Probabilistic Driving Style Determination by means of a Situation Based Analysis of the Vehicle Data

Tobias Bär, Dennis Nienhüser, Ralf Kohlhaas and J. Marius Zöllner
Intelligent Systems and Production Engineering (ISPE),
FZI Forschungszentrum Informatik
Haid-und-Neu-Str. 10-14, 76131 Karlsruhe, Germany
Email: {baer, nienhueser, kohlhaas, zoellner}@fzi.de

Abstract—Today, driver assistance systems assist the driver in manifold ways. Their acceptance and usefulness can be highly increased by adapting them to the needs and the personality of the driver.

In this work the driving style of the driver is determined by means of rating the drivers actions in commonly occurring traffic situations. Therefore, the vehicle data is evaluated and a probabilistic affiliation of the driver being aggressive, anxious, economical, keen, or sedate is made. The situations are chosen to be day-to-day traffic situations, for instance approaching a village, stopping on a stop sign, or passing through a tight bend. Based on the determined driving style, future driving assistance systems can be personalized to the individual driver and, thus, get more valuable. As a showcase, we adjust our Anticipatory Energy Saving Assistant (ANESA) to the drivers character, which is giving driving hints how to save energy in tight curves. By personalizing ANESA more credence is gained, resulting in extra savings of energy as we show in the experiments made.

I. INTRODUCTION

Driver Assistance Systems are an inherent part of todays vehicle equipment. Their performance, as well as their usability and acceptance by drivers highly depends on the needs and the skills of the driver. First and foremost, driver assistance systems must not confuse or distract the driver in any way. In critical, dangerous situations for instance, the driver does not care about energy saving advices, whereas driving in safe and uncritical circumstances, the driver is receptive to save fuel.

Besides the safety aspect, driver assistance systems become more valuable if they are tailored to the personality and the driving behavior of the driver. With ANESA\(^1\) our research group developed an Anticipatory Energy Saving Assistant System, helping the driver to approach upcoming velocity restrictions freewheeling - hence, the most economic way. ANESA also regards tight curves as velocity restrictions, since the driver can avoid loosing energy by letting the car freewheel ahead of the curve [1].

Test showed, that ANESA is more valuable if the advisory speed, of which tight curves are annotated with, is individually adjusted to the personality and the driving style of the driver. In experiments, a freewheeling advice with a low velocity was given to aggressive drivers, which were used to drive curves with much higher speed than proposed. As a result, they either simply ignored the advice, or took the advice first, but accelerated ahead of the curve nevertheless (see red line in figure 1). Neither of the behaviors is desired.

On the other hand, if tight curves are annotated with a velocity too fast for the drivers ability, our experiments showed that the drivers could not tap the full energy saving potential since they braked ahead of the curve nevertheless (see blue line in figure 1).

In figure 1 the effects of curves being annotated too fast or too slow are visualized. The figure shows, that only if the curve is annotated with an advisory speed individually tailored to the driver, the energy saving potential is fully utilized.

In this paper, the driving style of the driver is determined.

\(^1\)ANESA is a result of a long term cooperation between Harman/Becker Automotive Systems and the FZI.
II. RELATED WORK AND THE QUALIFYING OF THE RESEARCH CONTEXT

In section II-A this work is integrated into the context of modeling and understanding driver behavior. An overview of related work, dealing with classification of driving behavior or determining the driving style of the driver is given in II-B.

A. QUALIFYING THE RESEARCH CONTEXT

J.A. Michon proposed a two dimensional classification of driving behavior models (see table I) in 1985 already [2].

<table>
<thead>
<tr>
<th>Internal state (psychological)</th>
<th>Task analysis</th>
<th>Adaptive control models</th>
<th>Trait models</th>
</tr>
</thead>
<tbody>
<tr>
<td>[Behavioral]</td>
<td>[Taxonomic]</td>
<td>[Functional]</td>
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TABLE I
CLASSIFICATION OF DRIVER BEHAVIOR MODELS (ADAPTED FROM [2])

Task analysis models decompose driving into tasks and subtasks and relate them to driver requirements and abilities. Trait models attempt to capture individual personality characteristics, e.g. the aggressiveness or the cautiousness of the driver, the influence of stress, or how much the driver is prone to distraction.

Adaptive control models apply functional approach to capture behavioral changes. Motivational control models consider internal states as attitudes, subjective risk and insight as controlling factors.

The driver profile proposed in this paper can be dedicated to the trait models, since it attempts to estimate the probability of the driver belonging to a certain driving style class with the idea to have a general, probabilistic description of the driving behavior.

Having a general description of the driving style, further information, like the velocity the driver will choose to drive a tight curve, can be inferred.

B. RELATED WORK

Farida Saad defines driving style as a relatively stable description of the driver, which typifies their personal way of driving [3]. We assent to this definition.

Taubman-Ben-Ari et al. classify drivers in eight types: [disassociative], [anxious], [risky], [angry], [high-velocity], [distress-reduction], [patient], and [careful] [4]. Their aim was mainly to find statistic relationships. For example, they found that drivers with a higher education often developed a more anxious driving behavior. Their data was collected by means of a 44-item questionnaire named Multidimensional Driving Style Inventory (MDSI).

Y. Chung et al. defined four driving styles: [reckless and careless], [anxious], [angry and hostile], and [patient and careful] [5]. They tried to find a connection between the socio-demographic background of the drivers to their driving style by means of machine learning approaches (K-means cluster and logistic regression analysis). Their data was gained through written a questionnaire as well. Several attempts have been made to personalize adaptive cruise control (e.g. [6], [7]) or collision warning systems (e.g. [8]) to the consumers needs. Our objective is a general probabilistic description of the driving style rather than customized solutions for one application.

For our work, the definitions of the driving styles by Taubman-Ben-Ari and Chung served as a model to our defined driving styles. Contrary to these workings our determination of the driving style is based on vehicle data measurements and is aimed to be generated whilst driving.

Furthermore, we aim on adjusting and improving driver assistance systems, rather than to collecting links between driving style and the social background of the driver.

III. OVERVIEW

The purpose of this work is to determine the driving style of the driver. For this reason, five types of driving styles were defined. These are aggressive, anxious, keen, economic, sedate (roughly comparable to [4] and [5]). Section IV-A gives a more detailed description of the driving style classes and our interpretation of affinity.

The rating of the drivers affiliation to each particular driving style class is based on their actions in five well-defined traffic scenarios. The scenarios are chosen to be commonly occurring, day-to-day traffic scenes. Section IV-B explains the defined scenarios in more detail and describes their implementation in the driving simulator software. Furthermore, the recorded vehicle data characterizing the driver in the particular scene is explained.

To evaluate the actions of the drivers and determine the affinity to the different driving style classes, fuzzy-rules are applied. The rules find a detailed description in section V.

By means of the driving style of the driver, the driverspecific curve advisory velocity is deduced. Amongst other experiments, section VI compares drives undertaken with assistance of ANESA with and without a parametrization to the determined driving style.

IV. IMPLEMENTATION

A. Driving Style Classes

To rate the driving behavior, the driver is categorized into five driving style types. The driving styles are not mutually exclusive. For instance an economical driver can also be somehow sedate or keen. Our interpretation of the driving style is as follows:

**Aggressive:**

Aggressive drivers are characterized by driving at high speeds, high degrees of accelerations and decelerations, and generally a high risk taking behavior. Furthermore, they tend to drive too close to other road users and put other traffic participants at risk.

**Anxious:**

Anxious, or inexperienced defensive drivers are taking a very low level of risk. They tend to drive slower than sign-posted. In tight curves, they do not dare to drive too fast. Their accelerations are very low, whereas their decelerations are sometimes...
too intense due to misjudging the vehicle braking characteristic.

**Economical:**
Economical drivers are freewheeling to upcoming traffic restrictions. They try to hold the vehicle on a constant speed level and avoid unnecessary braking. However, their accelerations can be quite strong aiming to reach their desired traveling speed as efficient as possible.

**Keen:**
Keen drivers are aware of the vehicle characteristic and utilize the full dynamics of their vehicle. They are driving at the sign-posted speed limit, or slightly over it. However, compared to the aggressive drivers they do not threaten other road users and use their skills more responsible.

**Sedate:**
Sedate drivers are characterized as driving responsible and moderate. They obey the traffic rules and tend to drive at the sign-posted velocity (or slightly slower). Their interaction with other road users is calm, polite, and defensive.

### B. The Defined Traffic Situations and their Contribution to the Driving Style

The driving style of the driver is calculated by means of evaluating the following scenarios:

**Approaching a Village:** The driver is approaching a village on a country road. The velocity restriction on the country road is 100 km/h and the velocity restriction within the village is 50 km/h. 200 m in front of the village a 70 km/h sign is posted, which is very common in German traffic. The measurement starts 800 m ahead of the village and ends 50 m after entering the village (see figure 2). The following data are extracted from the village scenario to function as input for the fuzzy-rules:

**Approaching speed:** If the driver is approaching the village with a high speed, it is a good indicator for an aggressive or keen driving style. Lower speeds are typical for sedate or anxious drivers.

**Start of freewheeling:** Economical drivers start the freewheeling phase very early, whereas aggressive drivers usually do not freewheel at all and tend to lower their velocity by braking. Anxious drivers also tend to brake rather than freewheel. They are usually not aware of the vehicle dynamics.

**Average brake pressure:** Economical and experienced sedate drivers manage to drive the village scenario without braking. They are aware of the freewheeling-characteristic of the car and have a good feeling when to stop accelerating to reach the velocity signs with the sign-posted velocity. Though keen and aggressive drivers are often aware of the freewheeling-characteristic, they still drive the village scene with a heavy use of the brake, resulting in a faster travel-time. Anxious drivers also tend to brake in front of the village. However, this is caused by their inexperience rather than by the intention of faster travel.

**Driving the Country Road:** This measurement is a 10 m velocity snapshot taken on a country road without any velocity restriction sign-posted. According to the German traffic regulations, the allowed speed is 100 km/h. In this scenario, the velocity is the sole indicator to infer the driving style.

**Velocity:** Aggressive or keen drivers tend to drive faster than usually allowed, whereas anxious and sedate drivers tend to drive as advised or slightly slower. The intention of driving economically can hardly be determined by means of this measurement.

**Driving within a Village:** This measurement is a 10 m velocity snapshot taken within a village at an allowed speed of 50 km/h. In this scenario the same assumptions and rules than in ‘Driving the Country Road’ can be applied.

**Driving a Tight Bend:** This measurement is taken while the driver is approaching a tight curve on a country road. The curve is modeled with 45 degrees at a radius of 100 meters. Data is recorded 300 meters ahead and 100 meters after the curve. The following data are extracted and taken into account for the fuzzy-rules:

**Velocity at the angular point of the curve:** While anxious or sedate drivers usually tend to choose a lower speed in the curve, aggressive and keen drivers choose a higher velocity to travel the bend.

**Average acceleration after the curve:** Economical drivers usually drive the whole curve scenario with an almost constant speed. Therefore, their accelerations after the curve, as well as their decelerations ahead of the curve are not very strong. Measurements of aggressive or keen drivers have huge accelerations after the angular point of the curve. Measurements of anxious drivers have the lowest accelerations after the curve.

**Average deceleration ahead of the curve:** Ahead of the curve,
Stop Sign within a Village: In this measurement the drivers behavior approaching and leaving a stop sign is rated. The evaluated data are:

Minimum velocity: According to the law, the driver has to fully stop \((v = 0 \text{ km/h})\) in front of the stop sign. According to our measurements, aggressive drivers do not always slow down their car to zero.

Freewheeling distance ahead of the stop sign: As for the 'Approaching a Village' or 'Driving a Tight Bend' scenarios, the same observing of the freewheeling behavior on stop signs can be made.

Average acceleration after the stop sign: Likewise to the tight curve scenario, keen and aggressive drivers tend to accelerate a lot leaving the stop sign. Sedate drivers have moderate degrees of accelerations whereas anxious drivers have low acceleration values.

Average deceleration ahead of the stop sign: As for the tight curve scenario, keen and aggressive drivers tend to accelerate a lot leaving the stop sign, whereas sedate drivers have moderate degrees of accelerations. Anxious drivers have low acceleration values.

Number of Start Attempts: Anxious drivers often need more than one attempt to pass a stop sign. They tend to look left and right very carefully and leave the sign very hesitant.

V. FUZZY-RULE BASED DETERMINATION OF THE DRIVING STYLE

With the observations and assumptions made in IV-B, 112 fuzzy-rules were set up to characterize the driver. In table II the rules are listed for the situations 'Driving the Village' and 'Driving the Country Road' respectively. In table III the fuzzy-rules for the village scenario are defined. Figure 3 shows an abridgment of measured speeds for the 'Driving the Village' scenario and the according fuzzy interval defined.

As already mentioned, not all situations serve to gain good information for all driving styles. The 'Driving in the Country Road' scenario, for instance, is a good indicator to separate sedate or anxious drivers from aggressive or keen drivers. However, not much can be inferred about the economical behavior of the driver by means of this speed measurement only. The 'Stop Sign', 'Village Scenario', and the 'Tight Bend' scenario give much information how economical the behavior of the driver is. Hence, a weighting factor \(w_{ds,s}\) was introduced, defining how much a situation \(s \in \text{Situations}\) contributes to a particular driving style \(ds \in \text{DrivingStyles}\).

\[
\forall ds \in \text{DrivingStyles} : \sum_{s \in \text{Situations}} w_{ds,s} = 1
\]

Including the weighting factor, the driving style of the whole test run is calculated as

\[
P(ds) = \sum_{s \in \text{Situations}} w_{ds,s} \cdot P(ds|s),
\]

with \(P(ds|s)\) being the probability of the driver behaving with driving style \(ds\) in the given situation \(s\). \(P(ds)\) is the probability of the driver driving with driving style \(ds\) in the whole test run.

VI. EXPERIMENTS

To test the implemented driving style classification, a test track of 7 km was modeled. The track contains two villages...
and two tight curves of 45° and 100 m radius. Furthermore, the track contains a stop sign paced in the village. All together, the track contains 7 measurement points, where the vehicle data for the driving style estimation is recorded. Our experienced test drivers managed to drive the curves with approximately 85 km/h in our driving simulator, which is shown in figure 4.

Conducting the tests in a simulator has the advantage of comparable test results, because all participants are driving exactly the same scene under the same circumstances. The driving simulator consists of a reconstructed Smart Fortwo car, with the signals of the steering wheel and the pedals connected to a driving simulator software. The simulation software simulates various data as forces, momentums, and accelerations in real-time. The determination of the driving style is based on those simulated values.

In the driving simulator, there is a lack of feedback for speed and dangerousness. Nevertheless, since the vehicle spins out if the driver is driving too fast, the test persons intent to drive responsible.

A. Evaluating the Measurement Database

Our database consists of test drives, made by students, staff members, and visitors at the age of 20 to 55 with varying degrees of experience. The taken measurements were labeled as aggressive, anxious, economical, keen, or sedate. There is a thin line between keen and aggressive measurements. However, we labeled the measurements as keen, if the driver was driving fast but nevertheless responsible. If the driver was speeding without paying attention to any possible risk, we labeled the measurement as aggressive.

The evaluation based on our database can be seen in figure 5. As expected, measurements rated as keen have a high probability of being aggressive and vice versa. Furthermore, sedate and economical test runs can hardly be distinguished. According to the the maximum likelihood hypothesis, which is classifying the measurement $M$ to the driving style $ds$ with the highest probability, 83% of the measurements could be classified correctly.

$$ds_{ML} = \arg \max_{ds \in DS} (P(ds|M))$$

The aggressive and keen measurements could be classified without any mistake. The most confusion was between the sedate and the economical drives. 14% of the sedate test drives were rated as economic. However, as sedate test drives are not mutually exclusive economical, this confusion is bearable.

B. Driving Style Rating

To verify the rules in respect to someones own assessment, persons drove the test track and rated their behavior in a questionnaire according to the driving style description of section IV-A from 1 to 10 afterwards. Figure 6 shows a comparison between the own valuation and the valuation of our algorithms of four test persons. Generally, more than 75% of the test persons assigned themselves with the highest rating to the same class then the algorithm did.

All the test persons rated their ability to drive economical much higher than our system. This supports our hypothesis that most drivers do not utilize the full energy saving potential in their driving behavior.

C. Adjusting the Advised Velocity for Curves

Further tests were made evaluating the energy saving potential of ANESA giving speed hints adjusted to the driving style, rather than the default hint. Taking up the example depicted in section I, an individual advisory speed was derived based on the driving style. Mainly, the ratings of the driving style in terms of aggressiveness and anxiousness were used to generate the advisory curve velocity for the particular driver.

Figure 7 shows an anxious and an aggressive driver approaching the same curve (45° with 100 m radius). The advisory speed for the anxious driver was dedicated to be
55 km/h, whereas it was 85 km/h for the aggressive driver.

Both drivers drove the scene once with ANESA parametrized with their individual curve speed velocity and once with 70 km/h per default. Driving with the default velocity advice was suboptimal for both drivers. The aggressive driver started to mistrust the speed hint and lost energy on extra acceleration. The anxious driver lost energy due to braking. With the advisory speed adjusted to the determined driving behavior, both drivers were freewheeling to the speed they were comfortable with. This, in fact, is the optimum in terms of energy saving and time usage.

VII. CONCLUSIONS AND FUTURE WORKS

The value of future driver assistance systems can be highly increased by adapting them to the character of the driver. This work presents a probabilistic determination of the drivers driving style, based on situational evaluation of the vehicle data. To determine the individual driving style of a person, the behavior in day-to-day traffic situations was analyzed and a probabilistic affiliation of the driver being aggressive, anxious, economical, keen, or sedate was made by means of fuzzy-rules. Using the maximum likelihood hypothesis, 83% of the measurements in our database could be correctly classified. The most confusion was between sedate and economical drives. As a questionnaire test showed, the implemented algorithm rated the driving style of the drivers similar to their own ratings.

Further, the benefit of ANESA giving speed hints adjusted to the drivers personality was evaluated. Anxious drivers saved energy due to less braking was avoided, whereas for aggressive drivers additional accelerations could be mitigated. Since this tests are based on simulation only, further work will validate this evaluations in real traffic scenarios.

VIII. ACKNOWLEDGEMENTS

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REFERENCES