Fuel efficiency driver assistance system for manufacturer independent solutions

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Abstract— **Energy efficiency has become a major issue in modern trade, business and environmental perception. While the next generation of zero emission propulsion systems are still under development, it is already possible to increase fuel efficiency in regular vehicles by applying a more fuel efficient driving behaviour. This particularly holds true for transport companies, where even small percentage savings can accumulate to huge absolute savings. Although there are common fuel efficiency guidelines, they are often imprecise and not adapted to a specific vehicle. Furthermore drivers may not even know the fuel efficiency rules or lack the motivation to apply them in practice. In this paper, an online driving assistance system is presented that assist drivers during their journeys by giving them fuel efficiency guidelines that are suited for the current situation and vehicle. The driver assistance system uses an internal manufacturer independent model that can adapt to the current vehicle solely based on online CAN-Bus data.**

I. INTRODUCTION

Several authors have published solutions in the area of fuel efficient driving. The approaches range from complete vehicle control to passive driver assistance systems. Active approaches include the works of [1] [2] [3]. They are usually manufacturer specific due to the necessity of solid knowledge about the vehicle. Topology height maps and exterior sensors (e.g. radar and camera systems) are used to allow model predictive approaches. In contrast to active approaches, passive driver assistance systems only send audiovisual or other information to the driver so that he or she can follow the proposed guideline to his or her best ability [4]. They do not necessarily rely on complete vehicle models and only concentrate on the present situation. More rudimentary passive systems can be found among smartphone apps which only warn the driver of excessive acceleration and braking [5] [6] based on basic device internal sensors. The driver assistance system proposed in this paper is a passive system. It is an integral part of a larger fleet management assistance system called EXPERT (EXPert System for a more Efficient Road Transportation). The system is primarily designed for freight forwarding companies which want to improve the fuel and cost efficiency of their fleet. The functionality ranges from fleet management support to individual driver assistance. The latter will be the main focus of this paper. Different to model dependent and therefore often manufacturer specific approaches, EXPERT will be applicable to a great variety of vehicles due to an internal online multivariable adaptive partial power train model, which at the same time takes more vehicle specific characteristics into account than e.g. smartphone app approaches. The computations are done in the on-board EXPERT components within every individual vehicle. The adaptive model is then used in an optimization routine that can generate fuel efficient guidelines depending on the current vehicle and the current state. Because no height maps, slope information, object detection, traffic light information, speed limit information or route information is available, the system identification and the fuel efficiency guideline generation is solely based on CAN-Bus data. Fuel efficient route selection is not the topic of this paper, but rather the assistance of the driver during actual driving.

II. EXPERT SYSTEM

The EXPERT system is primarily designed for freight forwarding companies, which want to keep track of their fleet and increase the fuel efficiency of their drivers. An overview of the system is given in figure 1. From the figure the reader can see that EXPERT is a collaboration of different components. The ”EXPERT Information System” is a fleet management system, which resides at the management headquarters and communicates with vehicles within the fleet via the ”Green Box”. The ”Green Box” is the main communication hub of every EXPERT assisted vehicle that enables the communication of all other EXPERT hardware components. It is installed into every vehicle’s cabin. One of its most important tasks is to relay the current CAN-Bus information to other systems. CAN-Bus information in trucks is specified according to SAE J1939 [7]. But since manufacturers sometimes do not exactly comply with all specification standards, only a limited amount of CAN-Bus information can be used in EXPERT that can be expected to be valid for most vehicles. The CAN-Bus data used in EXPERT consists of vehicle velocity, fuel consumption rate, gear level, brake switch, clutch switch, engine speed, engine torque, acceleration pedal position, vehicle ID and driver ID. The different CAN-Bus messages have different update rates which range from 5 Hz (e.g. gear level) to 100 Hz (e.g. engine speed) and are synchronized according to the update rate of the assistance system (e.g. 1 Hz). Apart from the ”Green Box”, a HMI device (e.g. a tablet computer) is assigned to every driver of the fleet. It can be fixed to the dashboard of each vehicle. The HMI device contains the ”Driving Efficiency Module” software developed by Fraunhofer IOSB, which will be the main focus of this paper. The ”Driving Efficiency Module” (see figure 1) consists of an adaptive model and an optimization sub-module, which

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generates fuel efficient driving guidelines for the driver. These guidelines are relayed to the "Co-Pilot", which will display the information on the HMI device through numbers, colors and acoustic hints. During operation, the driver retains full control of the vehicle at all times. When the delivery is executed, the driver can unplug the HMI device and start with a new assignment in a different vehicle. There

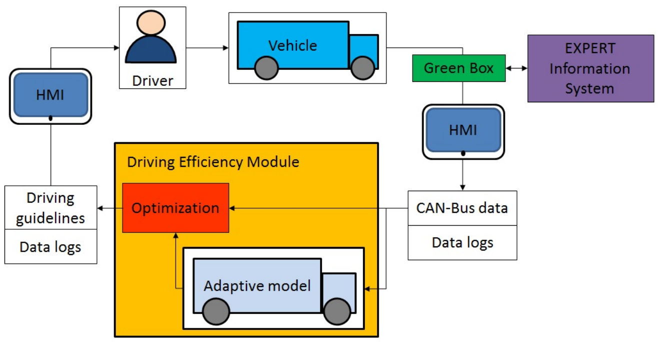

Fig. 1. EXPERT system overview

are currently several technical and economic constraints imposed on the EXPERT system. First of all, routes and position dependent velocity limits cannot always be provided by fleet headquarters. Furthermore, it can generally not be expected that the vehicles using EXPERT possess advanced object detection sensors like radar or camera systems. This makes velocity dependent guidelines difficult to implement in practice. Precise height maps are usually subject to fees [8] and free of charge height maps have a low resolution [9]. Therefore model predictive strategies [1] [2] are also infeasible. The strategies used in the "Driving Efficiency Module" instead will be explained in the upcoming sections.

III. ADAPTIVE PARTIAL POWER TRAIN MODEL

Due to the complex interaction of internal and external propelling and resistant forces in the different vehicle components, it is necessary to simplify the vehicle to obtain a unified model with a small amount of unknown parameters that can be adapted online and used for a great variety of different vehicles. For the purpose of EXPERT, the proposed power train model (see figure 2) is a static partial model of the vehicle's power train, which puts its focus on the current situation. It only contains an engine and a transmission model that additionally draws information from vehicle speed. In case of a vehicle with automatic transmission, only the engine is modelled. Vehicle internal slip and vehicle internal friction of any kind are neglected, because necessary measurements to estimate internal inertia and friction of the various components are not available. External resistance forces are also neglected. The reason for this type of partial model formulation is that due to the previously stated system constraints, the "Driving Efficiency Module" will not suggest precise velocity or acceleration pedal values to the driver or anticipate his or her behaviour (see section IV for further details). With the given constraints, model predictive approaches or long integration horizons are generally infeasible.

The transmission model is described by the static transmis-

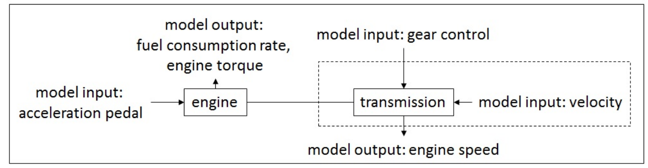

Fig. 2. Partial power train formulation with most important input and output signals after model adaptation

sion ratio $i_t(G)$ depending on the selected gear level G. It enables the estimation of the engine speed ω_e depending on the vehicle velocity v and vice versa. Internal inertia and clutch dynamics are neglected. Thus, measurement samples during gear shifts and open clutches are not used for estimation. The transmission ratio is the ratio of the input transmission rotation speed $\omega_{t,in}$ and the output transmission rotation speed $\omega_{t,out}$. Note that $\omega_{t,in}$ is assumed to be equivalent to the engine speed. The transmission ratio estimation is given in (1).

$$i_t(G) = \frac{\omega_{t,in}}{\omega_{t,out}} = \frac{\omega_e}{\omega_{t,out}} \quad (1)$$

$\omega_{t,out}$ is calculated from the current vehicle speed v and divided by the wheel radius r_w. If the wheel radius is unknown, it can be set to any positive non-zero value because the relation between vehicle speed and engine speed will still remain the same.

$$v = \omega_{t,out} r_w \quad (2)$$

The online calculated raw ratios are collected for each observed gear level category and saved in a corresponding ring buffer. In each category, the distribution of the ratios is estimated. If the standard deviation decreases below a certain threshold (design parameter), the raw ratio collection for the gear level is deemed as trustworthy. The ratio of this gear level category is then estimated as the median of the hitherto saved data. The estimation is updated every second. If the internal ring buffers are full, the new estimation update is set to the average of the current estimation and the previous estimation. Finally, a decreasing exponential function is fitted through the trustworthy medians to retrieve estimates for all gear levels.

The engine model is described by an engine torque map and a fuel consumption rate map. The fuel consumption rate map is defined as a polynomial of low degree (e.g. first to third degree). It depends on engine torque T_e and engine speed ω_e [10]. The equation is stated in (3). The polynomial coefficients are estimated using equality constrained least squares. The equality constraints enforce the expectation that if the engine speed is zero, the fuel consumption rate is also zero. The estimation primarily requires fuel consumption rate $\frac{dV_{fuel}}{dt}$, engine speed ω_e and engine torque information T_e from the CAN-Bus. Additionally, status information about clutch and gear level G are needed, because measurements during the transient gear shift process are not regarded.

$$\frac{dV_{fuel}}{dt} = a_0 + a_1 T_e + a_2 \omega_e + ... + a_M T_e^N \omega_e^N \quad (3)$$

The engine torque map is dependent on the acceleration pedal position u and engine speed ω_e [11]. It is initially described by a polynomial of low order if only sparse CAN-Bus data is available. This case typically arises if the "Driving Efficiency Module" is confronted with a new vehicle. As large data sets become available, e.g. collected over several hours, the characteristic map changes to a three segment spline $S(u, \omega_e)$ approximation. The segments are divided at certain acceleration pedal values, where significant changes in appearance are expected (e.g. at $u = 20\%$ and $u = 80\%$). Thus, the spline segments can use different types of polynomials to account for local engine torque map characteristics. The spline estimation is partitioned into three steps. Before the estimation can begin, a histogram test is performed to discard outliers. After the histogram test, a parabola shaped full load curve is estimated using engine torque and engine speed data for which $u > 80\%$. From the full load curve's only maximum, the torque maximizing engine speed $\omega_{e,m}$ can be retrieved. Finally, the spline coefficients are estimated using equality constrained least squares that takes the common spline intersection equality constraints into account [12]. The different polynomials are developed at different operation points: $\omega_{e,m}$, $u_h = 100\%$ and $u_m = 50\%$. All these methods support the reliability of the engine torque map and allow a robust interpolation and extrapolation behaviour within the observed data scope. The three polynomials of the spline are given in equations (4) to (6). The spline is stated in (7). The estimation requires acceleration pedal position, engine speed and engine torque information from the CAN-Bus.

$$P_1(u, \omega_e) = b_0 u^2 \quad (4)$$

$$\begin{aligned} P_2(u, \omega_e) =& c_0 + c_1(u - u_m) + \\ & c_2(\omega_e - \omega_{e,m}) + ... + \\ & c_{15}(u - u_m)^3(\omega_e - \omega_{e,m})^3 \end{aligned} \quad (5)$$

$$\begin{aligned} P_3(u, \omega_e) =& d_0 + d_1(u - u_h)^4 + \\ & d_2(\omega_e - \omega_{e,m})^2 + \\ & d_3(u - u_h)^4(\omega_e - \omega_{e,m})^2 \end{aligned} \quad (6)$$

$$T_e = S(u, \omega_e) = \begin{cases} P_1(u, \omega_e), & u < 20\% \\ P_2(u, \omega_e), & 20\% \leq u \leq 80\% \\ P_3(u, \omega_e), & u > 80\% \end{cases} \quad (7)$$

The estimation of the engine model is deemed as trustworthy when the internal ring buffers are filled. In the current system the buffers are set to a capacity of 30 minutes of valid data. The estimation is updated every second. If the ring buffers are full, the new estimation update is set to the average of the current estimation and the previous estimation. The parameters of the partial power train model components change little over time. Thus, it is beneficial to save the estimation parameters for future journeys. Otherwise, the system has to wait for the completion of the vehicle adaptation at the beginning of every new journey. By calculating the average of the historic parameter estimates and the current estimates, the model adaptation is able to improve over time.

IV. Optimization and fuel efficiency guideline generation

The fuel efficiency guidelines for the driver are calculated from the partial power train model and the current CAN-Bus data. The optimization uses cost function minimization, which penalizes unfavourable driving behaviour. In this paper, an unfavourable driving behaviour is regarded as a driving behaviour that leads to overall high fuel consumption and high attrition to the vehicle. Naturally, not driving at all is the best way to accomplish both goals. But at the same time, excessive deviation from the driver's wishes is also unwanted, which includes long trip duration. All these aspects can be highly contradictory to each other. Thus, the goal is to find an optimal trade-off. Due to the previously stated system constraints, the "Driving Efficiency Module" does not propose a precise set velocity to the driver, but a maximum tolerable acceleration pedal position (comparable to the approach in [4]) that should not be exceeded and two specific gear levels in case of a manual transmission. The maximum tolerable pedal position $u_{max,opt}$ is a trade-off between torque maximization and fuel consumption rate. In most cases, pressing down the acceleration pedal will generate a higher torque and higher vehicle acceleration, but will also lead to a higher fuel consumption rate (see figures 4 and 5 in section V). The inexpediency of a pedal position choice is described by the cost function (8) for the current discrete time-stamp t.

$$C_u(t) = C_{fuel}(t) + C_{torque}(t) + C_{smooth,G}(t, t-1) \quad (8)$$

The first cost term $C_{fuel}(t)$ penalizes the fuel consumption rate. Depending on the current engine speed $\omega_e(t)$ and a possible pedal candidate u_c, an engine torque candidate $T_{ec} = T_e(u_c, \omega_e(t))$ is computed using the estimated torque map (7). The torque candidate and the current engine speed will lead to a fuel consumption rate candidate $\frac{dV_{fuel}(T_{ec}, \omega_e(t))}{dt}$ calculated from the estimated fuel consumption rate map (3). At the same time, a second cost term $C_{torque}(t)$ encourages engine torque maximization to allow necessary vehicle acceleration. Because the two cost terms cannot be directly compared to each other, normalization values need to be introduced. The fuel consumption rate is normalized by a high fuel consumption rate value $\frac{dV_{max}}{dt}$. Naturally, it can be defined as the maximum value ever encountered in the collected CAN-Bus data. But in order to avoid excessive measurement errors or high values that rarely occur, it is beneficial to define the normalization as the sum of the expectation and the standard deviation of the collected fuel consumption rate data set. The normalization of the engine torque $T_{e,max}$ can defined in the same way. Finally a third cost term $C_{smooth,u}$ is added to the two previous cost terms. It serves as a regularization term that penalizes oscillations in the optimization result with the weighting λ_u as a design parameter. The cost terms are stated in (9) to (11).

$$C_{fuel}(t) = \frac{dV_{fuel}(T_{ec}, \omega_e(t))}{dV_{max}} \quad (9)$$

$$C_{torque}(t) = \frac{T_{e,max}}{T_e(u_c, \omega_e(t))} \quad (10)$$

$$C_{smooth,u}(t, t-1) = \lambda_u |u_c - u_{max,opt}(t-1)| \quad (11)$$

The maximum tolerable pedal position $u_{max,opt}(t)$ is the acceleration pedal position candidate u_c of all feasible pedal positions $\mathscr{U} = \{u | 0\% \leq u \leq 100\%\}$ that minimizes (8).

$$u_{max,opt}(t) = arg \min_{u_c \in \mathscr{U}} C_u(t) \quad (12)$$

In case of a manual transmission, two specific gear levels are proposed to the driver in addition to $u_{max,opt}(t)$. The first gear level proposal $G_{opt}(t)$ is a trade-off between fuel consumption and torque maximization, designed for regular driving and acceleration. The second gear level proposal $G_{brake}(t)$ maximizes the braking torque of the engine and is only needed if the driver wants to reduce speed through coasting. It is assumed that the driver can distinguish between the two cases. The calculation of $G_{opt}(t)$ is conducted in two steps. In the first step, two other gear candidates $G_{eco}(t)$ and $G_{torque}(t)$ are calculated. $G_{eco}(t)$ is a gear level that favours low fuel consumption, suitable for coasting or low torque demand situations, e.g. maintaining speed on flat terrain. In this case the gear should be chosen as high as possible. $G_{torque}(t)$ is a gear level that favours torque maximization, suitable during acceleration and hill climbing. The corresponding engine speed can be calculated from the torque map (7) and the current pedal position. In a second step, a cost function $C_{GG}(t)$ is defined as the weighted average of $G_{eco}(t)$ and $G_{torque}(t)$. The weighting is simply the current acceleration pedal position $u(t)$ ranging from 0 to 1. It is assumed that $u(t)$ is consistent with the driver's torque demand. A low pedal position will favour $G_{eco}(t)$ while a high pedal position will favour $G_{torque}(t)$.

$$\begin{aligned} C_{GG}(t) =& (1 - u(t)) |G_c - G_{eco}(t)| + \\ & u(t) |G_c - G_{torque}(t)| \end{aligned} \quad (13)$$

Finally, a temporal regularization term $C_{dG}(t, t-1)$ is added to avoid possible oscillations in the optimal solution. t_{shift} is the time stamp of the previous change in the G_{opt} solution. λ_G is a weighting value that describes the length of the time period, in which a change in G_{opt} is regarded as early (e.g. 2 seconds).

$$\begin{aligned} C_G(t) =& C_{GG}(t) + \\ & \begin{cases} 0, & G_c = G_{opt}(t-1) \\ C_{dG}(t, t-1), & otherwise \end{cases} \end{aligned} \quad (14)$$

$$C_{dG}(t, t-1) = \frac{\lambda_G}{|t - t_{shift}|} \quad (15)$$

The minimization of $C_G(t)$ with respect to all gear level candidates G_c within the feasible set $\mathscr{G}$ yields the optimal gear $G_{opt}(t)$. $\mathscr{G}$ only contains gear levels that do not lead to an engine speed that is lower than the estimated fuel cut-off engine speed $\omega_{e,cut}$ or higher than the estimated maximum engine speed $\omega_{e,max}$.

$$G_{opt}(t) = arg \min_{G_c \in \mathscr{G}} C_G(t) \quad (16)$$

The second gear proposal G_{brake} favours the lowest feasible gear level.

$$G_{brake}(t) = arg \min_{G_c \in \mathscr{G}} |G_c - \min\{\mathscr{G}\}| + C_{dG}(t, t-1) \quad (17)$$

Because the optimization depends on the current acceleration pedal position, short-time transient processes (e.g. gear shifts) must be additionally detected. In these scenarios the previous results are maintained. Apart from the previously discussed primary guidelines, the driver will be additionally notified to switch off the engine during idling phases and to coast instead of braking if the brake pedal is pressed. In autonomously controlled systems [1] [2], different optimization variables can be jointly calculated and applied. In the case of EXPERT, it is uncertain if the driver will apply both guidelines at the same time and it is always uncertain which pedal position will be chosen because only a maximum pedal position is suggested. Thus, the pedal optimization and the gear choice optimization are separately performed depending on the current input measurements of the respective cost functions. The optimization problem can be solved with a direct discrete search in real time on a tablet computer device. Although direct searches or enumerations are usually inefficient, consider that if the pedal discretization is set to 1% and the manual transmission has 6 gears, the model is only executed 106 times during optimization. Furthermore, direct searches have the benefit of finding the global minimum of the cost function if discretization is sufficiently subtle. The fuel efficiency guidelines and the model adaptation can be updated with a maximum frequency of at least 1 Hz. It is assumed that higher update rates will overwhelm the driver. The regularization terms assure that the generated guidelines will not excessively fluctuate, so that the driver does not need to constantly check the HMI. It is noted here that there are other characteristic maps that can be used to generate fuel efficiency guidelines, e.g. the specific fuel consumption or efficiency maps. The estimation of these maps has turned out to be challenging on the available test data taken from a real world test drive because the automatic transmission of the test vehicle mostly stayed within a confined operation area. This is also the main reason why neural networks approaches were not used for model adaptation.

V. Results

In this chapter the authors present results based on real world CAN-Bus data and simulated environment. The available CAN-Bus data are records of a truck delivery that stretches over six hours. This data is used to evaluate the performance of model adaptation. The transmission ratio estimation result is shown in figure 3 (top). It has as many as 12 gear levels because the transmission is an automatic transmission. A red interpolation curve shows the smooth and gradual decline of the ratio levels. Using the estimated gear ratios, the engine speed can be predicted depending on the vehicle speed and selected gear. The result on a random sequence is displayed in figure 3 (bottom), which shows that the estimated engine speed can mostly follow the engine speed measurement with slightly stronger deviations during gear shifts, because the transmission model is static.

The estimation result of the engine torque map is displayed in figure 4 (top). The measurement points which remain after the histogram outlier test are illustrated as red circles. Note that the engine torque provided by the CAN-Bus is the torque developed in the cylinders according to SAE J1939 specification [7]. It is therefore never negative. The three segment spline is fitted to the measurement points and shows stable interpolation and extrapolation behaviour. The spline equality constraints have been imposed on eight different support points along the acceleration pedal positions of 20% and 80%. Several outliers from the original measurement collection could not be discarded. But compared to the main measurement point concentration they are only few in numbers. Using the estimated torque map, the engine torque can be estimated. An example is given in figure 4 (bottom). The estimated engine torque qualitatively follows the recorded engine torque signal, but deviations of more than 10% can occur because the engine map is static and is composed of polynomials of low degree in order to avoid instabilities.

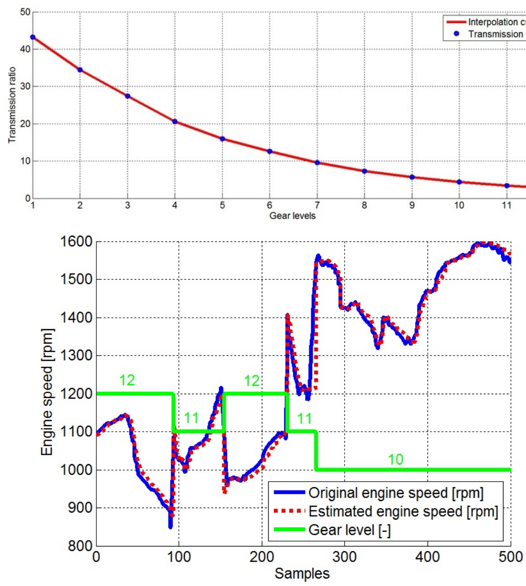

Fig. 3. Transmission ratio estimation (best viewed in color): Estimated transmission ratios (top), Estimated engine speed (bottom)

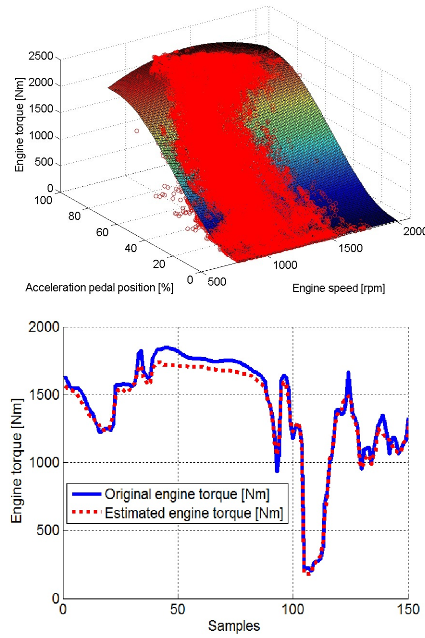

Fig. 4. Estimated engine torque (best viewed in color): Estimated engine torque map (Top), Estimated engine torque compared with CAN-Bus data (Bottom)

The estimation result of the fuel consumption rate map is displayed in figure 5 (top). The original measurement points are illustrated as red circles. A polynomial of third degree is fitted to the measurement points. It shows stable interpolation and extrapolation behaviour. Using the estimated fuel consumption rate map, the fuel consumption rate can be estimated. An example is given in figure 5 (bottom). The estimated fuel consumption rate qualitatively follows the fuel consumption rate measurement. Deviations of more than 10% can occur because the fuel consumption rate map is a static polynomial of third degree.

The effect of the application of the fuel efficiency guidelines has been evaluated within a Matlab/Simulink simulated environment. An example scenario is shown in figure 6. The simulated vehicle has a mass of 4000kg and 5 gear levels. The road topology has a length of 1800m with two hills. The desired travelling speed is $80\frac{km}{h}$. The simulated inexperienced driver is simulated by a PI controller, who shifts gears heuristically depending on certain velocity thresholds (e.g. $10\frac{km}{h}$, $30\frac{km}{h}$, $50\frac{km}{h}$, $70\frac{km}{h}$). In this example, it is apparent that the driver or PI controller makes full use of the maximum control range (acceleration pedal) and tends to remain at a high gear, which sometimes leads to long acceleration phases (0m to 600m). The EXPERT assisted driver does not completely press down the acceleration pedal and sometimes shifts to a lower gear if acceleration is demanded (e.g. 0m to 100m) or if the engine speed is too low (e.g. 1700m to 1800m). In this specific scenario, fuel savings of up to 11% could be achieved by the EXPERT assisted driver compared to the inexperienced driver, who shifts heuristically according to the current vehicle speed. Furthermore, the EXPERT assisted driver had a 2% shorter trip time. Note that in this specific experiment, the inexperienced driver actually shifts up earlier than the EXPERT assisted driver. The commonly known fuel saving guideline of "shifting up early" actually does not apply to all cases. Indeed, engines usually have their highest efficiency at mid-range engine speeds and high torque [10]. Thus, shifting to

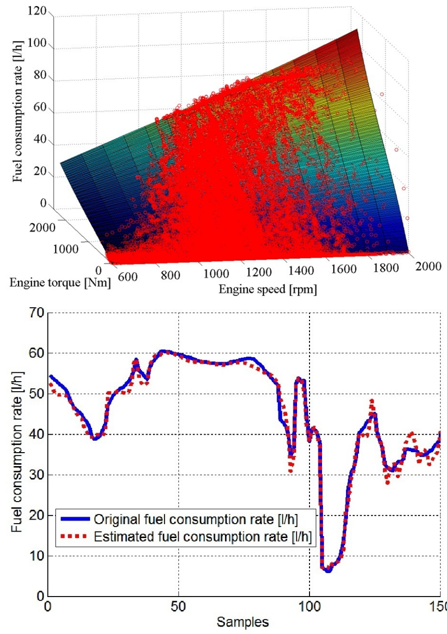

Fig. 5. Estimated fuel rate (best viewed in color): Estimated fuel rate map (Top), Estimated fuel rate compared with CAN-Bus data (Bottom)

a mid-range engine speed during acceleration can actually be more efficient than shifting to a low engine speed. Also note that the fuel savings naturally depend on comparison of scenarios and drivers and may vary from case to case.

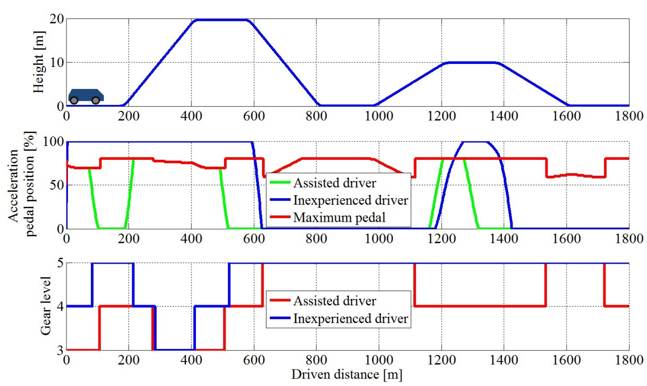

Fig. 6. Effect of fuel efficiency (best viewed in color): Topology (Top), Acceleration pedal position (Center),Gear change (Bottom)

VI. CONCLUSIONS

In this paper, the authors have presented the "Driving Efficiency Module", which is used in the EXPERT system that has also been briefly introduced. One of the main goals of EXPERT is to provide the driver with an online assistance system through the "Driving Efficiency Module", which generates fuel efficiency guidelines to improve fuel economic driving. An online adaptive partial power train model has been presented that can adapt to different vehicles through CAN-Bus data based system identification techniques. The partial power train model only considers a part of the power train, namely the engine and the transmission. The fuel efficiency guidelines primarily consist of a currently sensible maximum acceleration pedal position that should not be exceeded and two gear level proposals in case of a vehicle with manual transmission. The guidelines are obtained from the minimization of a pair of cost functions based on the model and the current CAN-Bus data. This optimization strategy only requires CAN-Bus data and no knowledge of the environment or object detection. Simulations have shown that significant fuel savings can be achieved compared to a driver with little experience in fuel efficiency driving. Future works include the improvement of the simulation framework. The driver simulation will be improved to emulate a more experienced driver. A driving simulator is also currently under construction. With additional CAN-Bus data records from different drivers and vehicles, it may be possible to estimate other types of characteristic maps (e.g. efficiency maps) that lead to a simpler and more precise optimization. Although a complete dynamic vehicle model is currently not used in EXPERT due to system constraints, the estimation of additional unknown vehicle and environment parameters (e.g. vehicle mass) is of great scientific interest. Should advanced information about the environment become available in the future, a model predictive approach would become feasible and the formulation of an adaptive dynamic vehicle model would be of great assistance. The "Driving Efficiency Module" has been implemented in an Java/Android environment and will be installed into several test vehicles. Upcoming field tests incorporating 30 different trucks and different drivers will be conducted over several months to evaluate the performance of EXPERT.

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