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An adaptive driving system regarding energy-efficiency and safety

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Abstract

Energy-efficiency and safety became an important factor for car manufacturers. Thus, the cars have been optimised regarding the energy consumption and safety by optimising for example the power train or the engine. Besides the optimisation of the car itself, energy-efficiency and safety can also be increased by adapting the individual driving behaviour to the current driving situation. This paper introduces a driving system, which is in development. Its goal is to optimise the driving behaviour in terms of energy-efficiency and safety by giving recommendations to the driver. For the creation of a recommendation the driving system monitors the driver and the current driving situation as well as the car using in-vehicle sensors and serial-bus systems. On the basis of the acquired data, the driving system will give individual energy-efficiency and safety recommendations in real-time. This will allow eliminating bad driving habits, while considering the driver needs.

1 Introduction

As the result of the climate change and society's awareness of the finiteness of oil, which increased due to several oil crises in the past, saving energy and protecting the environment became fundamental for politics and society [Yay, 2010]. Additionally, statistics showed that the increasing number of cars and drivers increased the accidents and fatalities on the road [Statistical Office, 2011]. Fan et al. [Fan et al., 2011] revealed that driving behaviour has a great factor to safety. Furthermore, an adaptation of the driving behaviour can save energy up to 30% [Haworth and Symmons, 2001; Helms et al., 2010; Van Mierlo et al., 2004].

On the basis of the above facts a driving system is presented in this paper, which has the goal to optimise the driving behaviour with respect to safety and energy-efficiency by giving adequate driving recommendation for the current driving situation. The recommendations will depend on the chosen are of improvement like safety and/or energy-efficiency. It is possible to fulfil energy-efficiency and safety potential, if the driver follows the given recommendations.

There are already several driving systems with the goal to optimise the driving behaviour by giving energy-efficiency or safety relevant hints [Fiat, 2013, Kia 2013; Lotan and Toledo, 2006]. These driving systems, however, cover either the area of energy-efficiency or safety. In contrast, our driving system will try to improve both areas. By using a driving profile, which represents the typical driving behaviour, our driving system will adapt itself to the individual driving behaviour. This will allow creating a warning based on any negative change of the driving behaviour or the driver condition. Furthermore, the acceptance of the driving system will be increased as it generates only useful recommendations. These recommendations will be given on time, as the driving system predicts the car state. Thus, the reaction of the driver to a dangerous driving situation will be appropriate. The first prototype of the driving system will be developed on the basis of a driving simulator. The second prototype will be connected to a real car, to test the driving system in a real environment.

2 Related Work

The goal of energy-efficient and safe driving is to change the driving habits of the driver to reduce the energy demand of the car and to increase the road safety. Energy-efficient and safe driving are described by a set of rules, why the cooperation for the driver is needed to achieve the goal of the reduced energy consumption and increased road safety.

In [Van Mierlo et al., 2004] driving rules for energy-efficient driving are evaluated. The results showed that the correct interpretation of the driving rules decreases the energy consumption and vehicle emissions. The drivers decreased the driving speed during the practice of the driving rules as well. As revealed in [Haworth and Symmons, 2001], the reduced driving speed leads to an increase of the road safety.

Beside the driving systems in the research area, there are also driving systems with the focus on energy-efficiency or ecological driving developed by the car manufacturers Kia and Fiat. The driving system of the manufacturer Kia [Kia 2013] gives feedback to the driver by activating different coloured lamps, which stand for energy-efficient driving, stand-by of the driving system or normal fuel consumption of the car. However, this driving system shows neither the

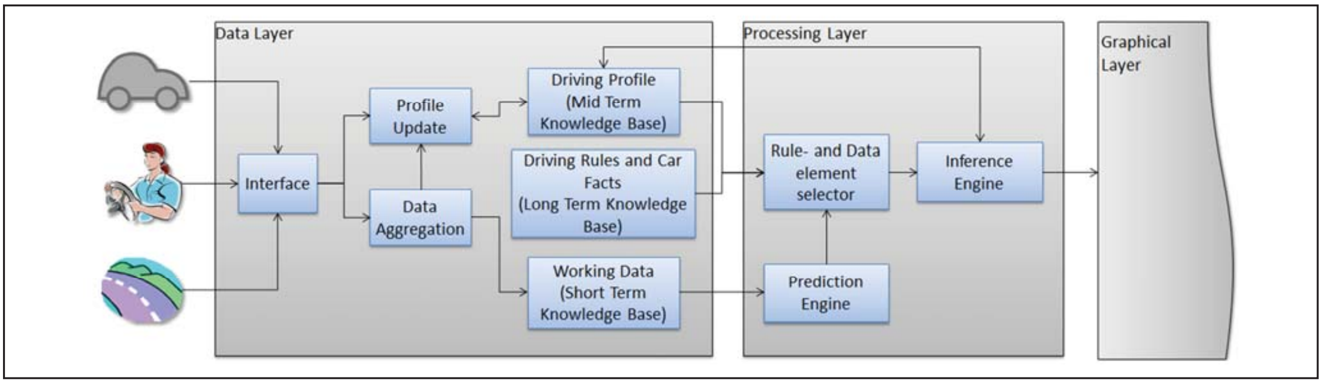

Figure 1: Architecture of our driving system

wrongdoings of the driver nor generates recommendations to eliminate the bad driving habits, which are the causes of the inefficient driving behaviour.

In contrast to the Kia's driving system, Fiat [Fiat, 2013] tries to improve the energy-efficient driving by analysing and rating the recorded driving behaviour on the Fiat website. Therefore, the driving system of Fiat first collects information about the driving behaviour, which the driver has then to upload the collected data on the Fiat website. However, this approach does not include a real-time feedback, which would allow an improvement of the driving behaviour by alerting human errors in terms of energy-efficiency.

Another eco-driving system is introduced in [Magana and Munoz Organero, 2011], which is based on the interaction between a car and a mobile device. The focus of this driving system is to educate the driver in eco-driving by giving hints to eliminate the bad driving habits. The driving system runs on a mobile device, why the needed information is gathered through the diagnostic port of the car and the internet connection of the mobile device. However, the driving system relies on an internet connection, why it is not guaranteed that it is able to obtain all needed data during the journey, as the internet connection may not be available during the whole journey. Furthermore, the driving system does not consider the individual driving behaviour, which can be used for the generation of individual driving hints.

Beside these driving systems with the focus on energy-efficiency, there are also driving systems with the goal to increase the road safety. However, an energy-efficient driving behaviour has also a positive effect on road safety, as it prevents an aggressive driving behaviour, which is the main cause of accidents [Haworth and Symmons, 2001].

Several safety relevant driving systems are trying to increase the road safety by warning the driver on recognition of a dangerous driving situation, like the driving system DAISY [Onken, 1994]. It monitors therefore the current driving situation and the driver condition. On the basis of the gathered information it recognises and warns the driver in dangerous situations, especially in situations, which are susceptible for distractions. However, DAISY does not try to improve the driving behaviour although the bad driving habits of the driver might have caused the dangerous situation.

Another driving system with the focus on safety is DriveDiagnostics [Lotan and Toleda, 2006]. In contrast to DAISY, it has the goal to educate the driver in safe driving. Therefore, it indicates the trip safety by monitoring and analysing the car movement. The real-time feedback warns the driver when his current driving behaviour does not match his typical driving behaviour or when the driver drives aggressively. In addition, DriveDiagnostics provides also an offline feedback by recording the trip and showing the average trip safety to the driver afterwards. However, the road safety could be increased more by observing the driver condition. This would allow recognising an untypical driver conditions like fatigue using tracking systems [Singh et al., 2010] and drowsiness using vital sensors [Sahayadhas et al., 2012]. Thus, dangerous driving situations could be detected also on the basis of the driver condition.

The driving systems presented in this chapter cover either the area of energy-efficiency or safety. Furthermore, they do not consider the individual driving behaviour or the driver condition, which are important factors in energy-efficiency and safety as well. In contrast to the presented driving systems, our driving system adapts itself to the individual driving behaviour as well as considers the driver condition. Furthermore, our driving system covers both areas: energy-efficiency and safety. This allows the generation of individual energy-efficiency and safety relevant recommendations in real-time, while considering the driver needs.

3 Architecture

Our driving system is based on the multi-tier architecture. Figure 1 shows the three main components of our driving system, which will be described in the following:

- **Data Layer**: It gathers all necessary data from the car, the driver and the environment. It is connected to the in-car serial-bus systems to gather data from the car, to vital sensors for monitoring the driver condition and to other sensors, which are relevant for acquiring information about the environment, like the current weather condition. The collected data is then fuzzified using fuzzy logic, as some data has more value when they are fuzzified. On the basis of the incoming data, the

Raw Data	Fuzzy set	Fuzzy rule
Engine speed	Very low - … - very high	-
Manner of driving	-	IF Engine speed low THEN driving style low speed; …
Acceleration	High negative - … - high positive	-
Weather condition	-	IF temperature at freeze point OR temperature less then freeze point AND is raining THEN danger is high; …
Rain	No rain - less - … - heavy rain	-
Temperature	Less than freeze point - at freeze point - higher than freeze point	-

Table 1: Excerpt of the fuzzy sets and rules

data layer creates a driving profile, which describes the typical driving behaviour of the driver. Beside the described tasks, the data layer administrates all relevant information, which is needed for further processing, as well.

- **Processing Layer**: The collected information and driver profile are used to analyse the driving behaviour in the Processing Layer. Additionally, it predicts the state of the car using the collected information stored in the Data Layer. Based on the prediction and the analysis of the driving behaviour, recommendations are generated, which guide the driver to drive energy-efficient or safe.
- **Graphical Layer**: Its main purpose is the rendering of the graphical user interface on the in-vehicle display unit. Furthermore, it shows the generated recommendations to the driver for example using the graphical user interface or an acoustic signal. The Graphical Layer provides also the opportunity to configure the driving profile by choosing an area of improvement: energy-efficiency, safety or both.

3.1 Data Layer

The Data Layer acquires all necessary data from the sensors and the in-car serial-bus system. Based on the gathered information it generates a driving profile, which represents the typical driving behaviour of the driver, and aggregates the incoming data using fuzzy logic. All necessary information for further processing such as the driving rules, the car facts, the collected and aggregated information are stored in the Data Layer. Figure 1 shows the different modules of the Data Layer, which will be described in the following.

Interface Module

The Interface Module is responsible for the communication with the in-car serial-bus systems and with the connected sensors. For the communication with the serial-bus systems it passes the message identifier of the desired information to the serial-bus system interface, which forwards then the corresponding data to the Interface Module. In contrast, the connected sensors send their data to the Interface Module without registering any identifier. After the collection of the data, it will be passed to the Data Aggregation and Profile Update Module for further processing.

Data Aggregation Module

The incoming data is prepared in the Data Aggregation Module using fuzzy logic, as some information has more value when it is fuzzy, for example it is clearer to define the manner of driving as high instead of using the crisp value1 of the engine speed to describe the manner of driving.

For the preparation of the incoming data the Data Aggregation Module uses Fuzzy logic. Its main purpose is to interpret fuzzy information with the help of fuzzy sets and fuzzy rules. Fuzzy sets are described by sets of elements, which have a degree of membership. Fuzzy rules are conditional statements, which are often used for control purposes. Table 1 shows an excerpt of fuzzy sets and rules used in the Data Aggregation Module to prepare the incoming data.

The first step of the Data Aggregation Module is the transformation of the incoming crisp data into grades of memberships of linguistic terms with the help of the defined fuzzy sets. This process is called the fuzzification. For example, the engine speed value 2000 rpm is transformed into the degree of membership of two linguistic terms: 80% low and 20% very low. The next step applies the defined fuzzy rules on the fuzzy values. The fuzzy rules allow the aggregation of different fuzzy values to get more information out of the existing data. For instance a dangerous driving weather condition is the result of heavy rain and temperature below freeze point.

Finally, the Data Aggregation Module transforms the linguistic terms, including the results of the fuzzy rules, into crisp values. This process is called defuzzification. There are different methods to transform the linguistic terms into crisp values. The simplest method is to choose the set with the highest degree of membership and ignore the other sets. Thus, in our example with the engine speed the defuzzification process would transform the 80% low into a crisp value, which represents a low engine speed.

The result of the defizzification process is then passed to the Profile Update Module. Simultaneously, the aggregated data

[1] A crisp value is an exact value like a real number. It is the opposite of a fuzzy value.

is stored along with the incoming data, which were not relevant to the fuzzification process, in the working memory.

Profile Update Module

The Profile Update Module is responsible for creating and updating the driving profile, which is used to describe the typical driving behaviour of the driver. The basis for the driving profile is the incoming data from the Interface- and the Data Aggregation Module. First, the Profile Update Module checks if a driving profile is available for the driver and creates a driving profile if it is not available. Every entry in the driving profile is described by the name of the value, the value itself, which represents the average value of that entry, and the update count of that value. For example the driving profile stores the driving behaviour, while a certain speed limit:

- Name of the value: Average speed at speed limit of 70 km/h
- Value:72 km/h
- Update count: 2000

In our example the value represents the average driving speed of the car during the speed limit of 70 km/h. The update process calculates the average the mean of the value by using the update count, the value itself and the incoming value. The update count is increased by one on every update of the value. The following formula shows the calculation of the average value:

$$\mathrm{newValue} = \frac{(\mathrm{count} \times \mathrm{profileValue}) + \mathrm{incomingValue}}{\mathrm{count} + 1}$$

Based on the calculation done by the Profile Update Module the driving profile represents the average or typical driving behaviour of the driver. The calculation is done and stored for every journey separately. This allows the driving system to analyse the driving behaviour over time to find positive or negative changes in the driving behaviour. However, when the Profile Update Module creates the driving profile, it has to be updated a couple times until the driving profile is able to represent the typical driving behaviour.

Short Term Knowledge Base

The prepared data from the Data Aggregation Module as well as the incoming data form the Interface Module are stored in the working memory, which is placed in the Short Term Knowledge Base. The stored information is used in the Processing Layer for further processing. The following list shows an excerpt of the stored values.

- speed
- speed limit
- distance to preceding car
- current gear
- acceleration force

Mid Term Knowledge Base

The driving profile, which is created and updated by the Profile Update Module, is stored in the Mid Term Knowledge Base. It contains information about the driving behaviour, the already given recommendations and the area of improvement that the driver has chosen. The stored information is used for the analysis of the driving behaviour and the generation of recommendations. The following list shows an excerpt of the stored values in the Mid Term Knowledge Base.

- Average Manner of driving
- Average Driving Speed
- Average Distance to preceding car
- Area of improvement
- History of given recommendations
- Adherence to the recommendations

Long Term Knowledge Base

The Long Term Knowledge Base is separated in two parts. One store the driving rules for energy-efficient and safe driving and the other part describes the facts about the car like the mileage, maximum speed or rpm. Both parts are the basis for the generation of the recommendations and will be described in the following:

Safety relevant driving rules

- Keep enough distance to preceding car
- Look ahead and anticipate to surrounding traffic
- Adapt your speed to the given situation
- Don't exceed the speed limit
- Avoid any distractions, for example don't use the mobile phone during the journey

Energy-efficient driving rules

- Shift the gear as soon as possible
- Drive at steady speed using the highest gear
- Skip gears when it is appropriate
- Decelerate smoothly by releasing the accelerator on time, while the car is in gear

3.2 Processing Layer

The Processing Layer is responsible for the analysis of the driving behaviour regarding the aspects of energy-efficiency and safety and for the generation of the recommendations, based on the individual driving behaviour. For these procedures an expert system is used, which is separated in two modules: the Rule- and Data Element Selector and Inference Engine. Furthermore, as our driving system tries to prevent bad driving habits, the Prediction Engine predicts the state of the car. This allows the expert system to generate a recommendation before a braking of a driving rule occurs. The data used in the expert system is gathered from the Long-, Mid- and Short Term Knowledge Base, which are placed in the Data Layer. The correlation between the different modules is illustrated in Figure 1. In the following chapters the modules of the Processing Layer will be described in detail.

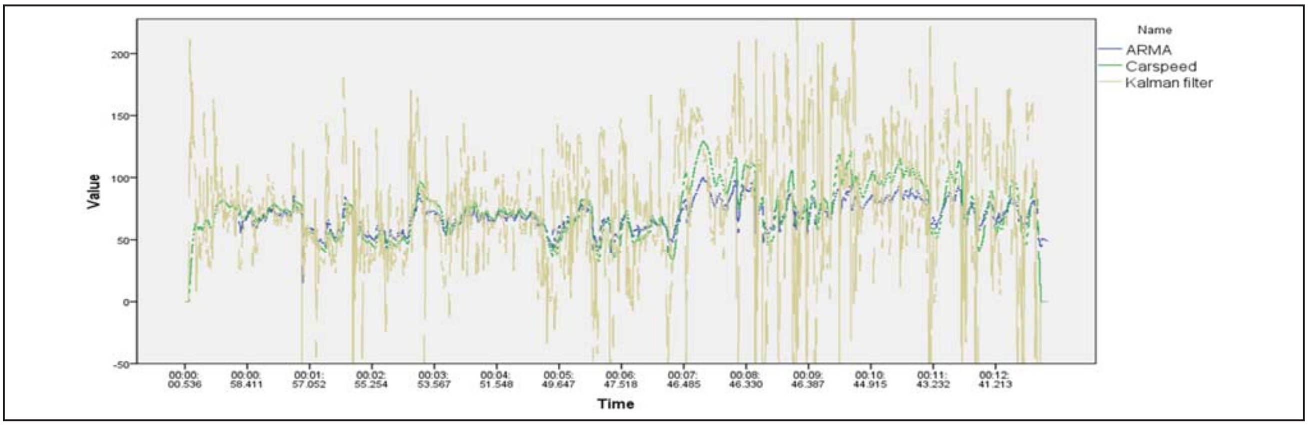

Figure 2: Result of 100 seconds prediction ahead using ARMA and Kalman filter

Prediction Engine Module

Our driving system has the goal to show energy-efficient and safe driving recommendations to the driver before a breaking of a driving rule occurs. Therefore, it is necessary to know the future state of the car. The Prediction Engine Module tries to predict the state of the car for the next cycles. A cycle is defined by passing the Processing Layer once from the Prediction Engine Module to the Inference Engine Module. It has to be figured out how many cycles are appropriate for the prediction. As the prediction is done in real-time and the performance is an important point, the Prediction Engine Module predicts only the values speed, distance to the preceding car and the engine speed. So, these values represent the state of the car in the Prediction Engine Module, as these values are the core values for the detection of the breakings of the rules. The prediction allows the expert system an early recognition of any breakings of the driving rules. Thus, the expert system can prevent the breaking of the driving rules by giving driving recommendations to the driver before the driver does a driving mistake.

There are prediction algorithms, which allow the prediction of the car state like the Kalman filter [Welch and Bishop, 2006] or the Auto-Regressive Moving-Average (ARMA) [Brockwell and Davis, 2002]. The car state in our case is represented by the values car speed, engine speed ant the distance to the preceding car.

The modelling and recognition of simulated driving behaviour is presented in [Pentland and Liu, 1999] using a Markov chain[2] with sequenced Kalman filters. According to Pentland and Liu the Kalman filter is only useful in short time prediction, for instance for the prediction of a quick hand motion. Thus, Pentland and Liu use the Kalman filter for a small-scale structure of the driving behaviour and coupled these together with a Markov chain, which represented the large-scale structure. The evaluation of this approach showed a prediction accuracy of 95% can be achieved. In contrast to the statement of Pentland and Liu, Bossanyi used the Kalman filter for the prediction of the short-term wind speed, where the Kalman filter predicted well for time periods below 10 minutes [Bossanyi, 1985].

The ARMA is another statistical prediction algorithm, which combines the autoregressive and the moving-average model. The output of the autoregressive model depends linearly on the previous output values. In contrast, the moving-average model is used to describe the mean of the time series data. The ARMA prediction is used for example in the area of econometrics, statistics or for wind speed prediction. In [Lujano-Rojas et al., 2011] an approach is presented for the hourly prediction of the average wind speed. The evaluation showed that the prediction accuracy for the time between one and then hours ahead can be improved about 17% using the presented approach.

The presented prediction algorithms have different approaches for the prediction of the values. Thus, we evaluated of the prediction algorithms using the data from the driving simulator. We collected the driving speed information of about 15 minutes of a journey. The result of the evaluation (see Figure 2) showed a more accuracy using the ARMA, as it considers the history of the values.

Rule and Data Element Selector Module

The Rule- and Data Element Selector Module is responsible for detecting any braking of a driving rule, deviation from the typical driving behaviour and any condition of the driver, which can be prejudicial for the driving task like anger, fatigue and so on. Thus, it compares the data from the working memory against the driving rules and car facts, which are stored in the Long Term Knowledge Base in the Data Layer. The data from the working memory is compared against the driving profile as well. The content of the working memory is not passed directly to the Rule and Data Element Selector Module. It is first passed to the Prediction Engine, which adds the predicted data to the data set of the working memory, and passes then the whole information to the Rule and Data Element Selector Module. On Recognition of a breaking of a driving rule, any deviation from the typical driving behaviour or an uncommon driver condition the associated data including the predicted data and the recognised abnormality is passed to the Inference Engine Module for further processing.

[2] A Markov chain describes the transition probability from one state to another state. Thus, it consists of states and transitions. The Markov chain is often used to model real world processes statistically.

The recognition of an abnormality in the driving behaviour is done by comparing each driving rule against the incoming data using fuzzy and crisp logic. Furthermore, the incoming data is also compared against the driving profile to detect any untypical driving behaviour or an uncommon driver condition. As there are only few driving rules for energy-efficient and safe driving and energy-efficient driving has a positive effect on safety, the module has not to deal with performance and contradictory driving rules. Hence, the Rule and Data Element Selector Module checks every single driving rule or value stored in the driving profile against the incoming data. However, if more driving rules or values to the driving profile are added, a solution to increase the performance and to solve driving rule conflicts has to be considered. A solution could be to weight manually the driving rules and values stored in the driving profile in relation to their importance to safety or energy-efficiency and to order them according to their relations to each other.

Inference Engine Module

The Inference Engine Module decides whether to generate and show a recommendation to the driver or not. Therefore, it checks the driver profile, especially the already given recommendations and the past reactions to them, if it is necessary to show the recommendation to the driver in order not to bother him. The reactions to the given recommendations will be analysed by checking the changes of the values during the next cycles, which are important for a specific recommendation. As there are delays until the driver is able to notice and to react to the given recommendation, the Inference Engine Module will wait a certain time until it starts the analysis of the driver reaction to the given recommendation. For example, after showing the recommendation "increase the distance to the preceding car" to the driver, the Inference Engine waits until it starts to measure the reaction. During the next cycles the distance to the preceding car will be analysed and checked if the distance is increased. On recognition of an increase the Inference Engine Module will assume that the given recommendation has been adhered. If an increase of the distance cannot be noticed, the Inference Engine Module will wait a certain time until a recommendation is given again, as it does not want to bother the driver by giving the same recommendation. In case of repeated ignorance of that recommendation, the Inference Engine will decrease the generation frequency of that ignored recommendation. This allows the driving system to consider the driver needs by adapting itself to the individual reaction to a given recommendation. Thus, the acceptance of the driving system can be increased as it avoids recommendations, which are unimportant in the sense of the driver.

Conclusion & Further Work

We presented in this paper an adaptive driving system, which is in development. The focus of the driving system is the analysis of the driving behaviour and the generation of adequate recommendations to improve the driving behaviour in terms of energy-efficiency and safety. In contrast to other existing driving systems the presented driving system considers energy-efficiency and safety as well as the individual driving behaviour and the driver condition while generation a recommendation. Furthermore, the driving system allows creating recommendations before the driver breaks a driving rule by predicting the car state.

As the driving system is under development, it has to be figured out, which algorithm fits the needs of the Inference Engine Module and the Rule- and Data Element Selector. Furthermore, a user friendly concept for the graphical user interface has to be worked out according to the usability guidelines for human-machine interfaces for in-vehicle systems [EU HMI, 1998]. Finally, the generated recommendations have to be displayed in a noticeable way without distracting the driver during the journey.

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