The Learning Vehicle

A virtual co-driver as trip companion?

The self-learning route memory is a method for the automatic generation and continuous updating of a vehicle internal database containing information about road characteristics of a frequently driven route. In the following sections the function and the idea behind the "learning vehicle" together with a possible application – the virtual co-driver – will be described.

1. Targets for sustainable mobility

An efficient and flexible transport system is crucial for our economy and way of life, and as a result we see the number of vehicles sharing our roads increasing. This leads to a substantial and ever growing threat to our environment and the social and economic systems. To reach the worldwide targets of increased mileage, reduced pollution from the transport sector, and improved road safety, it is no longer sufficient only to look at improvements regarding vehicle construction, i.e. engine and transmission technology, aerodynamics, lightweight material, and tire technology. Instead, also the operation of the vehicle has to be optimized; investigations have shown that the driver influences the fuel consumption with up to 50 percent. The average driver needs support and guiding to be able to operate the vehicle in an optimal way, both regarding safety and energy consumption. The above mentioned targets are also of prime importance for the OEMs as, aside from emission legislation, high fuel efficiency, low emissions, and high safety standards are important sales arguments. Fulfilling these targets also moves the transport sector a step further towards a sustainable mobility.

Ever since ABS became available in the end of the seventies, a variety of assistance and vehicle control systems have been introduced. Several studies show that the already impressive function of many of the existing assistance systems is further improved with preview information, i.e. information about the characteristics of the road ahead. Examples are predictive gear shifting, predictive energy management, curve speed warning, and improved object tracking for better reliability of the adaptive cruise control to mention a few. A number of systems using predictive control has been proposed and developed, but so far not widely spread as the required preview information is not yet available.

With relevant information about the expected road and traffic regulatory characteristics the performance of electric (EV) and hybrid-electric (HEV) vehicles can be greatly improved. For these propulsion techniques the potential of preview information is logically even higher than for conventional propulsion systems. As the available cruising range is often pointed out as the main drawback and limitation of electric vehicles, an optimization here might help to improve the acceptance and to introduce these vehicles as a real alternative to conventional vehicles.

A further important benefit of predictive vehicle operation is also the possibility to systematically improve both component performance and lifetime. Based on the knowledge about the characteristics of the driven route, the load of various vehicle components can be controlled better to "spare" critical components, e.g. batteries.

As a concrete example of the use of preview information, a contemporary issue is used to illustrate the benefits: The interest for introducing hybrid-electric busses for the local public transport is currently growing. Clearly, these busses are predestinated for preview information supplied by a learning system – the route is defined and the vehicles travel the same route over and over again. In this way not only the fuel efficiency, but also the environmental impacts such as noise and emissions can be improved.

2. Predictive driving

If the driver knows the road he is driving, he can use this memorized (i.e. preview) information together with the current or assumed activities of the other traffic participants to control the vehicle in a more predictive manner for improved safety and fuel economy. One of the greatest potentials for fuel savings lies in the avoidance of unnecessary acceleration and brake actuation and to keep the combustion engine in an optimal operating point. These actions are typical for so called "Eco Driving", which is a specialized form of predictive driving. Generally, a predictive driving style is characterized through a rather defensive but very active way of driving.

A predictive driving style is however very tedious for the driver as it needs a lot of concentration and physical activity (mainly thinking and shifting!). It is therefore not realistic to expect this driving style from the driver at all times. But, by providing the driver with information about the upcoming road and traffic situations for a preview horizon extending the visual horizon, the driver is allowed more time to react and plan his driving. This information could also be given in form of a recommendation for a suitable control action via some adequate interface, i.e. optic, acoustic, or haptic.

SUMMARY

An efficient and flexible transport system has become crucial for our economic system and way of life. The current (intra-continental) transport system shows a substantial and ever growing threat to the enviroment and to our health. This article contributes with an alternative method for supplying various assistance and vehicle control systems with the preview information required for predictive driving strategies. Not only the fuel efficiency but also the function of comfort and safety systems can be greatly improved by information about the upcoming road, e.g. optimized gear shifting strategies, energy management in hybrid-electric and electric vehicles, curve light, and curve speed warning. The approach bases on the fact that many vehicles are repeatedly driven the same routes, e.g. every day to and from work. The system automatically identifies relevant driving situations and road characterics along the road, describes these with a small number of attributes, and stores them in a vehicle internal database. The situation identification algorithms only require information from standard sensors fitted for the basic engine and drive train control and the vehicle stability system. By comparing newly identified situation descriptions with descriptions from earlier drives, the database is continuously extended and updated during each drive. The prototype implementation of the system in a driving simulator as well in a test vehicle realized with the special application „virtual co-driver" has shown positive results during testing.

2.1 Evolving assistance systems

As a result of the set targets for cleaner and safer transport, a lot of effort has been put into the research and development of driver assistance systems. A number of innovative functions, that just a couple of years ago seemed pioneering and futuristic, have today become more or less standard systems in many vehicle classes. These functions have, due to their considerable benefits, moved from being systems only available in upper class vehicles to be available also in the mid- and small class vehicle segment. This trend is also obvious within the (goods) transport sector.

Assistance systems can be divided into two main categories; active and passive systems. Active systems are directly controlling the vehicle operation, while passive systems are rather of informing, guiding or warning nature, partly leaving the final decision of action to the driver. Examples of systems in the safety and comfort categories are adaptive cruise control (ACC), lane departure warning (LDW), advanced front lighting (AFL), electronic stability, and curve speed warning. For energy purposes systems for intelligent gear selection can be mentioned. Typical for these systems is that their functionality usually bases on information from additional sensors installed in the vehicle and dedicated for each particular system. These sensors typically scan the vehicle's surrounding and together with information of the current vehicle state the systems can react appropriately.

Preview information provides a further basis for the decision-making in the control algorithms. Thus the control can be optimized with regard to the characteristics of the upcoming road, e.g. to turn the headlamps before curve entrance, to select an appropriate gear depending on the road gradient, or to inform the driver about changing speed limits well in advance. The benefits of the extended functionality of the assistance systems, especially the ones regarding energy management, are currently thoroughly investigated. With suitable research platforms they can be analyzed in a qualitative as well as quantitative way. On the one hand, the focus is put on systems that influence the energy consumption directly by controlling the power train and the onboard electrical system. Examples are intelligent strategies for gear selection or the control of the auxiliary consumers based on the actual and future demand. On the other hand, driver assistance and driver information systems, which indirectly lead to a reduction in energy use by supporting the driver to an energetically intelligent operation of the vehicle, are of particular interest.

2.2 Provision of preview information

The required preview information is usually assumed to be available either from enhanced digital maps or through communication with infrastructure or other vehicles. However, a great amount of this information is still lacking. The available in-vehicle sensors for scanning the nearest vehicle surrounding, e.g. cameras, radar, and laser, are still too expensive for use throughout all vehicle segments. Furthermore, the electronic horizon offered by the sensors' coverage range is limited and for many applications too short. A digital map offers a theoretically unlimited electronic horizon, but the digital maps available today do not contain the required information at all or with too little accuracy. The updating of the maps is also expensive and currently not frequent enough. Finally, the mentioned communication systems for information exchange (car-to-car, car-to-infrastructure) are dependent on a broad distribution or major (governmental) investments in the infrastructure for a proper functionality.

The *learning vehicle* offers an alternative approach for the provision of the required preview information. The system allows individual vehicles to "memorize" or to "learn" the characteristics of a driven route through repeated drives – just as an observant driver would do. With a *self-learning route memory* a database containing the required preview information of a frequently driven route can be automatically generated and continually updated in the vehicle during each drive. This approach bases on two facts: the travel behavior and the sensor infrastructure of the vehicles. It is a fact that most vehicles are moved on a very limited part of the road network, which is true not only for commuter, public transport, and commercial vehicles, but also for private traffic. It is also a fact that most vehicles are equipped with the necessary sensors for the required situation detection algorithms, originally fitted for other purposes though. The aim is to generate a continuous up-to-date digital picture of the currently driven road.

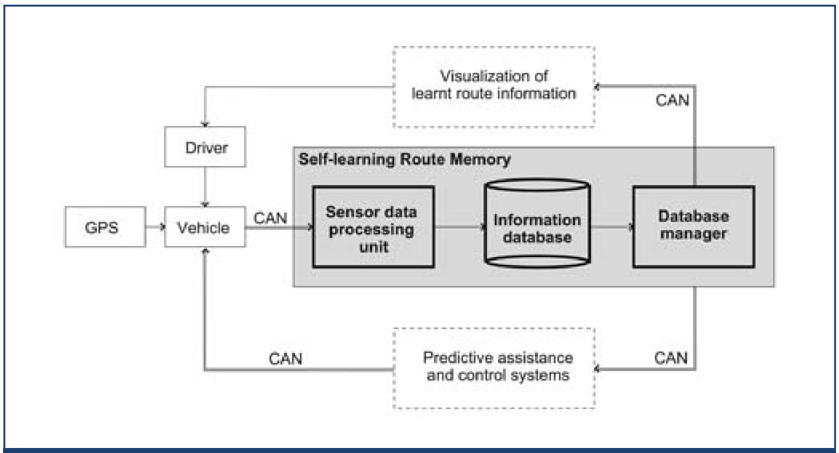
2.3 Advantages of self-learning

The „learning vehicle"-approach for collecting and managing the valuable preview information claims to be both cheaper and more flexible than other systems of this kind. One reason for this is that only sensors counting to the standard equipment in most modern vehicles are needed for the situation detection algorithms. Thus no further costs arise due to costly hardware (e.g. camera, radar). In contrast to digital maps that contain fairly basic information for a large geographical area, the route memory system will contain highly detailed information but for a small geographical area; the part of the road network where the vehicle is primarily moved. The proposed method is not dependent on road infrastructure or the system's distribution in other vehicles, as is the case with the mentioned communication systems. With this method, the amount and type of data to be stored are limited to the truly relevant information for a particular vehicle/driver combination.

3. The learning vehicle

3.1 System setup

The relations between the system's key processes are illustrated in **01**. The route memory system is connected to the vehicle via the real vehicle CAN network and has the ability to both receive and send data. During the drive data from various sensors, e.g. yaw rate, acceleration, and engine speed provide information about the vehicle's movements and actual state. This data indirectly provide information about the characteristics of the driven road as well as the driver activity. The sensor data are analyzed online to identify relevant road properties, such as slopes, curves or speed limit changes. The identification algorithms are based on pattern recognition methods extracting and categorizing typical features of the data stream indicating a certain road property. With a positioning system each identified situation is also associated with a geographical position along the driven route. Each set of data specifying an identified situation is simplified and intelligently compressed to reduce the amount of data to be stored. The target is to describe each category, e.g. curves, with a simple set of parameters. The descriptions of the identified road properties are written to a vehicle individual onboard database and are thus available as preview information during the next drive along the same route. Based on their category and geographical position along the route, each recognized road property or situation is used to update, improve, and verify the description of earlier entries for this property already existing in the database. Finally, the database manager unit selects plausible situation information from the database and provides various assistance, control, or information systems in the vehicle with up-to-date predictive route information.



01

Schematic illustration of the system setup for the prototype implementation of the self-learning route memory.

3.2 Situation detection

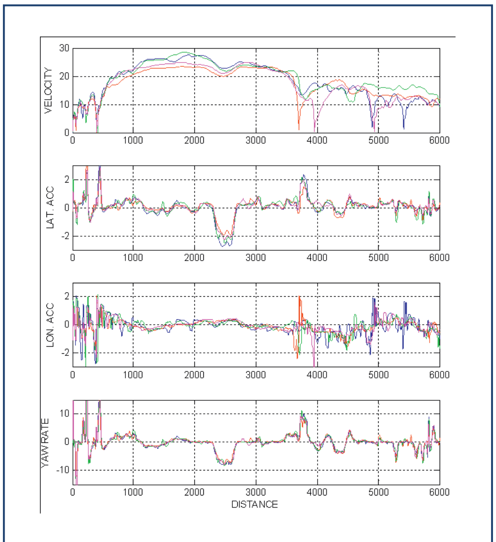
Today vehicles in all model ranges are equipped with a number of sensors necessary for the basic functionality of the vehicle, mainly for engine and transmission control, but ever more often also for passive and active safety as well as vehicle stability. One of the goals with this project was to use the unutilized potential of all these sensors and add functionality to the vehicle without adding further complexity through more sensors. Data analyses have shown that a number of situations relevant for predictive driving strategies can be identified using only the information already available in most of our vehicles – when combined in a proper way. This means that a number of already integrated sensors get a second use.

System	*Signal*	*Situation identification*
ABS	*Wheel speed*	*Curve, Stop, Slope, Speed*
ESC	*Yaw rate*	*Curve*
	Lateral acceleration	*Curve*
	Steering wheel angle	*Curve*
	Steering wheel angle velocity	*Curve*
Power train control	*Engine speed*	*Slope, Stop*
	Engine torque	*Slope*
	Clutch activation	*Stop, Slope*
	Brake pressure	*Stop, Speed, Slope*
	Accelerator pedal pressure	*Stop, Speed*
Navigation system	*Geographical position*	*All*
Clock	*Date, Time*	*All*

T01

Minimum requirement of sensors and their original and potential use.

The only additional "sensor" not yet counting as standard equipment but necessary for the learning system is a positioning system for defining the geographical position of the identified situations. This requirement does not imply a critical shortcoming of the system looking at the increased availability of portable navigation devices today. The used sensors, their original designation, and the possible extended use are listed in **T01**. With this minimum requirement and an intelligent numeric combination of the available signals, situations such as curves, slopes, speed limits, or stopping positions (i.e. traffic light or intersection) can be identified.



02

Selected sensor signals measured during four different drive sessions.

02 shows some selected sensor signals from a number of independent test drive sessions along the same road section. The measurements show a high degree of conformity across the different drives even though they were conducted with different drivers at slightly different day times. This conformity is partly a result of the limited possibility to freely select speed and driving style due to applicable traffic regulations and other traffic participants. Consequently, with a statistical approach and pattern recognition methods it is possible to identify the characteristics of the road and traffic conditions with a relatively high confidence.

The available sensor data are analyzed online in the vehicle during the drive and the features of each situation are recognized "on-the-fly". Also, the filtered or derived versions of the measurement data can be used when the relative time delay due to filtering is accounted for by the evaluation. Preset limits defining each event are used as "flags" for starting and stopping the recording of the measurement data.

The curvature of the driven route can be determined directly with information from the yaw rate sensor together with the vehicle velocity. A curve is identified where the pre-defined values for minimum curvature and length are fulfilled, see **03**. These values are set to be velocity dependent to allow the identification of both long curves with large radius at high speed (typically freeway) and short curves with small radius at lower speed as often the case in urban areas.

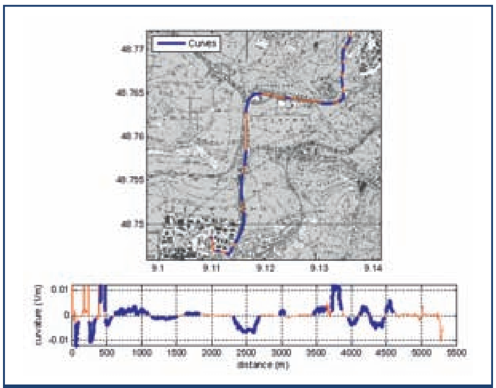
The easiest way of determining the longitudinal road gradient is with a high-resolution longitudinal acceleration sensor. As such sensors are usually not available as standard, methods based on e.g. estimations of vehicle output torque and vehicle acceleration, or observers of the road gradient must be used. In this case a method based on the vehicle output torque has shown functional. The selected method uses the engine output torque and road load to solve the equation of motion of the vehicle in the longitudinal direction, where the road load is the sum of the familiar driving resistances; rolling resistance, aerodynamic drag, and acceleration resistance.

The speed limit identification is a bit more complicated. First of all it must be decided if the identified speed should represent the valid speed limit as regulated by law or the speed selected by the driver based on his personal preferences or perhaps the traffic density. Without sensors identifying road signs, only an estimation of the speed limit can be made. Measurement data show larger velocity variations on freeways compared to urban roads, caused by the individual drivers, the traffic density as well as the traffic regulations. Therefore the speed limit identification algorithm needs to include both driver type (e.g. sportive, normal, or defensive) and road type classifications.

3.3 The memory concept

Each identified situation is described with a fixed set of parameters based on the situation category. Some of the attributes are common for all types of situations, others apply only for a specific situation type. The fields required for each situation category are illustrated in **T02**. The format of the content of the field "Magnitude" is different depending on category. For curves and slopes, this field contains the specification of an approximation function and its coefficients. For speed and traffic light information on the other hand, a single value for velocity or standstill duration is sufficient. Additional to the geographical position, each identified situation is also stored with information about date and time. Especially for non-static situations, such as speed limits and stopping situations, this is important to be able to take time-dependent variations into account, e.g. traffic density. The field ID is important for reference purposes, to be able to associate each identified situation with the correct route. The routes can for example be denoted as "home-workplace" or "home-supermarket". Similar fields as for the situation descriptions are used to specify each route, as shown in the last column in **T02**. The route counter holds information about the number of times a certain route was driven and is used for plausibility checks.

An identified situation is initially described through the extracted data features and the position information. For example, the trace of a curve is specified with the geographical coordinates for the beginning and end positions together with the measured curvature. The gradient of a slope is described similarly, only with road gradient as specific magnitude. Unless this data is highly compressed the storage of the data would not be practicable, both with regard to storage and communication capacity. To achieve this, the measurement values for curvature and gradient are approximated with a (continuous) mathematical model. By means of curve fitting methods, a series of data points and possible other constraints can be described with a finite number of parameters, i.e. the coefficients of the approximating function. Firstly, an approximating model that relates the response data to the predicted data with one or more coefficients must be selected. The result of the fitting process is then an estimation of the unknown model parameters. These coefficients are obtained by using the least square method to minimize the squared sum of the residuals. The challenge, however, is not the solution of the resulting (over determined) equation system but the selection of an appropriate function model and its degree.



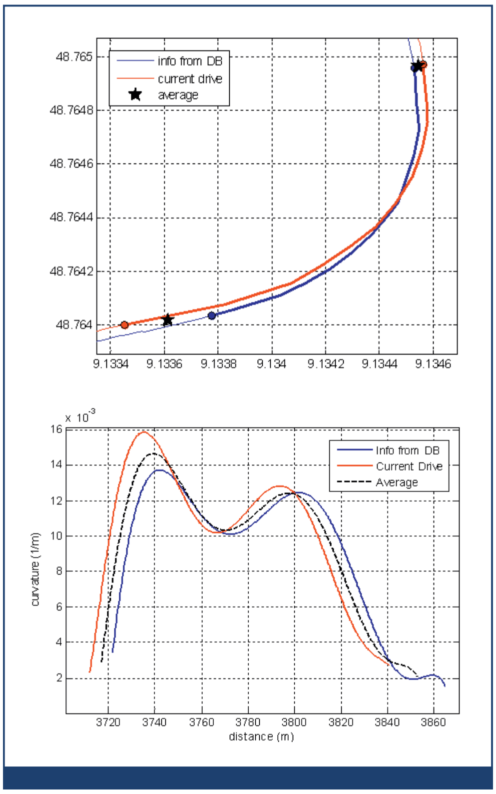
03

Graphical representation of the identified curvature of a driven path.

	Situation Category				
Fields	*Curve*	*Slope*	*Speed*	*Traffic light*	*Route*
Identity number (ID)	x	x	x	x	x
Geo. Coord. Beginning	x	x	x	x	x
Geo. Coord. End	x	x	x		x
Date	x	x	x	x	x
Time	x	x	x	x	x
Length	x	x	x		x
Heading	x				
Magnitude	*Approx. Function + Coefficients*	*Approx. Function + Coefficients*	*Velocity*	*Duration*	
Counter					x

T02

Matrix showing the fields required for the description of each situation category.



04

Illustration of situation description comparison and data update.

Based on the knowledge about the origin of the sample data and statistical analyses, an iterative algorithm for the computerized selection of an adequate model and its degree has been developed. As a result, it can be shown that the curvature and the gradient can be sufficiently approximated with e.g. a linear model up to degree six. According to the above, each identified situation is specified with a finite (and relatively small) number of parameters before it is stored in the vehicle internal database. The situation descriptions are classified into single- or multi-valued quantities depending on the situation category; curvature or road gradient are due to the approximation function denoted as multi-valued quantities while speed limit and standing duration are single-valued quantities. As a consequence, also the memory requirement for the two categories is different: multi-valued situation descriptions require approximately 69 byte compared to the 12 byte required for single-valued descriptions.

The implemented database structure, i.e. the memory of the learning vehicle, has been configured to contain several separate situation descriptions of various categories for one specific route, as well as a number of different routes; one single route can contain many situations of various categories, as well as one specific situation can appear in more than one of the stored routes (in case some sections of the routes coincide). In this way, each situation description will exist only once in the database, but can still be associated with several routes. The information about the connection between situations and routes are tracked with IDs and stored separately in the memory together with information such as situation category, driven distance from route begin, and validity information. In comparison to an ordinary navigation system where the complete route trace is available, the parameter "driven distance from route begin" is necessary for this method to be able to sequentially order the individual situations along the route. The described parameters and configuration serve for a clear structure and improved search performance of the database.

3.4 The learning process

All situations that are recognized during a drive are used to keep the database up to date and to improve the accuracy of the route characteristics recorded during previous drives. This is hence denoted as the *learning* process of the route memory system.

For the updating, the description of each situation identified during a drive is compared with similar situations in the database. As soon as a situation is recognized and completely recorded during a drive, a search algorithm is initiated to find all comparable events in the memory. The selection criteria are geographical position and situation category. Similar situation descriptions are extracted and a comparison algorithm is initiated. The newly recorded situation is individually compared with the extracted data. Depending on the outcome, the extracted data can be changed according to the new information. If no corresponding entries are found, or if the compared descriptions do not match, the new situation is added to the memory unit as a new event along the current route. For multi-valued situation descriptions the correlation coefficient between the two sets of (approximated) data is used as a measure for correspondence. Otherwise, the data values can be directly compared. For time-variant situations (i.e. traffic flow control) also the recorded daytime and week- day are taken into account by the comparison. This is done to differentiate between information collected during e.g. rush-hour and times with lower traffic density.

When the compared situation descriptions coincide within the tolerances, these two data sets must be combined into one. This is done with a weighted arithmetic mean to successively improve the description of the road features. Additionally, also a counter holding information about the number of times a certain situation was recognized is incremented. Finally the date and time information for the situation identification and database update is adjusted. For each drive along a certain route the route specific properties are modified if necessary, i.e. the counter parameter and date and time information.

Unlike the situation identification algorithms, which must be performed in real-time to avoid too large memory requirements, the comparison and update algorithms are not time critical during the current drive. This evaluation is, however, performed during the drive as well, but as a parallel process to leave the main CPU time for the situation detection algorithms. This basically means that the database is updated while waiting for the next situation to occur, i.e. on a straight leveled road section.

3.5 Situation selection

The identified, modified, and stored route information is now available as preview information during following drives. A selection algorithm is responsible for selecting correctly identified and learnt route information from the on-board memory and for passing this information on to various assistance, control, or information systems in the vehicle. By the selection the plausibility of the data is verified based on the counter values of the selected situation and its corresponding route. Depending on the target system, i.e. the intended use of the preview data, the amount and format of the retrieved information need to be customized. The required amount of data can be divided into three levels: a *simple* situation description (level 1), a *single* situation description (level 2), and *multiple* situation descriptions (level 3). A system for optimized gear selection or energy management in a hybrid-electric vehicle requires precise information about all upcoming slopes, speed limits, curves, stopping positions, etc. for the next 2-5 km to be able to make the necessary decisions, i.e. level 3. A curve light system only needs precise information about the next upcoming curve, i.e. level 2. The situation description for a driver information system on the other hand, must be reduced to an absolute minimum to prevent a driver information overload, hence level 1, containing only information about e.g. situation type and remaining distance, is sufficient.

Regularly obsolete entries are removed and separate situation descriptions that mutually (and coincidentally) approach each other due to the successive updating are merged. This is important to always ensure free memory capacity and to improve query time and search algorithms.

05

Implementation of the "virtual co-driver" in a static driving simulator for functional testing.

4. System Realization

A prototype of the self-learning route memory presented here is implemented in C++-code featuring a direct interface for reading the CAN-bus of the host vehicle. The identified road characteristics are stored in a database based on MySQL. For the communication between the route memory system and for example a driving strategy unit, an interface for Ethernet communication has been implemented. The ambition is to develop a system capable of real-time application and independent of platform. The development of the system algorithms, in particular the algorithms for the situation detection, bases on real measurement data collected during test drives over several thousands of kilometers.

One possible application for the learning system is for the display of route information in order to inform the driver about special situations ahead; for example, a changed speed limit or a narrow curve. Such information can help the driver to decelerate appropriately, i.e. optimized regarding energy, safety, and comfort. Well-timed information about the grade of upcoming slopes is useful especially for heavy vehicles in order to select the optimum gear.

4.1 Driving simulator

As a first step towards implementation in a real vehicle, a *virtual co-driver* has been realized in a real-time driving simulator. This is a convenient step in order to functionally test and optimize the software under realistic conditions. One major challenge within the development of situation detection algorithms is the variety of drivers and driving styles. An example is the infinite number of possible trajectories for driving through a certain curve in the road. A further example is the continuously changing vehicle speed. For such a learning system it is important that the situation detection is performed in a robust and deterministic manner. A driving simulator is a cost-efficient and time saving tool for the verification and optimization of situation detection algorithms because it allows quick variations of the test tracks or vehicle parameters in a safe and reproducible environment. Hence it is possible to evaluate the identification algorithms and assistance systems even in driving conditions close to the physical limits or under other unfavorable conditions.

The static driving simulator used for this implementation features a stereoscopic surround projection of the driving scene on three screens. A vehicle mockup is installed in the center of this projection facility. The mockup is equipped with a seat, pedals, a gear shift lever, and a high-performance force-feedback steering wheel drive. The steering drive enables dynamic feedback of the steering torque to the "driver" and hence a realistic feeling. The heart of the simulation is a vehicle dynamics model which calculates the motion of the vehicle body, the chassis, and the wheels using a multi-body system (MBS) approach. For realistic behavior of the interactive driving simulation it has to be ensured that the output of the vehicle simulation model is plausible in all imaginable driving states, e.g. in high-speed cornering on road surfaces with low friction coefficient or in reverse driving situations. The used model contains a fully nonlinear tire/surface model which covers all possible combinations of longitudinal slip, side slip, and vertical forces. The driving simulator is equipped with "virtual sensors", which calculate the longitudinal and lateral accelerations, yaw rate, position information (GPS emulator) as well as other sensor signals. This information is transmitted to the virtual co-driver via a real CAN network with communication parameters identical with an existing vehicle. This setup ensures that the virtual co-driver can be easily transferred from the driving simulator environment into a real test vehicle.

A short-coming of the static driving simulator is the lack of motion for a realistic reproduction of the real driver environment. This often results in motion sickness due to the discrepancy between the motions insinuated through the graphics and lack of motions actually perceived by the driver. Hence such a simulator is not appropriate for investigating driver activity, system acceptance issues, or the actual potential of developed systems. To be able to investigate these topics, a large dynamic driving simulator is currently under construction at the University of Stuttgart. This simulator is technically and systematically seen as an extension of the static simulator. The simulation setup is similar, only that the calculated motions of the vehicle body are transmitted to a powerful motion system translating these signals into real movements exerted on a platform. On the platform a real vehicle is installed compared to the vehicle mockup in the static driving simulator. The real vehicle increases the impression of reality by the test drivers and it also allows the evaluation of the tested system in the original vehicle environment, with the original control and display interfaces.

4.2 Real vehicle

The implemented configuration and setup of the virtual co-driver, as a special use of the learning system, allows an easy transfer to a real vehicle. A prototype of the co-driver for the use in a real vehicle has been realized on a Car-PC featuring hard- and software interfaces for a direct communication with the vehicle CAN. This permits an easy logging of the relevant sensor values for the situation identification algorithms. For the vehicle implementation also an alternative communication interface over Ethernet has been realized. In the prototype system this data format is preferred over standard CAN-communication because of the amount of data that needs to be transferred during the system verification process. This alternative communication method is available as the complete control strategy of the test vehicle is realized on an advanced rapid prototyping system offering the most common data and communication interfaces.

The various algorithms of the learning system have hence been subject to verification and validation tests under real driving conditions, in real traffic situations with real drivers. The results of these test drives are highly satisfactory.

5. ... and then?

To achieve the worldwide goals for reduced emissions from the traffic and less severe and fatal accidents on our roads a wide-spread adoption of systems for predictive driving is necessary. This can only be achieved if the systems are cheap, immediately available, easy to implement, reliable, and highly beneficial from the first system on the market. The main problem for a wide-spread use of such systems is currently the lack of the required preview information. The system introduced in this article presents an alternative solution of this problem.

However, the preview information is rather useless unless the route can be predicted. A simple route prediction algorithm as implemented for the virtual co-driver takes parameters such as day time, day, driver, situation sequence, etc. into account to determine which route the vehicle is traveling. Only based on this prediction, the correct preview information can be supplied. However, also the smallest deviation from the main route, e.g. a detour to the gas station or for picking someone up, would in this case distort the positioning of the situation prediction.

Today, there exist only a few observations for realized route selection prediction systems as route prediction is a complex topic. Especially within the research around traffic flow management route prediction is handled as a separate topic. Further, the proposed system shows a minimum requirement of sensors. Of course, the more sensors available, the more situations can be detected with higher precision. As a further improvement of the system, a data sharing system providing an interface for the exchange of collected route information would add functionality to the method. Hence each individual database can be filled and updated quicker – which is relevant especially for vehicle fleets.

Thus, the current state is far from the final destination but the first step is made. As a conclusion, predictive road information is required to achieve the desired improvements in direct controlling of the vehicle systems and driver support for an optimized vehicle operation. Consequently, there is an increasing demand for an alternative approach for the provision of the necessary preview information that meets the conditions mentioned above. •

Anne Piegsa und Hans-Christian Reuss

Acknowledgement

This work has evolved through funding from two foundations; the Geschwister-Heine Foundation, Fellbach, and the Friedrich-und-Elisabeth-Boysen Foundation, Stuttgart.

References

Back, M., "Praediktive Antriebsregelung zum energieoptimalen Betrieb von Hybridfahrzeugen", PhD Thesis, University of Karlsruhe, Germany, 2005.

Dorrer, C., "Effizienzbestimmung von Fahrweisen und Fahrerassistenz zur Reduzierung des Kraftstoffverbrauchs unter Nutzung von telematischen Informationen", PhD Thesis, University of Stuttgart, Germany, 2003.

Grein, F.G.; Wiedemann, J., "Prospects of foresight in driver assistance systems", 5th International Stuttgart Symposium. Expert-Verlag Renningen-Malmsheim, p. 628-642, 2003.

Abel, B.; Labahn, N., "Praedikative Steuerung dynamischen Kurvenlichtsysteme", VDI-Bericht: Elektronik im Kraftfahrzeug. VDI-Verlag Duesseldorf, no. 1547, 2000.

Schraut, M., "Umgebungserfassung auf Basis lernender digitaler Karten zur vorausschauenden Konditionierung von Fahrerassistenzsystemen", PhD Thesis. University of Munich, Germany, 2000.

Carlsson, A.; Baumann, G.; Reuss, H.-C., "Implementation of a Self-Learning Route Memory for Forward-Looking Driving", SAE World Congress. Detroit, USA, 2008.

Riemer, T.; Mauk, T.; Reuss, H.-C., "Determination of saving potential for a parallelhybrid powertrain using preview information", 8th International Stuttgart Symposium. Stuttgart, Germany, 2008

Carlsson, A.; "A system for the provision and management of route characteristic information to facilitate predictive driving strategies", PhD Thesis, Universität Stuttgart, Germany, 2008

THE AUTHORS

Dr.-Ing. Anne Piegsa

is employed at the Chair of Automotive Mechatronics since September 2003 with the work focus on assistance systems for improved fuel efficiency. Since 2008 she is managing the VALIDATE project at the institute. In 2008, Anne Piegsa received her PhD and has, as a native Swede, studied Engineering Physics at University of Uppsala, Sweden.

Prof. Dr.-Ing. Hans-Christian Reuss

see page 6 – Intelligente Fahrzeuge – Einleitung

Contact
Institut für Verbrennungsmotoren und Kraftfahrwesen (IVK)
Universität Stuttgart, Pfaffenwaldring 12, 70569 Stuttgart, Tel. 0711/685-68501, Fax 0711/685-68533
E-Mail: hans-christian.reuss@ivk.uni-stuttgart.de, http://www.ivk.uni-stuttgart.de/IVK/, http://www.fkfs.de