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Classification of Road Type and Driving Style using OBD Data

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Abstract

This paper investigates classifications of road type and driving style based on on-board diagnostic data, which is commonly accessible in modern vehicles. The outcomes of these classifications can be utilized in, for example, supporting the advanced driver assistance systems (ADAS) for enhancing safety and drivability, and online adaptation of engine controller for improving performance and fuel consumption. Furthermore, the classifications offer valuable information for fleet operators to consider when making decision on procurement plans, maintenance schedules and assisting fleet drivers in choosing suitable vehicles. To this end, a velocity-based road type classification method is evaluated on measurements collected from real driving conditions and compared to an open-sourced map. To produce representative results, two most commonly adopted driving style classification methods, i.e. acceleration and jerk-based methods are evaluated and compared on the same set of measurements. The classification results and their correlations with fuel consumption are also investigated and discussed. This investigation reveals that the acceleration and jerk-based driving style classifications are only applicable to certain driving conditions, prompting for the need of a more comprehensive classification of driving style.

Introduction

The advent of vehicular sensing and control technologies has led to the emergence of driving monitoring systems, advance driver assistance systems (ADAS) and big data fleet management systems. Underlying these systems are a set of classification algorithms that processes sensor data into useful attributes, such as road type, traffic congestion and driving style, which can be utilized for the intelligent control of vehicles and fleet management. For example, Langari and Woon [1] has proposed using the identified road type, congestion level and driving style to enhance the energy management of a hybrid electric vehicle. In addition, Johnson and Trivedi [2] has proposed using a driving style identification system to increase awareness and to promote driver safety for fleet operators. It is also well-known that different road types and driving styles have various degree of impact on the fuel consumption and vehicle wear and tear. If the statistics of these information are available, then fleet operators may utilize them when making procurement plans and maintenance schedules. Furthermore, an expert system may also be constructed to assist the fleet drivers to choose suitable vehicles to minimize fuel consumption by taking into account their driving style and intended traveled routes. The results from this research are anticipated to be applied to fleet operators, where knowing the typical traveled road type and driving style of individual and/or overall fleet drivers are beneficial for future procurement plans. One important factor to consider during new fleet vehicle procurement is the fuel economy.

By studying urban driving patterns, Ericsson [3] found that the road type has a larger impact on fuel consumption than driving behavior. Moreover, the analysis also showed that the average speed and acceleration are distinctively different for different road types, while the differences in deceleration are smaller. These findings are exploited by Daniel et al [4], where the average speed is used to classify the road type. Furthermore, if global positioning system (GPS) is available, then an automated road type classification system may be developed by comparing the vehicle position with a road map.

Ericsson [5] also singled out driving patterns that have the most influence on fuel consumption using factorial analysis, which include idling time, acceleration with strong and moderate power demand, speed oscillation, speed at motorway, braking intensity and timing of gear change. Since drivers with different driving behaviors show different driving patterns, these may be exploited in the driving style classifier.

Driving styles can be divided into three categories, calm, normal and aggressive [4, 6, 7]. The majority of the drivers demonstrate normal driving style with moderate acceleration and braking. However, calm drivers anticipate the movements of other road users and avoid sudden acceleration. On the other hand, aggressive drivers exhibit heavy acceleration and braking.

In [6], driving style is classified using the average and maximum acceleration. It is also demonstrated that the ranges of average and maximum acceleration vary with different road types. Furthermore, Murphey et al [7] proposed using jerk as a classifier and

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demonstrated that the standard deviation-to-mean ratio of jerk varies with driving styles. However, the acceleration-based and jerk-based classifiers do not consider the variations in engine power of different vehicles. Vehicles with large engines may exhibit large accelerations or jerks even when the drivers drive calmly. Therefore, these classification methods may not be suitable for analyzing experiment results obtained from vehicles with different power ratings.

Daniel et al [4] proposed using both the power demand and accelerator pedal position as the classifiers, hence taking into account the variations in engine power of different vehicles. Additional driving style classification methods based on acceleration, power demand and jerk can be found in the review by Wang et al [8]. However, these methods are not evaluated and compared on the same set of data.

To facilitate fuel consumption and emission analysis, the speed-time sequences or commonly known as the *drive cycles* are measured. Since drive cycles are repeatable in a chassis dynamometer under controlled environment, they are widely adopted in these investigations [9]. In light of widely available off-the-shelf on-board diagnostics (OBD) loggers, additional information such as air-fuel ratio, manifold absolute pressure and accelerator pedal position can be accessed through the OBD port. These additional data can be utilized for road type and driving style classifications.

In this paper, classification methods for road type and driving styles are evaluated and compared. To produce representative results, the methods are evaluated on the same set of measurements obtained from real driving conditions, where a university-owned fleet vehicle with spark ignition engine is utilized for data collection. Additionally, GPS traces and vehicle status from the OBD port are logged. The logged data comprises short trips in the vicinity of Linköping, Sweden and long trips that range from Stockholm to Malmö, therefore facilitating analysis on both short and long trips. Furthermore, the results of the classification methods and their correlations with fuel consumption are compared and discussed.

Collection of Data

The university owned fleet vehicle utilized in this work is a 2012 VW Passat with a 1.4 liter turbo-charged dual-fuel engine. It has a maximum power of 110 kW and a curb weight of 1626 kg. An older model (2009 VW Passat) test vehicle of similar class is depicted in Figure 1.

Figure 1. A 2009 VW Passat mounted on a chassis dynamometer.

Additionally, the vehicle was also equipped with an OBD-II logger. The logged signals included speed, ambient pressure, intake manifold pressure, engine coolant temperature, time since engine was started, engine rotations per minute (RPM), air-fuel ratio, throttle percentage and accelerator pedal position. Furthermore, a GPS unit was also mounted to record the position of the vehicle.

The data collection session started on February 4 and ended on June 16, 2014. Multiple drivers were involved in the data collection. Unfortunately, information about the drivers are not accessible at the time of writing. The resultant database consists of 261 trips, covers a total distance of 8494 km and 109 hours of logged data. However, only 93 trips that are longer than 5 km are used for the analysis. The GPS traces of the 93 trips are illustrated in Figure 2. Drive cycles shorter than 5 km in the dataset show extremely long idling time, which may have been recorded during the testing of measurement equipment. Since these data do not reflect the normal usage, they are discarded to avoid skewing the results. Note the 93 trips used in the analysis cover a total distance of 8252 km (or 97% of the total logged distance), but only 90% (or 98 hours) of the total data length, demonstrating that the discarded trips are insignificant for providing useful driving cycles.

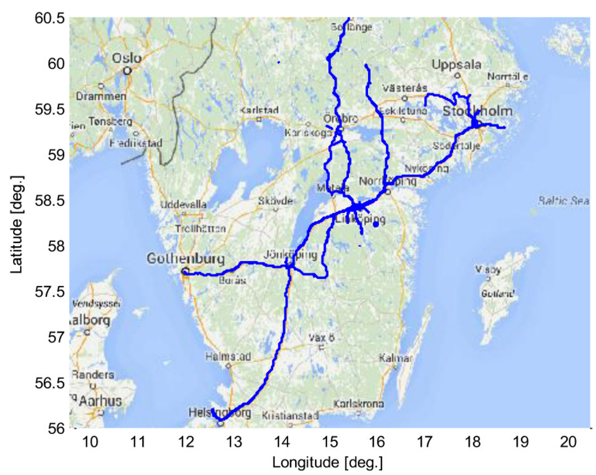

Figure 2. GPS traces of the 93 trips collected during experiments.

The mean speeds and travel distances of the 93 trips used in the study are illustrated in Figure 3. The trend of mean speed versus travel distance is illustrated by a moving average regression, where it is observed that the mean speed increases with travel distance up to approximately 100 km. This is because trips longer than 100 km typically involved traveling on high speed motorways.

The distributions of mean speed, travel time and travel distance are shown in Figure 4. Slightly more than 20% of the trips consist of short trips within 20 km, and the first, second and third quartiles are 21.7, 54.6 and 141.4 km respectively. Additionally, the majority of the trips are shorter than one hour, where the quartiles are 20.8, 44.6 and 92.3 minutes. The histogram of mean speed has a bin size of 5 km, where there are several peaks observed at the bins of 45-50, 60-65, 70-75, 75-80 and 90-95 km. These peaks closely correlate to the speed limits commonly observed in Swedish roads, which are 30, 40 and 50 km/h within urban areas, 60, 70 and 80 km/h within rural areas and 90, 100, 110 and 120 km/h within high speed motorways. This suggests that fleet drivers commonly drove close to the speed limits.

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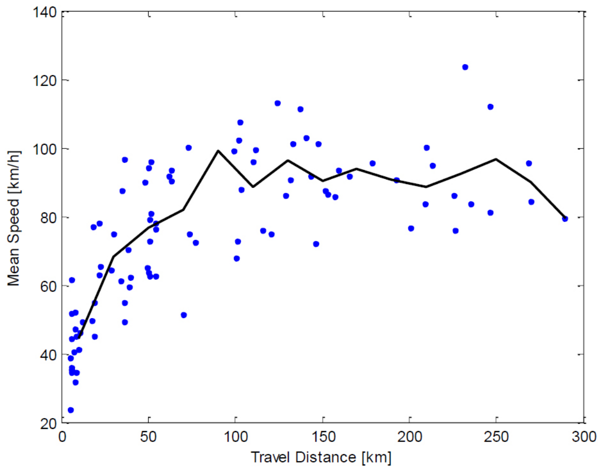

Figure 3. Mean speeds and travel distances of the 93 trips. The black solid line is calculated using the moving average method, illustrating the trend of mean speed versus travel distance.

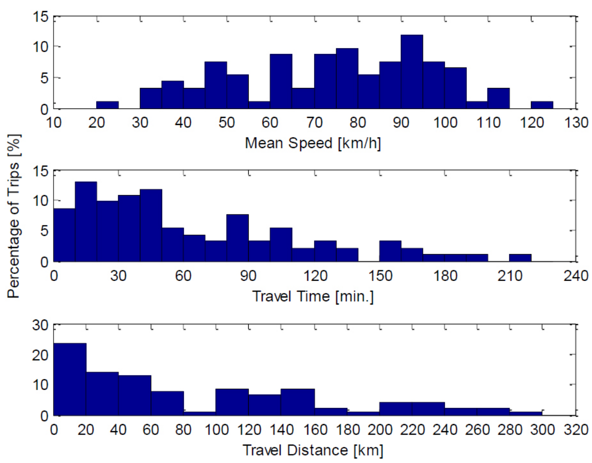

Figure 4. Distribution of mean speed, travel time and travel distance of the 93 trips.

Estimation of Fuel Consumption

The experimental setup described in the previous section is not capable of measuring the fuel consumption directly. Therefore, we resort to estimating the fuel rate using available OBD signals. The total fuel consumption for a trip can be obtained by integrating the fuel rate. The OBD signals utilized for the fuel rate estimation are air-fuel ratio, engine revolutions, and intake manifold pressure. The fuel rate model in Heywood [10] is adopted in this study and will be recapped as follows.

The fuel mass flow rate, $\dot{m}_f$ can be calculated using

$$\dot{m}_f = \dot{m}_a \cdot FAR, \tag{1}$$

where $\dot{m}_a$ and FAR are the air flow rate and fuel-air ratio respectively. Note the fuel-air ratio can be calculated using the lambda value, λ available from the OBD output, given by

$$FAR = \frac{1}{14.7\lambda}, \tag{2}$$

where 14.7 is the stoichiometric air-fuel ratio. Furthermore, the air flow rate is estimated by

$$\dot{m}_a = \eta_v \cdot V_d \cdot \left(\frac{N}{2}\right) \cdot \rho_a, \tag{3}$$

where N, V_d, η_v, ρ_a are engine RPM, engine volume, engine volumetric efficiency and air density respectively. The engine RPM is available from the OBD output, while the engine volume is provided in the vehicle specifications manual. Note the engine volumetric efficiency map of the test vehicle is not available and has to be estimated. It is well-known that the engine volumetric efficiency is dependent on engine speed [10]. However, if the engine is assumed to operate in a narrow speed range most of the time, then the volumetric efficiency may be approximated by a constant value. A constant volumetric efficiency is chosen such that the estimated fuel consumption matches the reported value. Additionally, the air density is estimated using the ideal gas law, given by

$$\rho_a = \frac{P}{RT}, \tag{4}$$

where P, R and T are the intake manifold pressure, individual gas constant and intake air temperature respectively. Note the intake manifold pressure measurements are available through the OBD. Since the intake air temperature was not logged during the measurement session, a constant value that reflects the typical weather in Sweden during the measurement session is used. It is anticipated that the error caused by the discrepancy in air temperature estimation is relatively insignificant. Finally, the fuel consumption in terms of liters per 100 km, FC can be calculated using

$$FC = 100 \cdot \frac{\int_0^{t_f} \dot{m}_f \, dt}{d \cdot \rho_f}, \tag{5}$$

where d, t_f and ρ_f are the travel distance in km, total travel time and fuel density respectively. Figure 5 illustrates the time histories of speed, accelerator pedal position and estimated fuel rate for a short trip. It can be seen that the estimated fuel rate has a good correlation with the pedal position.

Classification of Road Type

As alluded to in the introduction, road type has a major impact on fuel consumption. Furthermore, since driving patterns such as average speed, acceleration and deceleration vary with road types, classification of road type is needed to segregate the data before classification of driving style is performed.

In this section, roads are categorized into three types, urban roads, rural roads and motorways. The grouping is based on the allowable traveling speed in different road types, where the maximum speed limits for urban roads, rural roads and motorways are 50, 70 and 120 km/h respectively.

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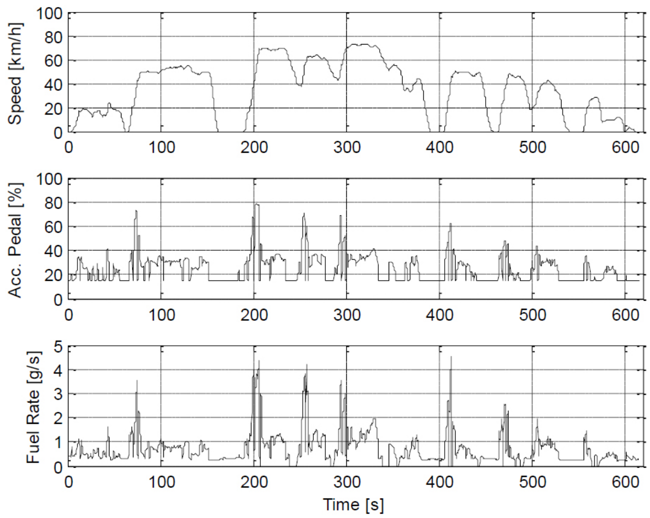

Figure 5. Time histories of speed, accelerator pedal position and estimated fuel rate.

A velocity-based method similar to Daniel et al [4] is employed for the classification of road type. The method is executed in two stages. At the first stage, the roads are segmented based on the measured speed, i.e. 0-50 km/h for urban roads, 50- 70km/h for rural roads, and 70km/h or above for motorways. To deal with misclassifications due to reduced speed at intersections and tight corners, road segments with durations shorter than some given thresholds are identified at the second stage before they are combined with their neighboring road segments. Idling events are also identified when the vehicle is stopped.

The results from the proposed road type classification method are compared with a map. To facilitate this, a computer program is developed to automatically identify the road names and road types for the recorded vehicle locations, where the open-sourced Open Street Map (OSM) database is employed for providing the road names and road types. Note the official road classification available in commercial maps may provide the most authoritative definition for road type. However, commercial maps are costly and may not be as widely accessible as the open-source maps. On the other hand, OSM is one of the most widely used open source map with large crowd contributions, and it is expected that its improving accuracy is sufficient to provide an examination ground for evaluating the road type classification method. The road type definitions used in the OSM are listed in Table 1, and are compared to the road type definitions used in this paper.

Figure 6 compares the road type classified using the velocity-based method and the OSM data for a 5.9 km short trip from Linköping University to Linköping University Hospital. The path taken during the trip is shown in Figure 7, where time-stamps with 100 seconds intervals are included in the map. It is observed that the secondary roads defined in the OSM are classified as either urban roads or rural roads. This is because the secondary roads in this trip are very narrow and the driver had to reduce the speed on some road segments. Note the isolated points on the OSM road type plot are caused by errors in identifying roads that the vehicle was traveling on, especially when there were a few roads in the vicinity of the vehicle. However, these errors remain isolated and do not affect the purpose of validation.

Table 1. Comparison of the road type definitions used in OSM and the definitions adopted in this paper.

Open Street Map		Road Types
ID	Descriptions	
0	Unclassified roads that are least important in a standard road network	-
1	Service roads	Urban
2	Residential smaller roads for access mostly to residential properties	Urban
3	Tertiary roads	Urban
4	Secondary roads	Rural
5	Primary roads	Motorway
6	Trunks	Motorway
7	Motorways, fast, restricted access roads	Motorway

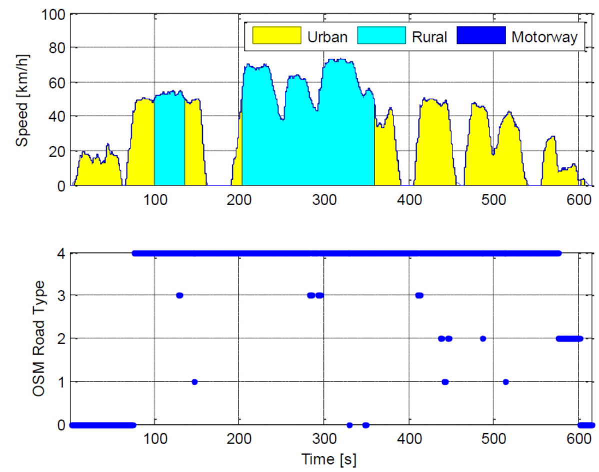

Figure 6. Comparison of classified road types with the OSM data for a short trip.

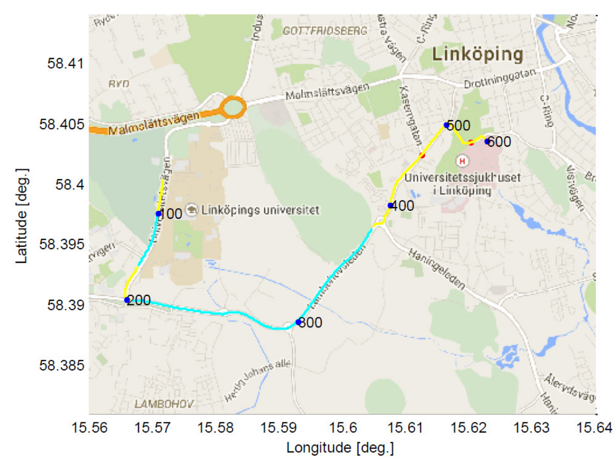

Figure 7. The path taken during the short trip, where the urban and rural roads are denoted by yellow and cyan lines respectively. The path is also marked with dots and time-stamps for every 100th seconds.

The road type classification method is also evaluated on a longer trip as shown in Figure 8, where the path taken during the trip is shown in Figure 9. It is demonstrated that the method compared well with the OSM data before 3597 seconds. However, the GPS signal was lost after 3597 seconds, thus the road type could not be determined from the OSM map. Note it is not uncommon to lose GPS signal when driving under thick foliages or surrounded by high mountains. This also highlights the need for a road type classification method based on signals collected from the OBD port even if a GPS unit is equipped on the test vehicle.

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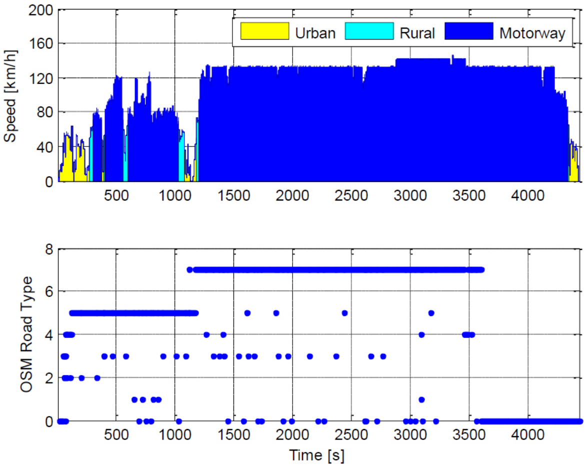

Figure 8. Comparison of classified road types with the OSM data for a long trip.

Figure 9. Majority of the roads traveled in this long trip consisted of motorway, which is denoted by blue line. The dots on the traveled path are spaced with 500 seconds intervals, where the time-stamps are included.

Classification of Driving Style

As reviewed in the introduction, driving patterns are heavily influenced by road types. To isolate the influences of road types and driving styles, the recorded data is first segregated based on the identified road types, then followed by applying a driving style classification method on the segregated data. In the following, two most commonly adopted driving style classification methods based on acceleration and jerk are evaluated and compared on the same set of measurements obtained from real driving conditions.

To facilitate the presentation of driving style classification methods, profiles for speed, acceleration, jerk and accelerator position for the short and long trips introduced in the previous section are plotted in Figure 10 and Figure 11 respectively. Note the acceleration is the first time-differentiation of speed, and the jerk is the second time-differentiation of speed. Additionally, the range for the accelerator position is between 15% and 82%. In Figure 11, it is noticed that the acceleration profiles are noticeably smoother at high speed motorway, especially when cruise control was activated (and the accelerator pedal was not pressed) between 1300 to 4200 seconds. The jerk profiles are also visibly smoother at regions where the accelerator position changes slowly.

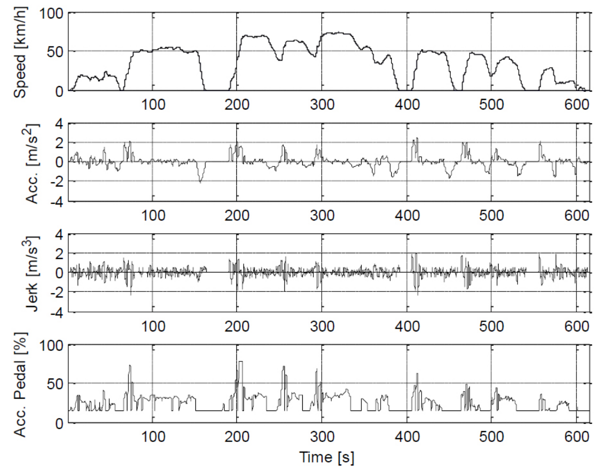

Figure 10. Speed, acceleration, jerk and accelerator position profiles for the short trip as shown in Figures 6 and 7.

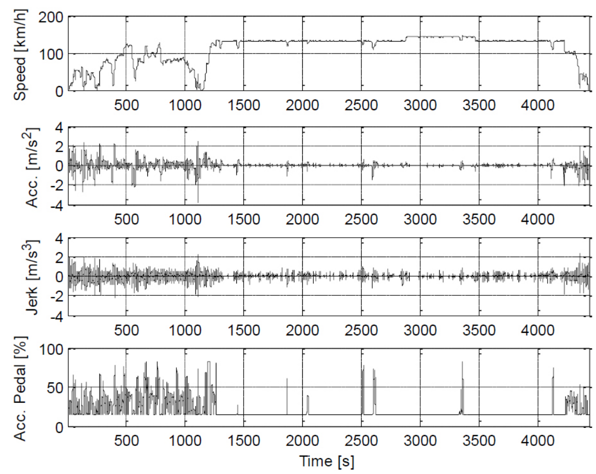

Figure 11. Speed, acceleration, jerk and accelerator position profiles for the long trip as shown in Figures 8 and 9.

To obtain driving patterns for different road types, the road type classification method presented in the previous section is first applied to the 93 collected trips. Then, data with the same road types are combined, where the distributions of speed, acceleration and jerk for different road types are shown in Figure 12. Additionally, statistical trends of speed, positive acceleration, deceleration and absolute jerk are listed in Table 2 and illustrated in Figure 13.

The frequency distribution for speed on urban roads is relatively flat compared to rural roads and motorways, and is reflected in its large coefficient of variation (CV), where the CV reflects the normalized spread of data, defined by

$$c_v = \frac{\sigma}{\mu}, \tag{6}$$

where the standard deviation (SD), σ is normalized by the mean, μ. Since urban roads are relatively short with many junctions, vehicle speeds are likely to vary when traveling from one end of a road segment to another, thus contributing to the larger dispersion in speed. On the other hand, rural roads and motorways have long stretches with relatively fixed speed limits, therefore their speed frequency distributions are relatively concentrated. Since the speed

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range for motorways (70 km/h and above) is more spread out compared to rural roads (50-70 km/h), a more dispersed spread in motorway speeds is observed compared to rural road speeds.

Acceleration

The acceleration is separated into positive acceleration and deceleration, where only the positive acceleration is used for driving style classification. The negative transients are excluded due to the lack of brake intensity measurements. Including the negative transients without considering the input from brake may lead to biased results.

Vehicles typically accelerate faster on urban roads, as demonstrated by the comparatively large positive acceleration mean, while motorways have the smallest mean. Furthermore, urban roads also attain a large third quartile in positive acceleration. The dispersions of positive accelerations decrease from urban roads to motorways, which can be observed from the reductions in standard deviations and interquartile ranges (IQRs), where the IQR is the difference between the first and the third quartiles, given by

$$IQR = Q3 - Q1. \tag{7}$$

Note the mean values for positive acceleration are typically small, therefore the CVs are sensitive to small changes in the means. On the other hand, the IQR is a more robust representation for the distribution of positive accelerations, and is used for the classification of driving style.

We consider the middle fifty of the frequency distribution as the normal positive acceleration, while the lower 25% and the upper 25% are calm and aggressive respectively. Q1 and Q3 set the upper and lower thresholds for calm and aggressive accelerations respectively.

Figure 14 shows the changes and spreads of driving styles during the short trip, which is predominantly consisted of urban roads. Since the vehicle speeds varied when traveling from one end of an urban road segment to another, there were a lot accelerations and decelerations. When the vehicle is decelerating, the driving style cannot be identified, as only the positive acceleration is used for driving style classification. This classification method indicates that the driver exhibited 48% of calm driving and 32% of normal driving during the short trip. By assessing the overall driving style, the driver is classified as a calm driver.

In Figure 15, the change and spread of driving styles for the long trip is shown, where the trip predominantly consisted of motorways. Since cruise control was activated most of the time, calm driving is the most common driving style. However, when cruise control was not activated, the driver behaved more aggressively, notably between 400 to 1100 seconds.

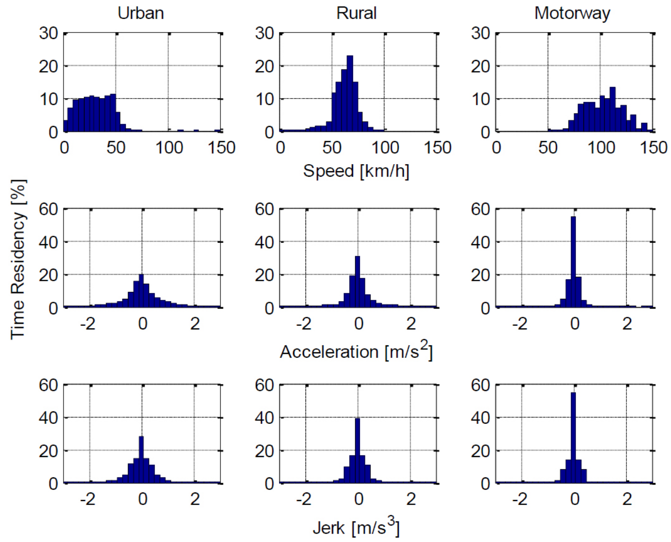

Figure 12. Distribution of velocity, acceleration and jerk for different road types.

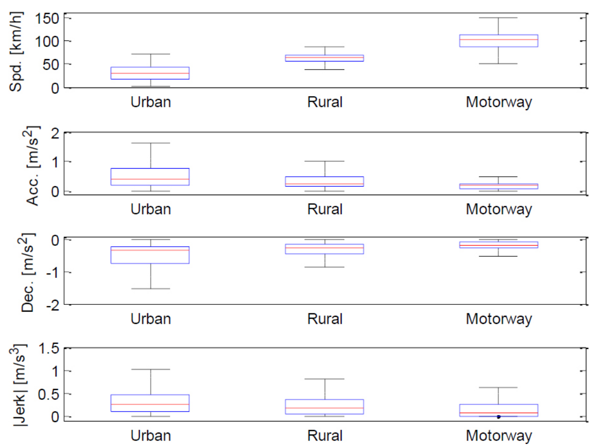

Figure 13. Box plots for speed, positive acceleration, deceleration and absolute jerk for different road types.

Table 2. Means, standard deviations (SD), coefficient of variations (CV), quartiles (Q1, Q2, Q3) and interquartile range (IQR) for speed, positive acceleration, deceleration and absolute jerk for different road types.

		Speed [km/h]	Accel. [m/s²]	Decel. [m/s²]	Absolute Jerk [m/s³]
Urban	Mean	29.9	0.547	-0.536	0.343
	SD	14.7	0.525	0.528	0.507
	CV	0.492	0.960	-0.985	1.478
	Q1	18.0	0.205	-0.727	0.086
	Q2	30.0	0.391	-0.341	0.248
	Q3	42.0	0.768	-0.202	0.459
	IQR	24.0	0.563	0.525	0.373
Rural	Mean	62.7	0.396	-0.387	0.235
	SD	10.9	0.435	0.457	0.305
	CV	0.174	1.098	-1.181	1.298
	Q1	56.8	0.145	-0.425	0.040
	Q2	64.0	0.240	-0.239	0.166
	Q3	69.6	0.499	-0.145	0.348
	IQR	12.8	0.354	0.280	0.308
Motorway	Mean	103.1	0.205	-0.214	0.146
	SD	17.3	0.231	0.237	0.328
	CV	0.168	1.127	-1.107	2.247
	Q1	89.0	0.072	-0.252	0
	Q2	104.0	0.190	-0.192	0.076
	Q3	115.0	0.240	-0.072	0.246
	IQR	26	0.168	0.180	0.246

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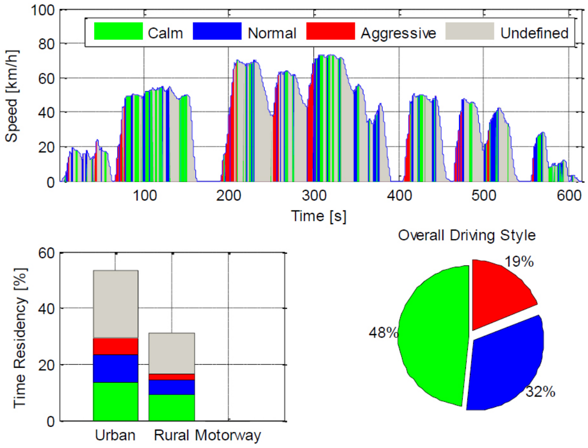

Figure 14. Distribution of driving styles classified using positive acceleration over a short trip. (Top) Variation of driving style versus time. (Bottom Left) Time residency of road type and driving style for the short trip. (Bottom Right) Spread of driving styles over the short trip.

Jerk

As shown in Figure 10 and Figure 11, when the accelerator pedal is pressed and released, spikes are observed in the jerk profiles. Note that the absolute value of jerk increases not only when the accelerator is pressed, but also when the accelerator is released. To take into account of both positive and negative values of jerk, the absolute jerk is used for the following analysis. Furthermore, the analysis considers drive cycle segments with positive accelerations. Decelerations are excluded due to the lack of brake intensity measurements, where including the negative transients without considering the input from brake may lead to biased results.

Similar to positive acceleration, the means and statistical dispersions of absolute jerk are higher for urban roads than rural roads and motorways. However, as the mean values for jerk are small, the CVs for jerk are sensitive to small changes in the means. On the other hand, the IQR is a more robust measure for the statistical dispersion of absolute jerks.

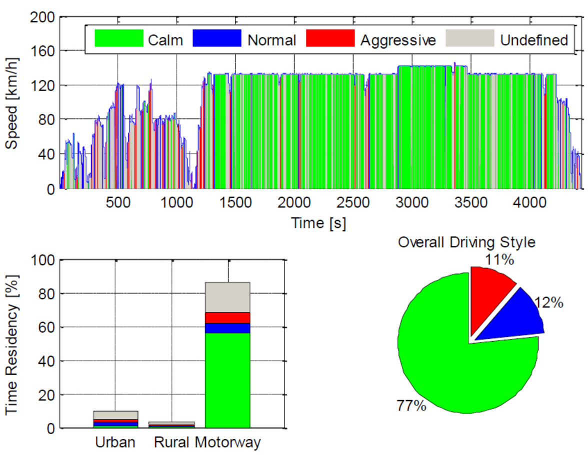

Figure 15. Distribution of driving styles classified using positive acceleration over a long trip. (Top) Variation of driving style versus time. (Bottom Left) Time residency of road type and driving style for the trip. (Bottom Right) Spread of driving styles over the trip.

Rather than using the CVs as the classifier as proposed in [7], driving style is determined by comparing the absolute jerk to the 25% and 75% quartiles (or Q1 and Q3) for each road type. The lower 25% and the upper 25% of the absolute jerks are respectively defined as calm and aggressive, while the middle fifty is defined as the norm.

Figure 16 show the spread of driving styles for the short trip. Compared to the classification method based on acceleration, the jerk-based classification method presents a larger constituent of normal and aggressive driving, where the driver was determined to be less calm and exhibited 39% normal and 27% aggressive driving. The discrepancy arises from the fact that the jerk-based method considers rapid release of accelerator as a relatively aggressive behavior, while the acceleration-based method classify that as a calm behavior. This can be seen by comparing the discrepancies of driving style time histories in Figure 14 and 15, togther with the accelerator profile in Figure 10. During the short trip, there are multiple events of rapid pressing and releasing of the accelerator, particularly when the driver was navigating around bends and narrow roads (see Figure 6).

Figure 17 shows the spread of driving styles for the long trip. Both the acceleration and jerk-based classification methods give similar result as cruise control was heavily used on motorways.

Discussion on the Classification Results and Fuel Consumption

In this section, the results of the road type and driving style classification methods presented in the previous section and their correlations with fuel economy are discussed.

Figure 18 shows the fuel consumption for different mean speeds and road types. The mean speed is calculated in bin sizes of 10 km/h using the data set that consists of 93 trips. It is shown that the fuel consumption values at low speed are high. The fuel consumption in these low speed segments includes the extra fuel spent on engine warm-up and frequent start-stops. Furthermore, low gears are also typically used in the low speed region, which account for low transmission efficiencies. The most efficient speed is at about 80 km/h. However, as speed increases, the fuel efficiency reduces due to the increased air drag. Since the classification of road types is closely related to vehicle speed, it is observed that the fuel consumption on urban roads are the highest at 11.2 l/100km. The fuel consumption reduces on rural roads at 7.56 1/100km. The mean speed for rural roads are 62.7 km/h, which is in the vicinity of the optimal speed for fuel economy. It is observed that the range of vehicle speed on motorways is relatively wide, from 70 km/h to approximately 145 km/h. Because of the wide vehicle speed range and the increasing fuel consumption above 80 km/h (due to the escalated air drag), the average fuel consumption on motorways is slightly more than on rural roads at 7.79 l/100km.

Figure 19 illustrates the fuel consumption for different driving styles classified using the positive acceleration and absolute jerk. On urban roads, results from the acceleration-based method suggest that fuel consumption decreases slightly with driving style aggressiveness, which is contradictory to common expectations. However, note the variations are very minor and can fall well within the estimation error of fuel consumption. On the other hand, the jerk-based method

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clearly associates the drivers' aggressiveness to heavy fuel consumption, where aggressive driving is deemed to result in 41.1% increase in fuel consumption.

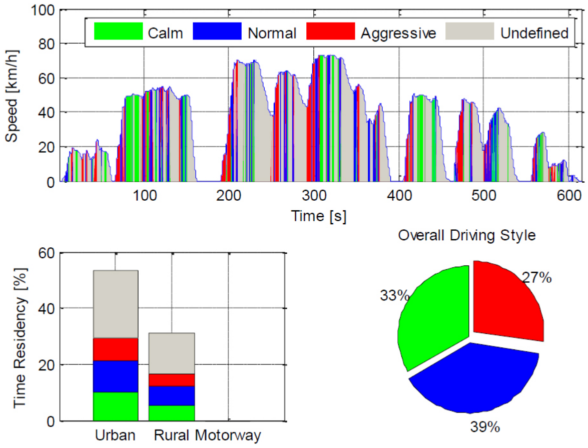

Figure 16. Distribution of driving styles classified using absolute jerk over a short trip. (Top) Variation of driving style versus time. (Bottom Left) Time residency of road type and driving style for the trip. (Bottom Right) Spread of driving styles over the trip.

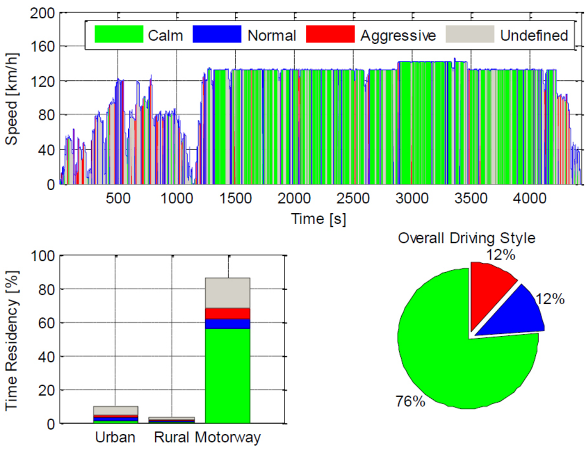

Figure 17. Distribution of driving styles classified using absolute jerk over a long trip. (Top) Variation of driving style versus time. (Bottom Left) Time residency of road type and driving style for the trip. (Bottom Right) Spread of driving styles over the trip.

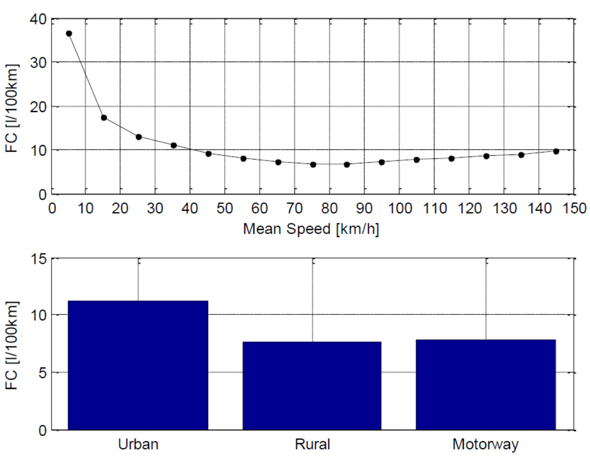

Figure 18. Variation of fuel consumption with mean speeds and road types.

On rural roads, both methods give similar trends and show the increase in fuel consumption with drivers' aggressiveness. Nonetheless, the jerk-based method provides a stronger association with drivers' aggressiveness and fuel consumption, where aggressive driving led to 2.8% increase in fuel consumption compared to 1.2% given by the acceleration-based method.

On motorways, both methods show higher fuel consumption for calm driving. A careful examination of the data reveals that the mean speed during calm driving is higher. For example, in the case of jerk-based method, the mean speeds for calm, normal and aggressive driving styles are 105, 100 and 98 km/h respectively. Moreover, the IQRs of speed on motorways are relatively large compared to urban and rural roads. On the other hand, the spreads for acceleration and jerk on motorways are relatively small. Since air drag increases quadratically with respect to speed, it is expected that speed has a relatively large influence on the fuel consumption on motorways. This suggests that the acceleration and jerk-based methods have some shortcomings when applied to motorway drive cycles and may be improved by including the speed in the classification.

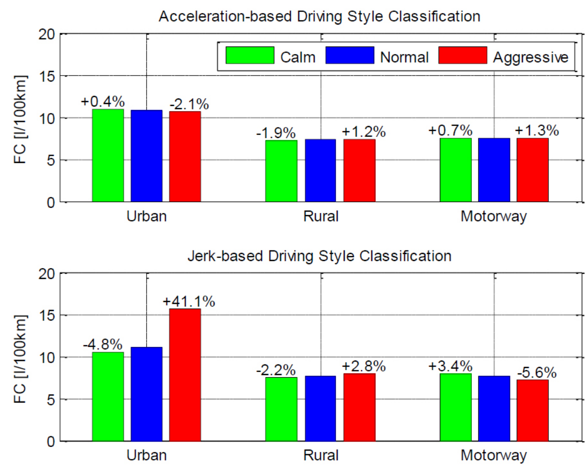

Figure 19. Variation of fuel consumption with driving styles, where the percentage differences in fuel consumption relative to the normal driving style are shown.

Conclusions

Road type and driving style classifications are valuable information for optimizing vehicle operations and improving fleet managements, where the latter is the intended goal of this investigation. For example, the classification may be used in devising strategies to minimize fuel expenditure in fleet operations. Additionally, the results may be applied in the study of variability in fuel consumption of a particular vehicle model to drivers' aggressiveness. This may assist fleet operators and drivers to choose among various internal combustion, hybrid and/or electric vehicles.

In order to develop a general applicable solution, on-board diagnostic (OBD) data is chosen for the classification. While the entire fleet may consists of vehicles with different models and brands, the OBD port is standard among modern vehicles. Therefore, by choosing the OBD as the source of data, a common hardware can be used throughout the entire fleet for assessing the data. This reduces cost and simplifies data collection.

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This study considers a velocity-based road type classification and two of the most commonly adopted driving style classification methods, which are based on acceleration and jerk. To present a representative comparison, these methods are evaluated and compared using a set of data collected from real driving conditions.

The results for road type classification method is compared using the GPS traces and the widely used Open Street Map (OSM), where reasonably matching results are demonstrated. OSM is chosen as the examination ground due to its availability and low cost, in addition to its improving accuracy with larger user base. However, validation using an authoritative commercial maps may be performed in the future.

Furthermore, by comparing the acceleration and jerk-based driving style classification methods, the latter shows a better correlation between high fuel consumption and aggressive driving on urban and rural roads. This suggests that the jerk-based method is more suited for classifying the driving style of fleet drivers, as fuel is a substantial expenditure for fleet operators. However, both methods are unreliable when applied to drive cycles on motorways. This motivates further improvements, perhaps by including the speed in the classification. Future work may also include experimental validation of fuel consumption estimation using an engine dynamometer.

References

1. Langari, Reza, and Won Jong-Seob. "Intelligent energy management agent for a parallel hybrid vehicle-part I: system architecture and design of the driving situation identification process," *IEEE Transactions on Vehicular Technology*, 54(3):925-934, 2005.
2. Johnson, Derick A., and Trivedi Mohan M.. "Driving style recognition using a smartphone as a sensor platform," *International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2011.
3. Ericsson, E., "Variability in urban driving patterns," *Transportation Research Part D: Transport and Environment* 5(5):337-354, 2000.
4. Daniel, R., Brooks, T., and Pates, D., "Analysis of US and EU Drive Styles to Improve Understanding of Market Usage and the Effects on OBD Monitor IUMPR," SAE Technical Paper 2009-01-0236, 2009, doi:10.4271/2009-01-0236.
5. Ericsson, E., "Independent driving pattern factors and their influence on fuel-use and exhaust emission factors," *Transportation Research Part D: Transport and Environment* 6(5), 325-345, 2001.
6. de Vlieger, I. "On board emission and fuel consumption measurement campaign on petrol-driven passenger cars," *Atmospheric Environment* 31(22):3753-3761, 1997.
7. Murphey, Y. L., Milton, R., and Kiliaris, L., "Driver's style classification using jerk analysis," in *IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems*, 2009.
8. Wang, R., and Lukic, S. M., "Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles," in *Vehicle Power and Propulsion Conference*, 2011.
9. Milkins, E. and Watson, H., "Comparison of Urban Driving Patterns," SAE Technical Paper 830939, 1983, doi:10.4271/830939.
10. Heywood, J. B., Internal combustion engine fundamentals, Mcgraw-hill New York, 1988.

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Definitions/Abbreviations

ADAS - Advanced Driver Assistance Systems

CV - Coefficient of Variation

FC - Fuel Consumption

GPS - Global Positioning System

IQR - Interquartile Range

OBD - On-Board Diagnostic

OSM - Open Street Map

RPM - Rotation Per Minute

SD - Standard Deviation

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