Methods to quantify and qualify truck driver performance

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Abstract

Fuel consumption is a major economical component of vehicles, particularly for heavy-duty vehicles. It is dependent on many factors, such as driver and environment, and control over some factors is present, e.g. route, and we can try to optimize others, e.g. driver. The driver is responsible for around 30% of the operational cost for the fleet operator and is therefore important to have efficient drivers as they also influence fuel consumption which is another major cost, amounting to around 40% of vehicle operation. The difference between good and bad drivers can be substantial, depending on the environment, experience and other factors.

In this thesis, two methods are proposed that aim at quantifying and qualifying driver performance of heavy duty vehicles with respect to fuel consumption. The first method, Fuel under Predefined Conditions (FPC), makes use of domain knowledge in order to incorporate effect of factors which are not measured. Due to the complexity of the vehicles, many factors cannot be quantified precisely or even measured, e.g. wind speed and direction, tire pressure. For FPC to be feasible, several assumptions need to be made regarding unmeasured variables. The effect of said unmeasured variables has to be quantified, which is done by defining specific conditions that enable their estimation. Having calculated the effect of unmeasured variables, the contribution of measured variables can be estimated. All the steps are required to be able to calculate the influence of the driver. The second method, Accelerator Pedal Position - Engine Speed (APPES) seeks to qualify driver performance irrespective of the external factors by analyzing driver intention. APPES is a 2D histogram build from the two mentioned signals. Driver performance is expressed, in this case, using features calculated from APPES.

The focus of first method is to quantify fuel consumption, giving us the possibility to estimate driver performance. The second method is more skewed towards qualitative analysis allowing a better understanding of driver decisions and how they affect fuel consumption. Both methods have the ability to give transferable knowledge that can be used to improve driver’s performance or automatic driving systems.
Throughout the thesis and attached articles we show that both methods are able to operate within the specified conditions and achieve the set goal.
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List of publications

The thesis summarizes the following papers:


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Chapter 1
Introduction

Vehicles have evolved over the years to come to where they are today. A vehicle is equipped with many systems and sensors designed to improve performance, increase safety, assist the driver during operation and other functions. Access to information about location, speed limit on the road and so on are readily available to driver and others that can connect to the vehicle. With the increase in available data, questions related to traffic safety and efficiency have gotten more attention.

We ask how can we quantify and qualify driver performance with respect to fuel consumption. Quantitatively we refer to the amount of fuel used compared to an optimal value given current status of vehicle and environment. Qualitatively, we understand the categorization of drivers and driver actions into categories depicting performance and style, e.g. aggressive (high variation in speed and acceleration pedal), normal (majority of drivers), safe (vehicle speed lower than speed limit, higher inter-vehicle distance). One challenge is the accurate estimation of best fuel consumption in naturalistic driving conditions. This is a result, mainly, of incomplete information in the form of missing or unmeasured variables. We work with data coming from naturalistic driving in Europe, and therefore we set the frame for our work in this context.

Vehicle speed is the main indicator from which we extract information regarding driver behavior and performance. For trucks, there are limitations for vehicle speed, coming from manufacturers and roads. This is important as it affects driver, especially drivers operating under a tight schedule, since they cannot drive faster to recuperate time lost due to traffic, for example.

Fuel is important as it influences the economical part of the transport but also affects environment, which leads to an ever increasing demand for reductions in fuel usage. This can be done through designing better vehicles and improving driving. In this work, we aim at estimating the performance of drivers operating under different conditions.
1.1 Motivation

We use transportation every day, be it for goods or persons and there are three ways we can do this: air, land or sea. The freight transportation among various regions in Europe is mostly done by land, at about 75% \[1\]. This mode of transportation can be considered a complex, partially observable system, with the two major components being the vehicle and the driver. We can look at this system from various points of view. We can also define performance in terms of energy used, safety, reliability and so on, and in our work we approach the problem of performance in terms of energy used.

Route optimization for transportation, vehicle and driver performance, have become tasks that receive more attention with the increase in data collection. Data collection has had a very rapid growth in the recent years with many reasons behind it, like increased storage capacity, cloud storage \[2\], increased computing capabilities, e.g. computer clusters \[3\]. With increased data collection, a number of new opportunities arise in form of the big data, a change in how data mining is approached and in general new scalable methods to deal with the increased complexity and quantity of data. The increasing amount of data being collected changed and will continue to change how companies approach their business.

The main indicator for driver performance, from energy point of view, is fuel consumption which is generally expressed in liters per 100 kilometers [L/100 km]. Comparing this value would include bias towards, for example, light vehicles traveling on mostly flat terrain. This is primarily a result of weight being major contributor to fuel consumption. Then one goal is to reduce or eliminate the bias due to weight and other factors for which the driver is not responsible.

1.2 Data

Throughout the work, we make use of data collected by Volvo Group Trucks Technology (VTT). The data is coming from two separate projects sharing many characteristics, but also with some unique features. Firstly, it was collected during EuroFOT project \[4\] in which VTT was a partner. During this three year project more than 50 thousands trips were recorded from several trucks driving across Europe in all seasons and conditions. The data is recorded at 10 Hz and contains information collected from a variety of sensors that describe the operation of the vehicle, such as vehicle speed, gear, engine speed, pedals positions, oil temperature, as well some information regarding the environment, like location, temperature, pressure and so on. The data is also enriched using offline databases, e.g. using GPS locations to retrieve road altitude profile.
1.3 Proposed methods

The proposed methods approach the problem with different strengths. FPC advantage is the more accurate estimation of driver performance while APPES explain it better and provides intuitive solutions to use the knowledge gained.

FPC

FPC is a feature that represents fuel consumption under specific conditions. The conditions are chosen with the goal of separating the effect of the variable of interest, i.e., driver, from other variables. We do not take into account other variables that are impacting vehicle performance and are due to driver, e.g., lateral acceleration, in-cabin electronics. FPC can achieve this separation by making use of domain knowledge to compute the effect of unmeasured or unknown factors, which is possible during certain situations, thus predefined conditions. The predefined conditions are selected based on domain knowledge and the goal, in our case estimation of unmeasured variables which is required for solving our problem of estimating driver performance. We consider changes in speed to represent driver actions. Setting speed to be constant means that, for as long as this condition is fulfilled, the driver is not performing any action. We can then compare the measured fuel consumption with the calculated FPC to get an estimation of the effect of driver.

APPES

APPES is a 2D histogram build from two signals, Accelerator Pedal Position (APP) and Engine Speed (ES). The choice of signals reveals information that is correlated with domain knowledge about driving behavior. The information is observed in the form of prominent regions corresponding to certain values for the selected variables. These regions can be referred to using terms that are understandable by vehicle operation experts and experienced drivers. This is highly relevant as it would allow for fast dissemination of results with no further need for explanation of concepts. We investigate two aspects regarding APPES:
the amount of time spent in each region and how the regions interact. One way to estimate driver performance is by correlating the amount of time spent in each region with variables of interest, i.e. fuel consumption. The interaction between regions provides insight into how the vehicle is operated and how it behaves while containing information about driver actions.

1.4 Goals, research questions and contributions

Project Goals

The main goal of this project is to provide robust methods or features that are able to provide a performance index for drivers. By robust we mean that they should not be dependent on vehicle characteristics or environment. We include in vehicle characteristics aspects such as vehicle type, engine, and so on. Environment is also broad including the type of road the mission takes places, weather conditions, traffic and other. They should work with data recorded in real operations of vehicles and offer the possibility of real-time analysis. This research utilizes data from real operations and it builds knowledge to complement or expand on current state of the art methods.

Methods that use fuel consumption as a metric for driver performance are generally biased towards drivers operating under favorable conditions, e.g. light vehicle load, low traffic. We strive to achieve estimation of driver performance that is expressed independent of other variables.

Research questions

We have set out to investigate driver performance with respect to fuel consumption. Several questions have to be answered before we can answer the question of how good a driver is. We have to recognize that drivers operate in different environment and therefore a method or feature that eliminates the differences, when comparing drivers, is needed. Then one question is “How can we provide a measure for performance or performance indicator that is independent of other variables?” We mean that the same driver should receive the same performance score irrespective of what kind of vehicle he or she operates and any other variables.

The ability to learn from our methods is important, and specifically drivers should be able to learn. We want then a method or feature that is capturing the behavior of the driver and associates it with some performance score. Given all of the above, the question is “Can driver performance be quantified and described in a way that can be transferred using some other system, e.g. driver coaching?”.

We talk about fuel consumption as being a performance indicator. It is then important to understand what and how affects fuel, what data we have access to and how can we design methods that are still able to function with
incomplete information regarding the system. The questions is “Can we predict fuel consumption with high enough accuracy when important information is missing?”.

Contributions

The main contribution is to enable the estimation of driver performance in naturalistic driving, which can also work with incomplete data. This contribution consists of two parts, FPC and APPES.

First, an approach that facilitates the use of field knowledge to calculate a regularization factor to be used with naturalistic driver data. The factor, namely FPC, provides the ability to compare driver performance in different environmental conditions and vehicle characteristics.

Second, data transformation of specific relevant signals to cope with the absence of complete knowledge for identification and quantification of driver behavior. The purpose is also to be able to estimate driver performance while not having complete knowledge. We achieve this by identifying the signals which give information regarding driver intent and vehicle operation.

The contributions are listed below with respect to each paper:

**FPC feature**

A new feature that facilitates comparison and estimation of driver performance under partially known conditions. This method makes use of domain knowledge to cope with missing information. [PAPER A].

**New space**

Provides insight into relations between APPES distribution and the performance indicator, namely fuel consumption. Expected correlations have been found as well as counter-intuitive ones, such as time spent in a regions has an inverse expected correlation [PAPER B].

**APPES features**

We introduce new features derived using APPES that will be used for our goals. We show that the features contain relevant information and that the quality of the information is high irrespective of unmeasured important variables, e.g. traffic [PAPER C].

1.5 Methods for problems with incomplete data

In recent years, more and more data is being recorded on vehicles and by other sources. An increase in data means more opportunities for developing new methods, and also an increased need for scalable and robust methods. We employ the data we have available and field knowledge to come up with methods that can overcome some of the challenges presented, e.g. incompleteness
of data, lack of ground truth. Whether this is possible or not depends on the applied field as some conditions have to be met. One condition would be that the relations between variables are known, especially for missing variables. Another condition is that the information, that the missing variables provide, is embedded in other measured variables.

With the goal of quantifying and qualifying driver performance the following conditions are required: the measure used must be able to estimate the effect of both measured and unmeasured relevant variables; be able to identify the occurrences where the driver is the source of changes in fuel consumption;

The system, in our case the vehicle, can be defined in a simple form by equation 1.1

$$m \cdot a = F_i - F_d - F_{rr} - F_p$$  \hspace{1cm} (1.1)

where $m$ is the weight of the vehicle, $a$ its acceleration, $F_i$ is the driving force acting on the direction of movement, $F_d$ is the resistance force due to motion through liquid, i.e. air drag force, $F_{rr}$ is the rolling resistance force while $F_p$ is the potential force resulting from altitude changes of the vehicle.

Using the system described by 1.1 we set to investigate a method that is able to provide unbiased comparison of driver performance under the circumstances given by the recorded data.
Chapter 2
Related work

2.1 Methods for estimating driver performance

State of the art

Driver performance with respect to fuel consumption for heavy-duty vehicles has not seen much public attention. Drivers that use less fuel to perform same tasks are important to have as fuel has both an economical aspect as well as environmental. Furthermore this knowledge can be used to design better autonomous systems for real driving environment.

Fleet management systems (FMS) come with the possibility of estimating driver performance using various methods. One of those systems is called Fleetmatics \[5\] and offers, among other features, reports regarding driver behavior in forms of selected key performance indicators (KPI), e.g. engine idle time, hard braking and acceleration events. Another system is DynaFleet \[6\], developed by Volvo Group and it is mostly used by long haul companies. DynaFleet uses also KPI to perform driver analysis and give reports to the fleet operator. These approaches are based on statistical analysis of the behavior of driver and do not always take into account driver independent conditions. This leads to a discrepancy between reported and the real performance.

As with the FMS, other methods prefer the statistical approach when it comes to driver behavior and performance. With respect to fuel consumption we have, for example, Volvo Trucks I-See \[7\] which is a system that works together with the cruise control system and aims at increased performance by making use of prior knowledge about road topography. This allows the system to have a speed profile that increases performance. A similar method has been also developed by Hellström et al. \[8\].

Another study has been performed by Mensing et al. \[9\] where they perform analysis of vehicle trajectory in order to reduce fuel consumption while maintaining same average speed which leads to, in their study, to a reduction of fuel consumption of up to 16%. Achieving this improvement requires a dif-
different speed profile than that of a normal driver which can lead to disruptions in traffic.

Generally we want drivers to complete their tasks as efficiently as possible. This can be done by providing them with ways to constantly improve. A natural choice for this are systems that analyze on-line and off-line their patterns and extract information in a way that can be understood by drivers. The feedback given to the driver by these systems is general and does not contribute to the development of the driver in an efficient manner. This is mainly caused by the lack of context for the feedback. For example, advising to reduce the alternative behavior of accelerating and braking is not always useful depending on the situation. In a slow moving heavy traffic, that is the expected behavior.

Drivers and replacement systems

Drivers are centers for various areas of interest in the field of automotive industry. Progress is being made in multiple ways for systems that either assist the driver in his task or perform a specific task thus relieving some responsibility from the driver and providing opportunities for other tasks.

One of the more complete systems that take the role of the driver is that of self-driving or autonomous vehicles. Self-driving vehicles aim at taking over the responsibilities of the driver. Many great strides are being done as of now from legislation, see [11], to real driving tests on public roads, such as Google self driving car [11]. These accomplishments could not have been done without innovation to other systems such as Adaptive Cruise Control (ACC) and the newer version of Cooperative Adaptive Cruise Control (CACC) [12], to image processing algorithms and signal processing. All systems have to work together to deliver the autonomous vehicles capable of driving on public roads, together with manned vehicles, pedestrians and other.

Self driving vehicles will have the same job as a driver has today, making sure that the goods and passengers are delivered to destination in an efficient, timely and safe manner. The transition, when it will occur, from a transportation system exclusive to human drivers to a system where all the driving will be automatic will be a slow one as many obstacles are still to be overcome.

However, same as with driver, there are many possible algorithms that could control the vehicle. When talking about performance with respect to fuel consumption, there would still be a need to estimate their performance irrespective of the situation under which they operate.

Furthermore, automatic systems can communicate in near real time which means they also offer the possibility for platoons. A platoon, in transportation, is a group of vehicles that travel in close proximity to each other for the benefit of all vehicles involved. Short inter-vehicle distance is hard to achieve by human drivers as they are acting on the information presented to them by the vehicle ahead, i.e. brake lights turning on signal that the vehicle ahead is braking but it does not provide information regarding the reason for braking.
or the intensity. However automated systems can communicate using some communication media, e.g. wireless, at low latency ensuring a higher degree of safety thus permitting a smaller inter-vehicle distance.

There are different platooning strategies, such as the one developed in SARTRE project \cite{SARTRE} where the lead vehicle is in charge of the whole platoon. They also suggest a business model similar to buses but instead of passengers using the bus for transportation, you would have vehicles joining the platoon. This of course is dependent on vehicles to be able to do automatic driving and that communication or planning are not an issue. From a macro perspective platoons have to be of reasonable length to allow for faster vehicles to overtake them as well provide opportunities for other vehicles to exit highways.

Same as drivers, different platooning strategies have to be evaluated from any number of perspective, one of which is fuel consumption. We argue again that is imperative that the comparison occurs under similar trip characteristics in order to provide a fair assessment of the performance. Similar trip characteristics can be achieved artificially by employing methods that modify the raw data.

Similarly, driver behavior is a strategy employed by the driver to deal with the situation at hand. Various elements present in a driving situation influence driver decisions as well their attention. A lot of thought and research is put into developing ways to detect driver distraction as it affects safety of themselves as well as other traffic participants. Devices such as mobile telephone are well known having a high distraction rate for the driver which leads in many cases to road accidents. Ghazizadeh and Boyle \cite{GhazizadehBoyle} tell us that, in Missouri, the leading cause for accidents, for passenger vehicles is cell phones. When talking about performance of drivers, careful consideration has to be given to other aspects such as this one, road safety. The challenge then is how to identify situations where the driver’s decisions are forced by the current situation due a safety risk and report driver’s performance accordingly.

Calculating driver performance is good but being able to improve drivers or use the knowledge for improving vehicle systems is also very important. This can be done in various ways and it depends on capabilities of the ones doing the implementation and the desired target, e.g. driver, adaptive cruise control. Before deploying any solution, regardless of field, it is usually tested in a controlled environment which in our case are driving simulators. They are able to simulate a variety of vehicles and environments in a reproducible way which allows the study of the effects of the proposed methods at a much lower cost.
Chapter 3
Methodology

We approach the problem from two different angles. One is using domain
knowledge to be able to estimate performance under partially known condi-
tions. This is achieved by identifying variables of importance, separating them
into measured or unmeasured, and developing a model that can take advantage
of domain known relations between the unmeasured variables and measured
ones. For example, one relation is that the air drag force is proportional to
the square of relative speed of vehicle to air, as well as to the frontal area.
The second method represents the information contained in the data using
2D histogram, from which we extract features that can be used to determine
performance and behavior.

3.1 Fuel under Predefined Conditions - FPC

We consider that driver actions are represented by vehicle speed, and con-
sequently acceleration. In the equation (1), we have incomplete information
about \( F_{rr} \) and \( F_d \), in most naturalistic data. The challenge is then how can
unmeasured but relevant variables be modeled.

We propose Fuel under Predefined Conditions, with primary purpose of
equalizing unknown or unmeasured variables for comparison of driver perfor-
mance. We continue by explaining the rationale behind FPC and the steps
required.

As mentioned, our main indicator for driver performance is fuel consump-
tion which is expressed in liters per 100 kilometers [L/100 km]. We could look
at this value and compare drivers but it would include bias towards light vehi-
cles traveling on mostly flat terrain. This is primarily a result of weight which
is a major contributor to fuel consumption. Our goal is then to reduce or
eliminate the bias due to weight and other factors for which the driver is not
responsible.

The first step is to understand how the system works and for this we use
domain knowledge. For example, we know that resistance forces are added,
like in equation 3.1. We also know that air drag is dependent on the square of speed \((v^2)\), which means that this force is more important at higher speed. Since most of our vehicles are on driving on highway, about 90% of data, air drag is highly relevant. By choosing segments with constant speed and making the assumption that wind is changing slowly or rare and abrupt, we essentially have constant air drag. This can be used as a reference value for comparison of later segments.

Our data includes fuel consumption, which is the variable we use to quantify driver performance. We choose to use a top-down approach where the measured fuel consumption is the sum of the effect of all variables. We want to split the fuel consumption into parts representing the driver, measured and unmeasured factors.

Segments where vehicle speed is constant, is equivalent to driver having no influence over fuel consumption while the effect of other variables is constant. Then, fuel consumption where vehicle speed is constant represents the cumulative effect of measured and unmeasured variables. Not only that, but based on equation 3.1 and 3.2, assuming outdoor conditions are constant, both air drag and rolling resistance are constant. However it is important to note that there are implied assumption without which FPC would lose meaning. We assume that the values of certain variables do not change rapidly or even that they remain constant. Example variables include wind speed and direction, traffic, road pavement, etc.

\[
F_d = \frac{1}{2} C_d \rho v^2 A
\]  (3.1)

where \(C_d\) is the drag coefficient, \(\rho\) is fluid density, \(v\) is vehicle speed, \(A\) is the frontal contact area of the vehicle with the fluid (air).

\[
F_{rr} = C_{rr} N
\]  (3.2)

where \(C_{rr}\) is the rolling resistance coefficient and \(N\) is the normal force.

FPC is calculated using equation 3.3, where \(s_0\) is the segment for which we calculate FPC, \(N\) is the length of the segment \(s_0\), \(fc(t)\) is the fuel consumption at time \(t\). The length of \(s_0\) has been chosen experimentally and values between 120 and 240 seconds perform similarly.

\[
FPC(s_0) = \frac{1}{N} \sum_{t=1}^{N} fc(t)
\]  (3.3)

By computing the difference from future measured fuel consumption to the calculated FPC we can estimate the relative effect of other variables, e.g. driver. Comparing consecutive FPCs also allows for quality analysis of the feature and validation of our assumptions. After calculating FPC we can then compute driver performance as given by equation 3.4. The length of the segment can vary from 1 sample (0.1 sec) up to the remainder of the trip.
However, there is still a variable with major effect on fuel consumption, road gradient. If we compute $P$ for long duration, the effect of road gradient is diminished but the same is not true for shorter duration segments.

\[ P = \frac{FC(s)}{FPC(s_0)} \tag{3.4} \]

An investigation of the relation between road gradient and fuel consumption reveals that a linear relation exists between them that is also weight dependent. This relation can be seen in figure 3.1. We have access to both an estimation of the weight and road gradient, and therefore we can calculate the effect of road gradient using a linear model. By removing the effect of road gradient from the measured fuel consumption, we set the road gradient for the chosen segment to 0, transforming to an artificial flat road. This improves the driver performance calculation significantly and we can use equation 3.5 to compute it, where $RGM(s)$ is the effect of the road gradient.

\[ P = \frac{FC(s) - RGM(s)}{FPC(s_0)} \tag{3.5} \]

### 3.2 APPES

**Histograms**

A histogram is a representation of the probability distribution of the data, in our case time series recorded on-board vehicle. Calculating the histogram is well defined and requires the selection of variables to be used. The parameters required is the range of the variables and number of bins. Histograms give an overview of the density of the underlying distribution of the data.
number of variables used to calculate it determines the dimensionality of the histogram. Histograms can be used to highlight interesting aspects of the data or relations between variables.

Variable selection

We select the signals to use based on our goals, which are to quantify and qualify driver performance, and on domain. For this task, we are inspired by Guo et al. [15], where they used accelerator pedal position and engine speed to calculate a histogram. In this histogram, they associate then areas which correspond to desired behavior, in terms of efficiency. We select the same signals to build upon. One of the major differences is that we have vehicles with automatic gearbox instead of manual which affects the distribution of ES variable and consequently the significance of each area inside APPES. Generally, the signals selected are based on domain knowledge and they are the ones that have a direct connection with the goal.

Data representation using APPES

APPES presents regions of interest that are relevant to our goals of classifying driver behavior. The most prominent regions represent certain types of well defined actions. Figure 3.2 is one example of how the distribution looks like. We identify four major regions present, e.g. full throttle, coasting, neutral and active driving. The regions correspond to areas of the histogram that are clearly identifiable. Each region has certain characteristics that define it. For example, neutral, is the region associated with low engine speed and accelerator pedal is not pressed. The regions are important as they can be used to convey results to non-experts and have an intuitive understanding.
3.2. APPES

Histograms can be normalized to resemble probability distribution, and together with defining regions of interest, we propose to use the probability of each region as a characteristic for a better understanding of how each region connects to driver behavior and performance.

We emphasize that the prominent regions are highly relevant and it is important to have a mathematical representation for them. For our work we choose Gaussian Mixture Model (GMM) as it offers both crisp and fuzzy region delimitation. We can then use the time spent in each region as features for the task of estimating driver performance.

Transitions and Patterns

We also propose that the original data can be represented symbols, where each symbol is associated with one of the regions in APPES, regions that are modeled using GMM. A trip can then be represented by a series of symbols. We define transitions as the event of moving from one region to another. To reduce the complexity of this representation we remove self-transitions, i.e. we remove the edges that connect the same region, thus leading to a representation with no consecutive identical symbols. Transitions provide information with respect to how each region is connected to others and how drivers operate in the space defined by APPES.

Naturally, the next step is to analyze how a sequence of transitions, which we define as an APPES pattern, further referred as just pattern, can be used for driver categorization and assessment of performance. We focus our attention on those patterns that have a high occurrence rate. The motivation to look for frequent pattern has to do with applicability. Finding patterns that define a good or bad behavior is obviously a desired outcome but it is important to find those patterns more often than rare. The number of patterns that exist is vast and grows exponentially with the length of the pattern. Each pattern has a minimum length of 2, i.e. it should include at least 1 non self-transition and no defined maximum length but bounded by the representation of the trip.

Estimating driver performance

By classifying patterns based on their effect on fuel consumption we can also use them to create a driver profile. This profile can then be used for estimation of driver performance. Furthermore, driver performance can be tracked and observations can be made with respect to changes in behavior that affect performance. This can also be correlated with outside factors that interact with the driver, such as driver coaching.
Chapter 4
Summary of Papers

In this chapter we present a summary of the appended papers. We start with FPC proposed in paper A, followed by paper B and C where we present the APPES method. As stated, all the work is done using naturalistic driving data.

4.1 Paper A

Title: Learning of aggregate features for comparing drivers based on naturalistic data.

In this paper we propose a new feature, namely *Fuel under Predefined Conditions*, to allow comparison of drivers, operating under different conditions, from fuel consumption point of view. The main motivation for this method is that not all variables, that are important, are measured and this leads to biased performance estimates.

Based on equation 1.1 and domain knowledge, we introduce *Fuel under Predefined Conditions (FPC)*. FPC is possible due to some key assumptions. One of them is that variables, e.g. wind, pavement, change at a low frequency, i.e. wind speed and direction do not change significantly during a short period of time.

As the name suggests, FPC must be measured under specific conditions which are chosen based on the available data and our goal of being able to compare performance under similar conditions. Equation 3.3 calculates FPC for a trip segment that fulfills the required conditions.

We analyze two aspects of FPC, reliability and stability. We also investigate its capability of correctly estimating driver performance based on how the vehicle is operated, and have no or reduce influence from other factors, e.g. vehicle load, road topology. Reliability refers to how often can we calculate FPC, given the set of conditions chosen, for a trip. The major implication being that with less frequent FPC, our assumptions regarding unmeasured variables are less likely to hold. Stability analysis looks at how stable multiple
FPCs for a trips are, i.e. how big is the standard deviation. This is one step in validating our assumptions with respect to a low change frequency for the variables that are included in FPC. This analysis shows that the method is usable and reliable under normal operating conditions.

\[ P(s) = \frac{FC(s)}{\text{FPC}(s_0)} \]  

where FC and P are the fuel consumption and performance score respectively for segment s, while \( s_0 \) is the segment for which FPC was calculated and always before s.

We also show that FPC is able to give similar performance rating, defined by \( P \), to drivers with similar behavior. By similar behavior, in this case, we meant that the speed profile of the drivers is similar. These results also validate that our assumptions regarding unmeasured variables are sound as we expect this kind of result. Figure 4.1 illustrates four selected segments with four different drivers. Three of the four drivers have the same speed profile. Using the measured fuel consumption would give incorrect results as it would give better score to driver with the dissimilar speed profile then one of the three with similar behavior. This is due to the fact that the influence of unmeasured factors is greater than the deviation that occurs when driving with different speed profile. FPC is able to capture the extra fuel used which was not caused by driver and correctly rank the drivers.

This approach enables the estimation of driver performance, when they operate in different conditions. By rearranging factors that affect fuel consumption, we show how to perform estimates of performance, with reduced bias, among trips. This also provides opportunities for separating the effect of driver from other variables.

4.2 Paper B

Title: *APPES maps as tools for quantifying performance of truck drivers.*

In this paper we propose the APPES space for describing and quantifying driver performance with easy to understand features. The method aims at
providing features that can be used to represent driver behavior and how it relates to fuel consumption.

APPES is a 2D histogram built from two signals, accelerator pedal and engine speed. We use the two signals based on domain knowledge which tells us that accelerator pedal is one of the important variables that is directly connected to driver behavior. Engine speed contains information pertinent to vehicle state. APPES exhibits regions of significance that have an intuitive correlation with known driving styles. We used a GMM with 4 components to represent each region.

The method looks at time spent in prominent regions found in the APPES map and how it relates to fuel consumption. We base this on the premise that spending time in some region is desirable. We find interesting relations, both expected and unexpected, between time spent in a given region and fuel consumption. For example, the region identified as “Neutral” has a positive correlation with fuel consumption, which is to be expected. On the other hand, time spent in “Driving” has a negative correlation with fuel consumption, which is unexpected as this region does not occur at constant speed which is generally acknowledged to be the most efficient driving style.

Initial analysis reveal that APPES can be used to determine driving performance by performing analysis on, in this case, the amount of time spent in each region. This is a building step for PAPER C where we expand APPES by adding other signals, e.g. brake pedal.

4.3 Paper C

This paper continues the work we started in PAPER B by extending APPES and introducing new features. In this paper we investigate how can they be used for classification of drivers. Characteristics such as reliability and stability were also analyzed to determine the usefulness of these new features.

We use APPES regions to symbolize the data. A GMM with 6 components has been used to represent APPES and symbolize the data from the original space. This is further extended by adding “Brake Pedal” and “Cruise Control” signals. We introduce the following features: transitions and patterns. Transitions represent the order in which symbols follow each other, while patterns are a sequence of transitions. We look at how patterns are connected to fuel consumption in order to determine whether they can be used to classify driver’s performance.

We perform experiments in order to determine the usefulness of patterns. We used different models to predict fuel consumption and compared them to existing literature and reference models. We find that patterns are robust and perform well with SVM.

APPES patterns can provide a compact way of representing the data while maintaining relevant information for driver classification.
Chapter 5
Conclusions and Future Work

5.1 Conclusions

FPC method makes use of domain knowledge to estimate the effect of unmeasured factors in order to separate them from driver. This is done by assuming certain characteristics for them, e.g. road pavement and tire pressure are constant for the immediate future. As the goal of this method is to estimate driver performance we do not need to be able to predict fuel consumption but extract the effect of the driver. To do this, we find, in our data, segments that fulfill certain conditions that enable the separation of effects for future segments. In other words, the data gives us the prediction for current conditions where driver effect is non-existent, which is then used to quantify the effect of driver in the following data. We show that our proposed method, FPC, gives the same score to drivers with similar speed profile, independent of outside conditions, while it is also able to give different score to drivers with other speed profile.

Furthermore, we propose APPES as an alternative representation of the data, with the added benefit of being intuitive and easy to understand by non-experts in the field. APPES is build from signals selected to encode information relevant to our goals. We choose to include signals indicative of driver behavior and vehicle operation. We build upon APPES by introducing novel features used to explain and classify driver behavior. The features can also be used for knowledge transfer, i.e. they represent driver actions and we can use beneficial patterns to train new drivers or design automated systems. We successfully show that patterns, specifically, can be used for our goal by detailed analysis of the relation to fuel consumption.

This thesis investigates the classification of drivers based on information collected on-board heavy duty vehicles in normal operation. FPC successfully quantifies the effect of driver, while we show that APPES contains the information required to classify drivers. The contributions of this thesis and appended papers include:
a) Proposed a method that makes use of domain knowledge to estimate the effect of unmeasured variables. This allows us to separate the effect of the driver and compare drivers operating under different conditions.

b) An intuitive representation, APPES, that encodes the information about driver and vehicle operation in its characteristics.

c) New features, patterns, to be used for classification of driver actions, and implicitly behavior.

5.2 Future Work

The goal is to estimate driver performance, in terms of fuel consumption, independent of other variables. In reality, this task is difficult due to the inability of directly validating the results. Specifically, FPC covers the majority of our data that is collected on highway, at high speed, but would not work very well in an urban environment due to one of the conditions, namely constant vehicle speed. Then, future work includes generalizing FPC to work in more varied environment. There are also special situations under which FPC does not fully eliminate bias. For example, climbing a steep hill will result in shifting the gear down for heavier vehicles, which results in worse performance, with no driver fault. Creating FPC profile for vehicles can be useful for detecting faults related to fuel consumptions, such as miss-firing cylinders.

APPES currently investigates frequent patterns and a topic for future work includes a similarity measure between patterns. This is relevant for determining an importance level for each pattern to be used instead of the we currently use, frequency. This will allow for less frequent but important patterns to have a higher impact on driver score as for the most part of a trip, drivers are using cruise control which has no effect over their performance score. Also, we aim at investigating patterns using fuzzy symbols as opposed to the current definition which uses well defined regions associated with a symbol. Furthermore, a better understanding of how patterns change in response to environmental condition. Create a driver profile, i.e. how consistent a driver is or how well it performs operating under specific situations, explained, in this case, in terms of patterns. This can be useful when a driver transitions from driving in a specific environment, e.g. low traffic, mostly flat road, to another kind of environment, e.g. high traffic, hilly roads.

Generalization of the methods to be applied to different fields and different environmental conditions is also one topic of future research. Our data comes from long haul trucks which rarely operate within a city. In this context, we want to investigate how can we apply our methods to vehicles operating in an environment like that as well as how it can be used for passenger cars and public transportation vehicles, e.g. buses.
References


REFERENCES


Learning of aggregate features for comparing drivers based on naturalistic data

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Learning of aggregate features for comparing drivers based on naturalistic data

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Abstract—Fuel used by heavy duty trucks is a major cost for logistics companies, and therefore improvements in this area are highly desired. Many of the factors that influence fuel consumption, such as the road type, vehicle configuration or external environment, are difficult to influence. One of the most under-explored ways to lower the costs is training and incentivizing drivers. However, today it is difficult to measure driver performance in a comprehensive way outside of controlled, experimental setting.

This paper proposes a machine learning methodology for quantifying and qualifying driver performance, with respect to fuel consumption, that is suitable for naturalistic driving situations. The approach is a knowledge-based feature extraction technique, constructing a normalizing fuel consumption value denoted Fuel under Predefined Conditions (FPC), which captures the effect of factors that are relevant but are not measured directly.

The FPC, together with information available from truck sensors, is then compared against the actual fuel used on a given road segment, quantifying the effects associated with driver behavior or other variables of interest. We show that raw fuel consumption is a biased measure of driver performance, being heavily influenced by other factors such as high load or adversary weather conditions, and that using FPC leads to more accurate results. In this paper we also show evaluation the proposed method using large-scale, real-world, naturalistic database of heavy-duty vehicle operation.

I. INTRODUCTION

The majority of goods transport within Europe is done on roads using heavy duty vehicles, which means that decreasing the associated fuel consumption is very important. For example, those trucks contribute with a large portion of CO₂ emissions, approximately 20%. In addition, fuel expenses are up to 40% of the operating cost for the truck fleet (cf. Barnes and Langworthy [1]). Various aspects of this issue are being addressed by both the industry and the research community. In this paper we focus on the influence of drivers, who can make up to 30% difference in terms of fuel consumption, according to Nylund [2].

The most common way of expressing vehicle fuel usage is the amount of fuel consumed divided by distance traveled, typically expressed as liters per 100 kilometers. This metric is also often used as a way of comparing the performance of drivers. However it is, in many circumstances, inadequate for identifying areas for improvement and as an incentive mechanism. One example is that for heavy duty trucks the gross weight (including cargo) can be over ten times the weight of the tractor. Since the fuel consumption is directly dependent on the total weight, it is clear that its range is very wide, and highly dependent on the specifics of the individual mission. The effect of the driver is not as prominent, and to make it visible, it is necessary to use a different scale.

Much existing literature on comparing driver performance is based on predicting how much fuel would be used given different actions. Bifulco et al. [3] developed a method for calculating instantaneous fuel consumption based on speed, acceleration, gas pedal position and engine air intake. Constantinescu et al. [4] derived 5 categories of aggressiveness for the driver based on a number of predefined driving parameters, such as positive acceleration. Typically, aggressiveness is associated with performance. However, it shares many drawbacks of fuel consumption when used as performance indicator, since it is also missing normalization for drivers operating in different conditions.

The US patent [5] proposes using pre-calculated reference values for selected road segments, capturing both environment variables as well as vehicle operation characteristics. The fuel consumption reference value for a given segment is then modified by fuel consumption modeled based on deviations from the reference values for the other variables. This approach is based on a similar idea to ours, however, we create the reference values dynamically, based on the current measurements only, without the need to assume that most trips on a road segment share similar profiles.

We propose a framework that makes use of expert knowledge, i.e., the physical relations governing the behavior of the system in question. Understanding the vehicle on the road lets us compare the effect of the variable of interest under different conditions. In this work we specifically target driver influence, but the approach can be generalized to other areas. An accurate and precise way of comparing fuel-related driver performance allows for better understanding of when changes in performance occur and how to transfer the best results to others, be it other human drivers or automatic systems. We aim to be able to categorize maneuvers with respect to fuel consumption, provide alternatives to improve bad ones, as well as understand specific skills of a driver, e.g., if they are doing poorly all the time or only in specific situations.

It is clear that the automotive industry is moving towards autonomous driving, where new factors like communication and advanced cruise control strategies also affect the vehicle operation. Such systems also benefit from a deeper understanding of what kind of actions lead to better performance. However, the driver is still the primary and final decision maker in the transportation process.

To summarize, driver performance in naturalistic driving...
scenarios is particularly hard to estimate due to the fact that many of the relevant factors are not being measured. To be able to compare, train and incentivize drivers, we need to learn new features that capture their performance even in the absence of complete information. Such features need to incorporate the factors that we have no information about but also be robust enough to facilitate integration of measured variables.

II. DATA

We use two large datasets that have been collected in research and development projects within Volvo Group Trucks Technology (GTT). The first dataset comes from European Field Operational Test (EuroFOT) project [6], in which GTT was a partner with the role of testing Fuel Efficiency Advisor functionality. The other is an internal Volvo project called Customer Fuel Follow-up (CuFF). In both projects, data from multiple trucks have been collected, covering a wide area in Europe and also spanning over a long period of time, offering a variety of both geographic and ambient conditions.

Each truck has an automatic gearbox with 12 gears and a Cruise Control system. The data contains over one hundred signals that are logged from the vehicles’ internal Controller Area Network (CAN), as well as additional sensors, at 10 Hz sampling frequency. In conjunction with on-board data that was recorded, we make use of off-line databases that provide map information.

The data recorded is extensive but not complete. Variables measured include ambient air temperature, vehicle speed, distance to vehicle in front, etc. Some variables can be obtained through multiple sensors, such as vehicle speed which can be obtained using both the GPS location and the wheel-based odometer. Unmeasured variables include wind conditions, tire pressure, pavement characteristics, etc. Other signals, recorded for EuroFOT but not for CuFF database, include distance to vehicle ahead and video data from several cameras.

III. METHODOLOGY

The equation of motion for a vehicle on the road moving through air is:

$$m \cdot a = F_p - F_r - F_d - F_c$$  \hspace{2cm} (1)

where \(m\) is the weight of the vehicle, \(a\) its acceleration, \(F_p\) is the driving force, \(F_r\) is the rolling resistance force, \(F_d\) is the air drag force and \(F_c\) is the climbing force. \(F_p\) is dominated by the deformation of tires in contact with the road surface (Clark & Dodge [7]). \(F_d\) is dominated by the relative speed of vehicle in relation to the air around it, while \(F_c\) is dominated by the slope of the road coupled with the weight of the vehicle. Driver influences the vehicle by increasing or decreasing \(F_p\) force, however, they have no real control over the others.

Based on the sensor data available in our databases, it is not possible to calculate all the terms in equation 1. For example, there is no information regarding the wind, neither speed nor direction. Such factors of interest that are missing include both dynamic and static aspects of the vehicle as well as the environment. However, many of those aspects remain approximately constant, or experience minimal changes, across periods of time, geographical location, or even the whole trip. Examples include tire pressure, gross vehicle weight, engine efficiency, wind parameters or road pavement.

We exploit this fact by means of Fuel under Predefined Conditions (FPC) concept, whose purpose is to provide a comparison term which captures some of the unmeasured factors. FPC is calculated on certain trip segments within the trip, based on a predefined set of characteristics. It can later be used on other segments, as long as they share those characteristics, and provides a means for fair comparison of driver performance. The “predefined conditions” need to be selected so that they have a high presence in the data. In our case, which covers mostly highway driving, one example is constant speed, within the 85 to 90 km/h range. An FPC value obtained in such a setting captures a number of vehicle and environment characteristics, while being independent from the driver. Comparing the fuel used on another road segment, for such as when approaching an intersection or overtaking a hill, allows us to highlight the influence of driver performance while diminishing the influence of other factors.

FPC is calculated according to the following equation:

$$FPC(s_0) = \frac{1}{N} \sum_{t \in s_0} f_c(t),$$  \hspace{2cm} (2)

where \(N\) is the length of the trip segment, and \(f_c(t)\) is instantaneous fuel consumption measured at time \(t\). Smaller values of \(N\) offer more opportunities to calculate FPC, however, due to the high amount of noise in the available sensors, the value is less accurate. On the other hand, there is a limit to how long a FPC segment can be, as trip characteristics can change significantly.

Then we can express driver performance \(P(s)\), over any trip segment \(s\), as the ratio between actual fuel consumption and the FPC:

$$P(s) = \frac{FC(s)}{FPC}$$  \hspace{2cm} (3)

where \(FC(s)\) is the fuel used on segment \(s\).

The FPC value is calculated on some segment in the trip and then used afterwards on other segments. A particular FPC corresponds to a set of characteristics and when comparing drivers by \(P(s)\), it is important to ensure that \(s\) shares this set of characteristics with the FPC used.

An illustrative example of the generality of the concept we will use multi-vehicle platooning. It is regarded as fuel saver, reducing air drag for all involved (Alam et al. [8]). However, platooning strategies differ and they are not always beneficial. Question as to when should a vehicle join a platoon directly affect how much fuel is saved or used. Platooning strategies can be defined by i) when a vehicle joins a platoon, ii) what distance should be kept from vehicle ahead and iii) when should a vehicle leave the platoon. We can then compare different platooning strategies using equation 3 where \(P(s)\) now represents the performance of some platooning strategy.

The most clear benefit of using FPC is to provide a space where comparisons are meaningful and allow ranking of drivers, taking into account both long- and short-term performance. This can be done based on any set of factors
of interest, for example, geographical location. Given several trips that share a road segment, we can calculate FPCs for those trips, and then perform statistical inference on any other variable, such as traffic based on time of day and day of week, or road characteristics like road gradient and surface type.

IV. EXPERIMENTS

In this section we present the results of our experiments with estimating FPC using two different sets of predefined characteristics. We begin by identifying the conditions under which the effect of road gradient, wind, surface type, tire pressure, and so on can be estimated.

A. Base FPC

We approach the problem as a successive approximation, starting with a basic set of characteristics. Since we are looking to quantify driver effect, the first condition has to be that the vehicle speed is constant. Decisions of the driver that we are interested in directly correspond to changes in speed, having constant speed means that there is no driver influence. Therefore, we can later compare other segment $s$ against such an FPC value, and make sure that the effects of driver decisions made there are captured by $P(s)$.

In our study, almost all occasions where constant speed occurs for more than one minute also correspond to having the highest gear. In general transmission setting is a factor that would be important to consider, but in practice we can simply ignore all other situations without losing significant amount of data. Therefore, the base set of characteristics for which we calculate FPC contains two aspects i) constant speed and ii) maximum gear. We denoted it as $C_0$. We write $FPC_0$ when necessary to specify for which set of conditions this FPC was calculated. It is important to note that FPC is calculated over a particular trip segment $s_0$, however, it is used to compare driver performance at segments $s_{1,...,n}$.

In long-haul truck operation, $C_0$ is a common scenario, in particular given the frequent use of cruise control. In addition, it captures the situation when the driver has minimal effect on fuel usage. Differences in fuel consumption are due to other factors, so selecting situations when cruise control is enabled corresponds to having essentially removed the influence of the driver.

A number of characteristics captured by $FPC_0$ follow our assumptions about being constant or slow-changing: cargo weight, tire pressure, wind, etc. However, one which does not is the road gradient — and that can have very profound effect of the fuel usage. Therefore, our $P(s_i)$ measure will only be reliable if we can ensure that the road profile of segment $s_i$ is similar to the road profile of segment $s_0$. In practice, given our setting, this only happens if both road segments are flat.$^1$

B. Adjustment for road inclination

One of the drawbacks of the approach presented in subsection IV-A is that flat roads, while the most common profile, are still quite rare in practice. Having the road flat and the speed constant for the required duration is overly limiting.

However, the effect of road gradient on fuel consumption can be estimated. As seen in figure 1, a simple linear road gradient model (RGM) is enough. RGM is specific to a vehicle type, however, in our data all vehicles have the same attributes. Having such a model allows for another set of characteristics under which we can calculate FPC.

For $FPC_1$ therefore we add a third characteristic, making $C_1$ be i) constant speed, ii) maximum gear and iii) road gradient of 0. It is important to note that we can calculate $FPC_1$ over segments with any road gradient profile. We take the effect of the climbing force $F_c$ (see Equation 1), estimate the change in fuel consumption using RGM, and the resultant $FPC_1$ is considered to correspond to a flat road:

$$FPC_1(s_0) = FPC_0(s_0) - RGM(s_0) = FPC_0 - q \cdot \theta \cdot M \quad (4)$$

where $q$ is an empirical constant, $\theta$ is the road gradient, and $M$ is the estimated total weight of the vehicle. One of the drawbacks of this methods is that our data is collected from the tractor but not the trailer. This results in inaccurate weight estimations, which translates into higher variation in the $FPC_1$ values.

It can be seen that $FPC_1$ is equivalent to $FPC_0$ when calculated on a road segment $s$ which is “naturally” flat. However, when $s$ is uphill, $FPC_1$ will be generally smaller than $FPC_0$, and when $s$ is downhill, it will be larger. Most importantly, though, the opportunities to calculate FPC on a truly flat road are scarce. And as mentioned in the previous section, while we can calculate $FPC_0$ on non-flat roads, they are not useful for driver comparisons. On the other hand, using the road model and $FPC_1$, we can calculate $P(s)$ based on:

$$P(s) = \frac{FC(s) - RGM(s)}{FPC_1}. \quad (5)$$

$^1$However, this is not necessarily true in other settings. For example, in the case of city buses that drive in the same area, other road profiles can also be repeated often.
C. FPC Comparison

In section III we have introduced the FPC feature, and in the subsections above we have defined two set of conditions, namely $C_0$ and $C_1$. Here we present the comparison between the two, and demonstrate the necessity of introducing $FPC_1$ despite the extra complications it involves. The main criteria for this comparison will be the standard deviation of FPCs within the same trip, and the time between consecutive FPCs within a trip. Those two measures capture how reliable a support system for driver or fleet operator can be. This data is presented in Figure 2.

We start by looking at reliability, i.e., how likely it is that we can even calculate the FPC in a given trip. In those experiments we require a segment of 150 seconds to calculate FPC. For $FPC_0$ with flat road we have 30% of trips with one FPC segment, and less than 5% of trips with five FPC segments. On the other hand, with $FPC_1$, we have over 60% of trips with at least three FPC segments and almost 40% of trips ten or more FPC segments.

Another aspect is the time it takes before conditions are met and the system is able to calculate the first FPC. This is represented in figure 3(left) for $FPC_0$ and figure 3(right) for $FPC_1$, respectively. Those figures show that one of the main concerns for $FPC_0$ is the long time from the start of the trip until we meet the conditions required. It is on average 72 minutes, compared to 33 minutes for $FPC_1$. This high time required to have an $FPC_0$ lowers the attractiveness of the method, especially if we consider online driver support applications, as a large part of the support can only be available after the first FPC is calculated.

Next we look at stability, expressed as the standard deviation of all FPCs within a single trip. This is used to validate our assumptions regarding how fast the unmeasured aspects of the environment change, as well as our approach to computing FPC. Figure 2(left) shows that $FPC_0$ with flat road has low and constant standard deviation regardless of how far apart consecutive FPC segments are. This verifies our main expectation regarding slow changes in most of the unmeasured factors, like wind speed or pavement type. On the other hand, Figure 2(right) shows that we have — to some degree — traded quality for quantity. In particular, the average time between consecutive $FPC_1$ is consistently a lot lower than that for $FPC_0$. At the same time, $FPC_1$ has a much higher variability between different FPCs calculated from the same trip. This value is quite a bit higher than expected, which means that the inaccuracies introduced by the road model and imprecise estimation of vehicle weight lead to lower quality.

Figure 4(left) displays the standard deviation for $FPC_0$.
with flat road within a trip. We attribute this variability to changes in unmeasured factors, inaccuracies in sensors and noise, and for the FPC to be useful we require the variability to be small. From our experiments we see that 60% of the FPC are within 1 standard deviation, and 91% are within 2 standard deviations, respectively, which is close to a normal distribution and what we would expect as the most dynamic factor, wind, can be modeled with a standard distribution, according to Aksoy et al. [9]. We perform the same analysis for FPC1. In figure 4(right) we can see that the mean of standard deviation is higher than that of FPC0, at 1.84 compared to 1.03 [L/100km]. At the same time, the number of FPC1s available is 13.5 times higher than the number of FPC0s.

The natural question is then where does the increase in variability comes from: the changing environment conditions, the inaccuracies in the calculations or both. Figure 1 can answer partly, as we employed a linear model to fit that data, so we expect this to introduce some amount of noise. However the tradeoff still improves the usability of the method by increasing the number of missions for which we can calculate FPC, and especially multiple FPCs, as well as provides more up-to-date information.

Even though the time gaps in calculating FPC0 vary significantly, we can see in figure 2(left) that the variation in FPC0 is not dependent on how long time has passed since the previous FPC was calculated. The reliability aspect of FPC1 is illustrated in figure 2(right) and it shows the same thing as for FPC0, i.e. the quality of FPC, measured through standard deviation, is not dependent on the time between consecutive values.

Finally, we look timeliness, i.e., for how long do we need to use an FPC before it can replace it with a more up-to-date one. We can see a distribution of this in figure 5a, with mean of 40 minutes for FPC0 and 15 minutes for FPC1, respectively. We believe that a reasonable maximums for the FPC to be used for is 30-40 minutes, and after that time we would like it to be replaced with a newer one even though as we see in figure 2 the variability of FPC is not time dependent.

However, the mean of timeliness is not the most interesting metric. It can be heavily dominated by areas where many FPCs can be calculated easily and often. On the other hand, there is very little difference between FPC being replaced by a new one after 1 or 5 minutes — it’s the extremes, the tail of the distribution, that is interesting.
D. FPC Evaluation

Finally, we look at what we perceive similar and different driver profiles. The most evident situation where driver behavior is similar is when their speeds match on a particular road segment, and the behavior is different when one driver maintains constant speed while another does not. Initially, we consider the fuel consumption as the indicator for driver performance. To increase the likelihood that the conditions in which the trips occur are the same, we select trips that occur on same road segment and we also select vehicles with similar characteristics, i.e. engine type, vehicle load, etc.

Figure 6(left) shows the fuel consumption profile for 4 trips with the specified characteristics. Three trips have similar fuel consumption and speed (not shown): they share the same shape for both curves. The fourth, on the other hand, has speed profile that changes in the middle of the depicted segment. The effect of this change can be readily seen in the fuel consumption plot.

We consider the lowest fuel consumption (red line) as the reference and then we have the following performances compared to it: blue 101%, red (reference) 100%, yellow 126% and black 116% respectively. The first three have the similar speed profile. The conclusion based on those numbers would be that “yellow” driver has the worst performance. However, this conclusions changes when comparing the \( P(s) \) values, i.e., fuel consumption normalized by FPC as depicted in figure 6(right). Here we can see that “yellow” driver has performance very similar to “red” and “blue” drivers. The performances given by the average normalized fuel consumption are: blue 113%, red 113%, yellow 109% and black 131%.

To summarize, we have the following order given by measured fuel consumption: red, blue, purple, yellow. The driver performance measure based on the approach proposed in this paper gives us: yellow, red, blue, purple. Given the speed profiles, the second ranking is much more believable.

We can also conclude that impact of other factors is significant, in this case around 26%, which also indicates that better methods for estimating performance in terms of fuel consumptions are needed.

V. CONCLUSIONS AND FUTURE WORK

The paper presents an approach towards quantifying the effects of specific conditions in the presence of factors for which measurements are incomplete or missing, but when general relations between those factors are known. We apply it for a specific case of comparing truck driver performance. In this setting we propose a normalization term, called Fuel under Predefined Conditions.

Using FPC we facilitate the comparison among trips having different characteristics. By arranging the factors responsible for fuel consumption into different categories, we show how to perform better comparison among trips, as well as provide better estimation of driver performance.

We have identified some issues with our current approach, for example, how the inaccuracies that propagate from imprecise sensors affect the values of \( \text{FPC} \). Improving this aspect of the method is an important task for the future.

Another essential question to consider is when does the driver have actual freedom to make decisions and when external conditions are the limit. Driver decisions are influenced by many factors, such as traffic or delivery deadlines. Fuel consumption is only one of the criteria — so a comprehensive evaluation method should take bigger picture into account.

We aim at extrapolating driver influence as well as the method for assessing freedom of driver when making choices that lead to changes in fuel consumptions. For this, however, additional information is required, e.g. mission parameters such as delivery deadline.

REFERENCES

Paper B

APPES maps as tools for quantifying performance of truck drivers

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APPES Maps as Tools for Quantifying Performance of Truck Drivers

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Abstract—Understanding and quantifying drivers’ influence on fuel consumption is an important and challenging problem. A number of commonly used approaches are based on collection of Accelerator Pedal Position - Engine Speed (APPES) maps. Up until now, however, most publicly available results are based on limited amounts of data collected in experiments performed under well-controlled conditions. Before APPES maps can be considered a reliable solution, there is a need to evaluate the usefulness of those models on a larger and more representative data.

In this paper we present analysis of APPES maps that were collected, under actual operating conditions, on more than 1200 trips performed by a fleet of 5 Volvo trucks owned by a commercial transporter in Europe. We use Gaussian Mixture Models to identify areas of those maps that correspond to different types of driver behaviour, and investigate how the parameters of those models relate to variables of interest such as vehicle weight or fuel consumption.

I. INTRODUCTION

Road transportation is one of the ways most often used to move goods and people from one point to another in Europe. According to [1], almost 75% of all the cargo transported in 2011 in Europe was done with trucks, summing to approximately 520 billion tonne-kilometres. As a consequence the fuel burned by vehicles accounts for around 20% of the CO$_2$ emissions in the region.

In addition, fuel expense is one of the most important cost factors, accounting for approximately 30% of the total operating expenses of a heavy duty vehicle. Fuel efficiency is very important for modern vehicles for environmental as well as financial reasons.

There are many factors influencing fuel consumption of a vehicle. Some of them the transporters and vehicle manufacturers have little or no control over, such as weather or road topology. However, there are many others that they can affect, for example route planning, aerodynamics or tires. Furthermore, a factor that has been widely recognised as being very important is the driver.

One asset that is recently becoming available are large quantities of data collected over long time under real driving conditions. This data can generally be made available and processes either on-board or off-board the vehicle. Each of these two options have their own advantages and disadvantages. Storage and analysis of high frequency data consisting of hundreds of signals requires large amounts of memory and computation power, neither of which is commonly available or feasible to implement on commercial trucks. On the other hand, data transmission costs are currently too high to justify a fully off-board solution. Therefore, a promising approach is to investigate data representation abstractions that can be easily computed and stored on-board, but which also contain enough information to provide valuable knowledge when analysed off-board.

In order to find opportunities for reducing fuel consumption there is a need to analyse this newly available data. This paper is one step in this direction.

A. Related Work

Fuel consumption for heavy duty vehicles is an issue that affects our daily lives. The recently adopted Euro VI standard exemplifies the importance of fuel consumption reduction, as it directly affects particle emissions. The Euro VI standard enforces reduction of noxious emissions by 66% and of nitrogen oxide emissions (NOx) by 80%, compared to Euro V.

Liimatainen [2] has demonstrated how to use fuel consumption as an incentive for drivers to increase their fuel efficiency. He also points out that it is difficult to take external factors into account when assessing drivers’ performance. Ting et al [3] have, in a simulation study, shown the importance of driver and address the issue of driver fatigue and its effects on driving capabilities. Another study of driver performance and its classification is done in [4].

Rafael-Morales and de Gortar [5] conducted an extensive field study to determine the effects of so called “technical driving” for reducing fuel consumption. Authors investigate several means of using vehicle in an efficient manner looking from various perspectives, including analysis of relation between torque and engine speed.

In this paper we expand on the work of of Guo et al [6], who investigate using Accelerator Pedal Position - Engine Speed (APPES) map for evaluating drivers’ performance. Guo et al identify different regions of this map that correspond to higher or lower fuel consumption. The weakest point of their work is the limited variety of data used to validate the method: only one vehicle was driven on the same route by the same driver. We show that APPES maps can be correlated with a number of relevant factors not only under controlled experimental conditions, but also during actual commercial operation.

II. DATA

We use two large datasets that have been collected in research and development projects within Volvo Group Trucks...
Technology (VGTT). The first dataset comes from European Field Operational Test (EuroFOT) project [7], in which VGTT was a partner with the role of testing Fuel Efficiency Advisor functionality. The other is an internal Volvo project called Customer Fuel Follow-up (CuFF). In both projects, data from multiple trucks have been collected, covering a wide area in Europe and also spanning over a long period of time, offering a variety of both geographic and ambient conditions.

The subset of data that we base our results on consists of over 1200 trips, performed by five Volvo trucks. Each truck has an automatic gearbox with 12 gears and Cruise Control system. Each trip contains over one hundred signals that are logged from the vehicles’ internal Controller Area Network (CAN) as well as additional sensors, at 10 Hz sampling frequency.

The complete database amounts to approximately 100 TB of data. Even with this large amount of information, we do not have complete knowledge of all the relevant circumstances. Among the most important factors that we are missing are traffic and weather conditions.

III. METHODOLOGY

The first step in quantifying a driver’s behaviour is finding a good representation of it, one that is simple enough to reason about, but at the same captures all the important aspects. In this work we have decided to focus on Accelerator Pedal Position - Engine Speed (APPES) maps. It is a way to describe truck usage information that is commonly employed both by automotive engineers and in driver training, as those maps are easy to understand and have very intuitive interpretations. An example of APPES map for a single trip is presented in Figure 1.

In this work we focus on analysis of driver performance. Therefore, we are only considering the time where the cruise control has been disabled. The surface represents how much time has been spent in various combinations of accelerator pedal position and engine speed during a trip. The first of those signals can be thought of as the request from the driver, while the second as an overall response of the vehicle. Most important aspects of truck operation are directly reflected in this map. For example circumstances such as road gradient, engine power or vehicle weight all affect how fast the speed will be changing when the accelerator pedal is pressed to a given level.

Another benefit of APPES maps is that they can be easily obtained from commercial vehicles, for example using telematics technology. Computing them on-board is a small effort, and they can be efficiently stored in existing control units to be periodically transmitted, either via wireless networks or during garage visits.

In the past, APPES maps have been used to evaluate drivers, but mostly in controlled experiments, under well-known conditions. Their potential and usefulness in a realistic setting have not been fully explored yet. For example, in [6] the authors focus on identifying regions of the APPES map that can be correlated to fuel consumption. They show increased vehicle efficiency through better driving, but their results are based on a single truck being driven on a pre-specified route.

The contribution of our work is to demonstrate the usefulness of APPES maps in realistic scenarios, when the external conditions of driving vary in unpredictable ways. Actual situations on the road will put many constraints on what is possible for the driver to do, but we are interested in finding similarities and differences between different driving styles. We can use this to communicate to drivers information regarding their driving behaviour, for example give them advice on how to achieve better fuel efficiency.

One important aspect of vehicle operation that is not explicit in the APPES map is the gearbox. Different gears should be used at different speeds in order to maximise fuel efficiency. Modern truck engines always generate power by burning fuel, but some of this power is lost, as heat. The lost amount, however, varies depending on parameters such as torque and engine speed — each engine manufacturer designs their products with a specific efficiency map in mind. By changing gears, driver can optimise power output for any desired vehicle speed, by controlling the ratio between the engine and wheel speeds. This power is then used to overcome resisting forces, gravity and to maintain or increase velocity.

Figure 2 shows the APPES map for all the trips we are considering in this paper. We have identified four important regions in this distribution. We refer to them as Neutral, Free Roll, Driving and Full Throttle. Those names indicate the intuitive interpretation of the physical behaviour of the truck that corresponds to each of those regions in the APPES map.

The region we call Neutral corresponds to low engine speed, with the exact value depending on engine specification, and acceleration pedal being fully released. It can be seen in Figure 2 as the peak in the lower left corner. Those conditions can be achieved when the truck is in neutral gear, but it can be either stationary or moving.

The Free Roll region is characterised by the accelerator pedal being fully released, but engine is rotating above idle speed. This generally means that the vehicle is in gear other than neutral and that it is moving forward. In this mode
the engine is not using any fuel. This situation most often happens when travelling downhill, where the driver can use gravity to maintain the desired speed, or when they anticipate that a speed reduction will be needed in the near future, and use kinetic energy to propel the vehicle forward for a short time. In Figure 2, this region corresponds to the ridge along the bottom.

_Full Throttle_ corresponds to the accelerator pedal being fully pressed. It can either indicate that the driver is attempting to reach the desired speed in the minimum amount of time or trying to maintain the highest speed allowed by the electronic limiter, which is set to 90 km/h. This region can be seen as the peak near the top right corner of Figure 2.

Finally, the _Driving_ region captures the full spectrum of driver behaviour in between the three aforementioned extremes. It covers engine speeds that correspond to driving using different gears and at different velocities, as well as how much the accelerator pedal is pushed, either for acceleration or for compensating for road conditions such as hills. This region is probably the most interesting one, since the exact distribution of data within it can tell us, for example, when this particular driver changes gears, possibly leading to creation of driver profiles that can later be used, with long term observation, to track driver performance. In Figure 2, this region can be seen as the triangle-like shape in the middle of the plot.

Based on this rough classification, we have decided to model the data using a Gaussian Mixture Model. Figure 3 shows the obtained result. Blue dots correspond to the data that was extracted from the APPES map using uniform random sampling within each map cell. The four red dots denote the location of means of the four Gaussians that were fitted to this data. As can be seen, they correspond quite well to the four regions we identified above. The coloured ellipses around each mean visualise the covariance matrix of each model.

In the following section we will present the results of comparing the parameters of those Gaussians across different trips.

**IV. Results**

In this section we report the results of our experiments concerning the usefulness of APPES maps in a real setting, especially with respect to fuel consumption. We base our analysis on comparing parameters of the Gaussians Mixture Models corresponding to the four types of driving that we have introduced in the previous section. There are three important comments regarding our methodology that need to be explained before we present actual results.

First of all, the goal is to relate various factors of interest to the APPES regions that we have identified as the most important ones. In order to do that, it is useful to categorise those factors as either _cause_ or _effect_, in particular from the driver’s point of view. For example, traffic density requires drivers to change their desired behaviour and affects their decisions. In this paper we analyse a factor from each category, choosing ones that are easy to understand and using available expert knowledge. As a _cause_ type we have selected gross vehicle weight, while as an _effect_ type, fuel consumption. We have decided upon those two because it is interesting to analyse how weight affects driving style, while at the same time we are very much aware that it also heavily influences vehicle fuel usage.

Second, since our data comes from real commercial trips, we do not have access to any form of ground truth concerning actual performance level of drivers. Therefore, we are interested in a finding as few parameters describing each APPES map as possible, preferably ones that are easy to visualise and whose correlation to variables of interest can be discussed in this text. To this end, we have chosen to only take into consideration the proportion that each Gaussian occupies in the complete model, ignoring both the exact location of the mean and the covariance matrix.

Finally, many of the individual trips did not have enough data to build reliable Gaussian Mixture Models with all four regions of interest properly represented. Individual drivers rarely cover all of them in one trip, which is a direct effect of the length of those trips as well as high usage of cruise control. This often caused undesired effects of Gaussian
A. Vehicle Weight

Vehicle weight is a factor that is known to be very important for fuel consumption. However, there are no large scale, systematic studies of how a driver’s behaviour is affected by vehicle weight. Therefore, in this section we present results that can be seen as a starting point towards this goal.

As explained before, APPES maps show a driver’s behaviour for a given trip or a group of trips. We can describe each map by four numbers, the mixing proportions of the Gaussian models corresponding to each type of driving: Free Roll, Neutral, Full Throttle and Driving. Those proportions correspond to the amount of time that was spent in each of the regions. In order to analyse the relation between driver’s performance and vehicle weight, we want to observe changes that happen when driving trucks with different loads. Therefore, we group similar trips and plot the mixing proportions of each APPES Gaussian, looking for interesting relations.

The clearest correlation, with value of 0.7, can be seen in Figure 4, top left. Each point on this plot corresponds to a group of 8 trips, with similar vehicle weights. The Y value represents the mixing proportion of the Free Roll Gaussian, while the X value represents the average weight within the group. As can be seen, the lightest vehicles very rarely use free roll, while the share of this driving type generally increases as the vehicle becomes heavier.

This is an anticipated result, since heavier vehicles have
more inertia and therefore lose speed less rapidly. However, free rolling with a vehicle does not only depend on vehicle weight but also on a skill of the driver, mainly their ability to anticipate future situations and use ambient conditions to better use the vehicle. One circumstance that a good driver takes advantage of is coasting in gear. In such a case, if the road gradient is enough to keep the vehicle at desired speed, a Free Roll can reduce the fuel usage to zero. However, the APPES map itself does not contain enough information to identify such situations, and finding them is a topic for future work. An anticipation situation is more often encountered in towns or in high traffic scenarios, where change of speed is more common. For example, driving towards a stop light and anticipating having red light upon arrival might prompt the driver to stop accelerating and let the vehicle roll. This situation could result, depending on the gear, in either Free Roll or Neutral behaviour.

Another aspect to consider is that heavier vehicles, having more inertia, also offer more opportunities to use free roll. For example, in anticipation of a steep downhill, the driver can choose to Free Roll for some time, on the flat road, and lose some speed which can then be regained during the downhill section.

Another aspect to consider for this Gaussian is what happens after the Free Roll ends. This, again, is not actually included in the APPES map, but Free Roll followed by, e.g., high acceleration is often an indication of insufficient anticipation. There are many possibilities and analysing them will reveal further information regarding drivers’ behaviour in various scenarios.

Continuing to Figure 4, top right, the Full Throttle Gaussian, we can also notice a high correlation, at 0.62. This relation can be explained by the fact that engine power is a limiting factor for heavier trucks, and desired acceleration can often only be achieved by pressing the pedal fully. It could also be attributed to the fact that drivers are less inclined to try and optimise fuel usage for heavy loads, since in most cases their performance is measured in absolute terms, and therefore they know they cannot compete with lighter trucks.

If validated, this could be a strong argument towards introducing performance indicators that analyse fuel consumption and also consider vehicle and ambient conditions. As all trucks involved in this analysis are the same model, it is also
possible that lighter trucks do not require full power from the engine, especially if there is an acceleration level which generally satisfies the drivers. Heavier trucks may never reach said acceleration, even with full throttle, leading to higher amount of time spent in that region.

Correlation for Figure 4, bottom left, the Neutral region has the value of −0.47. Weight seems to have a minor influence, if any at all, for time spent in neutral gear. One possible explanation for slightly higher average values for heavy vehicles is lower inertia. Instead of using Free Roll where engine braking occurs, lighter trucks choose to use Neutral. This way they keep vehicle rolling longer.

Figure 4, bottom right, Driving, shows a stronger negative correlation of −0.66. One explanation can be the opposite of Full Throttle: since drivers rarely need to use full throttle to maintain the desired vehicle speed profile, they end up in the Driving region more often. However, it is important to remember that the mixing proportions for all the Gaussian always sum up to 1. Looking at Figure 4, top left and top right respectively, we notice that the time spent in those regions is very small, which means that it has to be distributed among the remaining two regions.

Finally, the four regions can be also seen as two groups of complementary driving styles. We can consider the first to be comprised of Full Throttle and Driving Gaussians, where light vehicles tend to spend more time in the Driving region while heavy vehicles end up in Full Throttle more often. The second group is formed by Neutral and Free Roll. Lower inertia and engine braking being relatively stronger make light vehicles use neutral gear more often, while heavier vehicles do not require it so much.

B. Fuel Consumption

As mentioned earlier, we consider fuel consumption to be an effect of driving style. Therefore, observing how different driving styles influence fuel consumption can be directly used to assess performance of drivers. We can estimate how beneficial it is to be in one region or another, ignoring other factors. However, the degree to which positioning oneself in the APPES map is up to a driver is unclear, as there are many conditions that constrain their decisions.

One of the surprising results is that there is no clear correlation, at a value of 0.22, between Free Roll and fuel consumption, as seen in Figure 5, top left. Expert knowledge tells us that if a vehicle is in gear and the acceleration pedal is released, the engine will not use any fuel. This has been verified directly with real world data and it strongly suggests that Free Roll is highly desirable behaviour.

One possible explanation could be that the beneficial effects are clouded by detrimental effects of other regions. Another would be that other factors, for example heavy traffic or hilly terrain, heavily influence when a driver can choose to Free Roll, and their own detrimental effect can outweigh the benefits. Further investigation is required before a more concrete conclusion can be reached, as this observation contradicts prior beliefs. However, it motivates our original thesis that APPES maps, due to their simplicity, can uncover interesting relations in the data.

It is also interesting to note that this region has higher correlation with weight, as depicted in previous subsection, Figure 4, top left. Consequently, further investigation should focus on how both weight and fuel consumption influence each Gaussian.

Figure 5, top right, corresponding to the Full Throttle region, shows 0.32 correlation. Even despite it being so low we can notice that there is a tendency for low fuel consumption to be associated with low Full Throttle proportion. One way of explaining this is by taking into account a cause, such as the previously discussed vehicle weight. We noticed a much higher usage of full throttle for heavier vehicles, which in turn can be associated with higher fuel consumption. This suggests that APPES maps can also be used to link relations between various factors.
On the other hand, a strong positive correlation of 0.68 can be seen in Figure 5, bottom left, for Neutral mixing proportion. This agrees with our expectations, since we measure fuel consumption in L/100km and having a vehicle in neutral gear burns fuel but does not propel the truck forward. However, some drivers may choose to use Neutral instead of Free Roll under certain circumstances, as it means no engine braking.

The final Gaussian, Driving, shown in Figure 5, bottom right, exhibits a very strong negative correlation of \(-0.88\). We conclude that adapting the fuel demand as well as keeping an appropriate speed, both of whom can be done by active driving, uses the fuel most efficiently.

For comparison, Figure 6 presents the same relations as the previous four figures, except this time each point represents a group of 4 trips. We have chosen two different group sizes to show the amount of noise that is present when less data is available to fit each Gaussian Mixture Model. Overall, however, very similar relations can be found between fuel consumption and time spent in each region, but increasing the number of trips in each group makes them clearer.

Figure 8 shows the changes in correlation coefficients between fuel consumption and the Gaussians, for different group sizes. The largest decrease occurs for Neutral and Driving at 3 trips in each group. The other two regions display more stable relations.

We also present the positions of the four Gaussian means for all the groups, of both 4 and 8 trips, in Figure 7. It can be seen that there is significantly less variation in the data for the right plot. This observation agrees with Figure 8, where we see a decrease in correlation coefficient with lower number of trips per group.

It is important to stress once more that this data comes from real operation of commercial vehicles, and thus captures the actual situations that take place. In particular, there are individual trips with extremely unusual patterns — for example, over 50% of time spent in neutral. It is therefore important that any analysis method designed for real world use can handle such outliers and does not assume too much conformity to the “expected norm”.

V. Conclusions and Future Work

In this paper we have analysed the usefulness of Accelerator Pedal Position - Engine Speed (APPES) maps for evaluating drivers’ behaviour from the point of view of fuel consumption. Such maps are an inciting tool, because they are very easy to calculate on-board and have very intuitive interpretations.

We have used data collected during commercial operation of a fleet consisting of five Volvo trucks used by multiple drivers, under the full range of operating conditions on over 1200 trips. This gives us confidence that the results are relevant for future products and services.

The goal of our work was to compare the performance of different driver, describe them using simple to understand features, and correlate those features to key performance indicators, such as fuel consumption. APPES maps can be easily used both for evaluating as well as for training drivers.

Our approach is based on fitting Gaussian Mixture Model to the data, and analysing the relative importance of the four regions we have identified as being of particular interest. We have shown that several of those are highly correlated with factors such as vehicle weight or fuel consumption.

The results presented in this paper are encouraging, but final conclusions have not yet been reached. We have identified both intuitive correlations, e.g., driving in neutral should be avoided, as well as counter-intuitive correlations, e.g., Free Roll leads to higher fuel consumption. We believe that that the next step is to find ways to identify external conditions that affect different trips in different ways: for example, it is plausible that Free Roll is more common in hilly areas, which would explain higher fuel consumption.

Future work ideas also include investigation of other ways to compare APPES maps. In the current approach, we only investigate the proportion between various Gaussians, but the position of individual means is likely to also contain interesting information. In addition, more complex Gaussian Mixture Models, as well as other formalisms, should be explored in the future.

References

Paper C
Features extracted from APPES for enabling the categorization of heavy-duty vehicle drivers

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Features extracted from APPES to enable the categorization of heavy-duty vehicle drivers

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Abstract—Improving the performance of systems is a goal pursued in all areas and vehicles are no exception. In places like Europe, where the majority of goods are transported over land, it is imperative for fleet operators to have the best efficiency, which results in efforts to improve all aspects of truck operations. We focus on drivers and their performance with respect to fuel consumption. Some of the relevant factors are not accounted for in available naturalistic data, since it is not feasible to measure them. An alternative is to set up experiments to investigate driver performance but these are expensive and the results are not always conclusive. For example, drivers are usually aware of the experiment’s parameters and adapt their behavior.

This paper proposes a method that addresses some of the challenges related to categorizing driver performance with respect to fuel consumption in a naturalistic environment. We use expert knowledge to transform the data and explore the resulting structure in a new space. We also show that the regions found in APPES provide useful information related to fuel consumption. The connection between APPES patterns and fuel consumption can be used to, for example, cluster drivers in groups that correspond to high or low performance.

I. INTRODUCTION

Heavy-duty vehicles are a major component of traffic on motorways, especially in Europe where approximately 70% of the goods are transported by land. Traffic is also a major contributor to pollution, with trucks being responsible for around 20% of CO₂. Finally, fuel cost can account for up to 40% of the operating cost of a truck, cf. Barnes and Langworthy [1]. All those are important reasons to increase efficiency of vehicles in general. In this paper we focus on the effects a driver has over fuel consumption and we aim at providing a comparison method for driver behavior.

One of the ways we express performance of vehicles is the amount of fuel used to travel a given distance, typically liters per 100 kilometers [L/100 km]. This metric is used for expressing performance of both the engine and the driver, but it is also commonly accepted to be flawed. Alternative metrics include “key performance indicators” (KPI) usually manually selected, that are used to calculate a score or ranking for driver performance. One of the caveats of KPI metrics is that they do not generalize well.

In real driving scenarios, it is hard to compare performance among various vehicles and drivers as the conditions under which they operate are hard to quantify. On the other hand, controlled experiments tend to be expensive and often fail to capture many of the important factors that affect fuel consumption and driver behavior. In this work we aim to, based on the data coming from driving under real conditions, extract features that are able to cope with such lack of complete knowledge. One example is incorporating the effect of unmeasured factors, e.g. air drag. Equally important, for those features, is to allow for the effect of other factors, e.g. vehicle speed or road gradient, to be isolated and quantified separately.

Existing literature on comparing driver performance is based on predicting what the fuel consumption would be, given different actions. Bifulco et al. [2] developed a method for calculating instantaneous fuel consumption, with some measure of success. Constantinescu et al. [3] derived five categories of aggressiveness for drivers based on a number of parameters related to driving, for example positive acceleration. Typically, aggression is associated with performance and lacks in the same manner as when fuel consumption is used as a performance indicator. Nylund [4], states that the differences between a good and bad driver, with respect to fuel consumption, can be up to 30% for heavy-duty vehicles.

Vehicle speed and acceleration are outcomes of driver decisions and depend on the current driving conditions. They are controlled primarily by the driver, through the use of acceleration and braking pedals, but also by the longitudinal control systems, such as cruise control, see Teetor [5]. Monitoring the use of pedals, specifically the acceleration pedal, is a direct way of quantifying driver intention. However, driver intentions are motivated by the current goal, but also by conditions under which the driver operates, e.g. vehicle and environment characteristics.

Engine speed is one indicator of a vehicle’s state that also contains information regarding the efficiency of the engine. Typically, each manufacturer has a recommended use of the vehicle for best performance, including which engine speed is the best, from a performance point of view, for different conditions. This makes engine speed an important parameter to monitor when analyzing driver performance.

We propose a space defined by the accelerator pedal position (APP) and the engine speed (ES), namely APPES. We use a histogram mapping how the driver’s intentions are affecting the vehicle’s operation. We believe that various useful features can be extracted from this mapping, in particular ones that can express the connection between driver behavior and fuel consumption. The distribution of APPES and its relation with other variables, e.g. fuel consumption, have been investigated in [6]. Authors show a high correlation among certain, clearly visible, areas in APPES and variables of interest. For example, one of the regions, namely “neutral”, corresponds to the area where APP is not pressed and ES is low, i.e. the vehicle being in neutral gear. We find that trips where a large percentage of time was spent in the "neutral" region exhibit an increase in fuel consumption.

We further extend the APPES concept by adding new features, namely transitions between regions, and common
sequences of such transitions, to be extracted. Transitions represent how the data travels in APPES space, i.e. which symbol comes next after the current one. Patterns are representative sequences of transitions. We also show that the new features are meaningful with respect to fuel consumption, the main indicator we use for categorizing driver performance.

The paper is organized as follows: Section II presents an overview of the work in the field. A summary of the data we use is presented in section II-A. In section III we describe the methodology, followed by section IV, experiments. We finish with section V.

II. BACKGROUND

Some methods prefer the statistical approach when it comes to driver behavior and performance. With respect to fuel consumption we have, for example, Volvo Trucks I-See [7], which is a system that works together with the cruise control and aims at increased performance by making use of prior knowledge about road topography. This lets it achieve a better speed profile. Such a system makes use of expert knowledge in the field on how it is best to drive in hilly terrain. A similar method has been also developed by Hellström et al. [8].

Another study has been performed by Mensing et al. [9] where they perform an analysis of vehicle trajectory in order to reduce fuel consumption while maintaining the same average speed which leads to, in their study, to a reduction of fuel consumption of up to 16%. Achieving this improvement requires a different speed profile than that of a normal driver which can lead to disruptions in traffic.

There are a few key differences between our work and Guo et al. [10]. We have data collected from vehicles with an automatic gearbox while Guo et al. had manual. This is an important distinction as it enforces certain values for engine speed. We also have many vehicles operating under different conditions. They are also operated by different drivers. In contrast, in Guo et al. there was one vehicle and the whole process resembled more of a controlled experiment.

A. Data symbolization

We test and develop our methods on naturalistic data recorded in EuroFOT\textsuperscript{1} project, see [11], by Volvo Group Trucks Technology (GTT), and Customer Fuel Follow-up\textsuperscript{2} (CuFF) project.

In both projects, the data is recorded at 10 Hz from a variety of sensors, such as vehicle speed, axle weight, ambient air temperature, and many more. Furthermore, the data is enriched with information from off-line databases, such as road gradient. The vehicles are operated by many drivers and are in use throughout Europe, enabling analysis under varied conditions.

\textsuperscript{1}European Field Operational Test, gathered naturalistic driving data for assessing the impact of use of “Intelligent transportation systems” with respect to safety and fuel efficiency.

\textsuperscript{2}GTT project that aims at providing better service to GTT partners.

\begin{figure}[h]
  \centering
  \includegraphics[width=0.5\textwidth]{APPES.pdf}
  \caption{APPES}
\end{figure}

III. METHODOLOGY

APPES is a 2D histogram and it is derived from signals recorded on-board heavy-duty vehicles in normal operation. The two signals, Accelerator Pedal Position and Engine Speed, are selected based on domain knowledge. Our goal is to have a good representation of time series for qualifying driver actions with respect to fuel consumption.

The first step is to form APPES from the two selected time series. We proceed by symbolizing the data in the new space as described in section III-A. We then further generalize APPES by including additional information not captured by the two primary signals. Finally, we define the concepts of regions and transitions.

A. Data symbolization

An example of APPES can be seen in figure 1. We symbolize the data by assigning different symbols to each of the prominent regions in this space. This assignment can be done in several ways. Some of the options available are manual delimitations for each region, crisp separation such as the one offered by k-means algorithm, or fuzzy regions which can be obtained using, for example, Gaussian Mixture Model (GMM). For robustness we have chosen to use GMM. The mixture model is presented in mathematical form in equation 1.

\begin{equation}
  P(\theta) = \sum_{i=1}^{K} \phi_i N(\mu_i, \Sigma_i)
\end{equation}

where $\phi$ is a vector of weights, $\mu$ and $\Sigma$ are the means and covariance matrices respectively.

We have used an interative approach, we fit models with an increasing number of components to the data from multiple trips, and measure Kullback-Leibler divergence between subsequent GMMs:

\begin{equation}
  D_{KL}(P \parallel Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}
\end{equation}
where $P$ and $Q$ are probability distributions obtained by using different number of components. The procedure stops when the more complex model is not significantly different from a simpler one. In our case, this procedure leads to selecting six components.

It is worth noting that the time information, i.e. the order in which data points come, is lost when we represent data with APPES, as is typical when transforming time series into histograms.

We assign a symbol to each component in GMM. This is done by computing, for each data point, the probabilities corresponding to each component in GMM and selecting the highest one, for the six symbols associated directly with APPES. In summary, we start with a two time series which we combine into one new time series using APPES. As GMM associate probabilities to each new data point, we use equation 3 to determine the appropriate symbol.

$$
\text{symbol}(x) = \arg \max_{i=abcdef} GMM(x) \quad (3)
$$

where $i$ is $i^{th}$ component in GMM.

**B. Extended APPES**

We recognize that the information captured by APPES is incomplete and can be complemented with the use of domain knowledge. For example, a system such as cruise control allows the driver to gain speed without the use of the accelerator pedal. APPES, in the current state, would fail to capture this behavior and could provide misleading estimates of driving performance. However, in our representation, we can easily include the cruise control signal as an additional symbol. Following similar reasoning, we also include the braking pedal as a symbol. We assign the symbols designated for cruise control and braking whenever cruise control is enabled or the brake pedal is pressed, regardless of the values of APP and ES signals.

We have now a symbolic representation of the data, with the symbols “abcdef” being associated with regions in APPES, while “gh” represent the cruise control and braking pedal respectively. We can then express each trip as one string consisting of 8 aforementioned symbols.

**C. APPES Transitions and Patterns**

Transitions represent the information about the order in which symbols occur in the data. The order, in which symbols, are appearing is useful as we can define a sequence of transitions as a pattern, e.g. cruise control followed by braking is different from braking followed by cruise control. Patterns are intuitive, can easily be understood and can be used to define driver behavior and performance. The number of possible patterns grows exponentially, $8^n$, where $n$ is the pattern length.

We define interestingness as the frequency of each pattern. This enables the study of a smaller subset of patterns, while still maintaining that the results have a higher applicability since these patterns occur often.

**IV. EXPERIMENTS**

We set up our experiments in order to understand the usefulness for patterns. We lack ground truth regarding driver performance, therefore we focus on relations with fuel consumption. For evaluation we use 800 trips, where each one is at least 30 minutes long and has less than 5% missing data. We select segments of different lengths from these trips, aiming to investigate the short and long term effect of patterns. The shortest selected segment has a duration of 10 minutes while the longest corresponds to a full trip duration, which is on average 3 hours.

We select representative patterns, which means patterns that occur often, in this case at least 500 occurrences, and are diverse, i.e. they are not a subset of longer patterns, within the selected ones. This gives us 81 patterns for the selected trips.

The predictive power of this data, with respect to fuel consumption, is indicative of the information contained within. We argue that APPES patterns capture useful information based on how we construct them, however this assumption needs to be validated. For each segment, we create a binary
Fuel consumption is the response variable. We select three regression models: linear (LR), support vector machines (SVM) and random forests (RF). We anticipate that the relation between patterns and fuel consumption is non-linear but still use a linear model for comparison purposes. We have used the implementations provided by Matlab 2016a.

We also choose other methods for comparison. As an initial baseline, we select a model where each prediction is the average of the data, as well as linear regression where the total vehicle weight is the only input. We also use a model based on acceleration and speed inspired by Ahn et al. [12]. Lastly, a model based on FPC, described in [13], which combines an alternative response variable and a linear model with inputs from acceleration and vehicle speed.

The results are presented in figure 2, which shows the relation between MSE for each model for different segment length. For each model we use 10 fold cross validation. The most visible result is a decrease in error as segments become longer. This is an interesting observation and we decided it warrants further analysis. We have identified several possible reasons for this.

First, it can partly be explained by the variance in the data. By this we mean that as duration of segments increases, fuel consumption variance decreases. For most models, this leads to a natural decrease in the error. The standard deviation corresponding to each segment duration can be seen in figure 3.

Another reason for this trend is that some segments have the same input feature vector but not the same output. This is true mostly when they have a null binary vector, i.e. none of the representative patterns are present in the given segment, and occurs more often in shorter segments. This is tied to the variance of fuel consumption as each model will try to predict the average over data with the same inputs. Figure 4 shows how many patterns are present, on average, in a segment of a given length.

We want to analyze how segments that have only 0’s in the binary vector affect the MSE. We select segments that have at least one pattern present and exclude all other segments from both training and testing. We present the results in figure 5. When comparing the performance of models with and without...
segments with 0 presence we expected an improvement for both SVM and RF. However, no significant change is present which would mean that both methods can handle the 0s vectors. LR shows a slight improvement, which is to be expected.

Also we want to see how important are outliers when computing MSE. For a given segment length, we select all segments where the response variable is falling within the 75% percentile. Results are illustrated in figure 6. Both SVM and RF show a significant improvement from which we conclude that outliers contribute the most to the error.

Following the same logic, we use the best subset of our data to do prediction, i.e. no outliers and no segments that do not contain any pattern. The results are presented in figure 7. The major difference observed is the reduction in error uncertainty.

For a better understanding of the results, we perform one more analysis. We state that unmeasured factors give a biased result when assessing driver performance and in our other work we argue that we can take into account the effect of said factors. We then want to see how well we can predict a modified response variable based on FPC, see [13]. We want to analyze how much of the unmeasured factors we are able to capture using the APPES patterns. FPC contains the effect of other factors, such as air drag, facilitating comparison of desired variables, in our case the driver, under similar conditions.

The new output is given by equation (4), where $P$ is the new output, $FC$ is fuel consumption for the segment in question, $RGM$ is fuel used associated with road gradient while $FPC$ is fuel for the trip which segment $s_o$ belongs to.

$$P(s_o) = \frac{FC(s_o) - RGM(s_o)}{FPC}$$

Figures 8 and 9 show the results. Both, SVM and RF, perform comparably and do not exhibit the same trend as in figure 2. In this case, we do not see the clear improvement correlated with segment length, as we have observed in the other cases.

We end with computing the percent of segments for each chosen length, that are predicted correctly, i.e. within 5% error. The results are in figure 10. For both response variables, the results are similar, with over 60% of segments being correctly predicted for the full trip when using SVM.

**V. CONCLUSIONS AND FUTURE WORK**

We have proposed a new space, APPES, and a method on how to extract features from this space. We show that the new features contain relevant information to the task of classifying driver performance. We also conclude that SVM is a good candidate for future predictions using patterns. There is also evidence that the patterns are robust and, together with a powerful classifier like SVM, can handle the incompleteness of data and still perform adequately, while a weak classifier, like LR, will perform poorly. The biggest challenge identified in this work comes in the form of outliers. The selected patterns are unable to capture the high variance in the data, i.e. neither of our patterns can capture spikes in response variable.

Future work includes analyzing how well patterns perform when symbols are fuzzy, i.e. instead of a single symbol we have a combination of symbols with associated intensity.
for each data point. We also want to analyze what is the contribution of each pattern to driver performance, how it relates to environmental conditions and vehicle characteristics. Understanding how to select the relevant signals depending on the domain, will enable generalization of the concept.

We also want to investigate how we can quantify the importance of each pattern. This is particularly useful for defining interesting patterns, not just based on how often they occur but also based on how important they are.

REFERENCES


