase occurred due to the fact that nearly all TPs were driving more aggressive and overtook every EV. This is noticeable through the sawtooth-similar progress at the end of the distance plot. The corresponding abnormality results are caused by the abrupt changes of headway distance and regularly filtered out in the next processing level. Short abnormality signals are also oppressed in the case of an EV enters or leaves the predefined sensory region.

5 Outlook

Currently we are working on the expanding of the presented setup. Therefore, we plan the integration of physiological parameters to further tune the single agents by additional parameters like visual attention, mental state, etc. Also, we are working on the integration of the presented framework into real interaction concepts to further gain from the findings in this contribution.

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