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Driver Classification for Optimization of Energy Usage in a Vehicle

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Abstract

Real time monitoring of some key dynamical parameters of a vehicle provide critical information about the driving styles and expectations of vehicle drivers. Some of these key dynamical parameters include vehicle acceleration, braking, speeding index and throttle activity index. This paper presents a simple classifier that uses the estimated values of the above parameters to classify a driver into one of three categories, aggressive, moderate and conservative. The proposed classifier is computationally more efficient compared to other conventional classifiers, such as K-nearest neighbor algorithm, and hidden Markov model. Also, it filters the reference data set in an intelligent fashion. In a dual-power vehicle, such as a hybrid electric vehicle, this kind of classifier can be used to develop an optimum shift schedule, or an optimum engine on-off strategy, and estimate the available amount of regenerative energy.

Keywords: Driver classification; K-Nearest Neighbor algorithm; powertrain signals; principal component analysis

1. Introduction

To optimize the driving experience of a driver, significant improvements have been made to vehicle powertrains and their control strategies during the past few years. However, most of these strategies target a particular segment of drivers based on market segment studies. This strategy works well if the focus is on a particular demographic section, which it is designed for. However, if the powertrain controller can adapt itself to the short-term and long-term driving styles of a specific driver, the vehicle would be appealing to a broader section of customers. If the powertrain could learn the driving style of a driver and adjust its parameters, such as shift map, transmission gear-shifting style, pedal map, and engine operating point, it would greatly enhance the driving experience of the driver. The powertrain parameters can then be adjusted to maximize fuel economy based on the driver's long-term driving style, whereas short-term learning can be used to adjust the powertrain for the driver's instantaneous power requirement needs.

A few studies on driver classification have appeared in recent literature. Wada [1] proposed a performance based index that estimates the driver's attentiveness by monitoring the driving patterns and the deceleration profiles under various driving and braking events. An empirical classifier is modelled to index drivers based on their visual capabilities and alertness. SangJo Choi [2] used hidden Markov models (HMMs) to model the driving characteristic data gathered from the CAN-bus information of a vehicle. The emphasis of this paper is more towards identifying some of the actions taken by a driver, such as turning or braking, and deciding whether the driver is distracted by some secondary tasks. Nobuyuki [3] proposed a driver behaviour recognition model using HMMs to characterize and detect driving maneuvers and place it in the framework of a cognitive model of human behaviour. This study focuses on lane change maneuvers using measures, such as steering angle, steering angle velocity and steering force. However, an algorithm is used to classify the driving skill of the driver during a lane change, but not the power demands of the driver. Hsin Guan [4] used a fuzzy decision making model that calculates an index of driving safety (IDS) based on the geometrical characteristics of the road ahead and the driver's response, driver handiness based on how busy the driver is

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with the steering wheel at steady speeds, and driving legality based on how the driver obeys the traffic statute for passing vehicles etc.

Lin [5] presented a quantitative analysis for on-going assessment of a driver's cognitive responses by investigating the neurobiological information associated with electroencephalographic (EEG) brain dynamics in traffic light experiments. Nonparametric feature extraction, principal component analysis and discriminant analysis were applied to reduce the dimension of the feature vector. A combination of K-nearest neighbour (KNN) and naïve Bayes classifier (NBC) was used for classification. Ehmann [6] presented a parametric driver classifier that classifies the driver into four categories, namely, unskilled non-aggressive, unskilled aggressive, skilled aggressive, and skilled non-aggressive. The classification is based on driving speed, preview distance used to make braking decisions, rate of slowing down, and maximum steering wheel angle change rate. Veeraraghavan [7] proposed classification algorithm that classifies the actions of a driver as safe or unsafe. Bjorklund [8] showed that a positive relationship exists between a driver's irritation and an increase in the frequency of aggressive actions. Ma [9] used a fuzzy clustering algorithm to analyze human driving behaviour with respect to car following and lane change maneuvering based on longitudinal and lateral acceleration, applied brake pressure, engine speed and some GPS data, such as speed, travel time and distance. These were used to classify a driver's aggressiveness with respect to lane changes and car-following.

Although the above authors attempt to characterize a driver in one way or another, they do not attempt to classify the drivers based on their power demands from the vehicle powertrain. Such a characterization is important for developing an adaptive powertrain optimizer that can optimize the energy usage in a vehicle, promote greener ways of driving, and enhance fuel economy. This paper presents an attempt toward that.

2. Data acquisition and preprocessing

In the training phase of the classifier, data was collected from ten different drivers driving the same instrumented vehicle over a pre-selected route. The instrumented vehicle is capable of measuring the signals listed below at a frequency of 320 Hz. The drivers were asked to drive the first lap as an acclimatization lap. Then they were asked to make three laps of the route in conservative, moderate and aggressive driving styles. The route was chosen to have a good mix of various road attributes, such as grade changes, stop signs, traffic lights, left or right turns, and different speed limits along the route. The signals collected were chosen to cover all aspects of driving, such as vehicle speed, acceleration, torque, accelerator pedal, steering wheel angle and brake pedal force. The raw data collected for the purpose of driver characterization included the signals shown in Table 1 below.

Table 1: Signals Collected for Data Analysis

Signal Name	*Symbol*	*Unit*
Lateral Acceleration	α_{Lat}	*m/s*^{2}
Longitudinal Acceleration	α_{Long}	*m/s*^{2}
Accelerator Pedal percentage	α_d	*%*
Vehicle Speed	β_v	*km/hr.*
Output shaft acceleration	α_{shaft}	*rpm/sec*
Driver intended brake torque	τ_B	*Nm*
Steering wheel angle	θ	degree
Axle Torque	τ_{axle}	*Nm*
Vehicle Torque Request	$\tau_{request}$	*Nm*
Vehicle Acceleration	α_v	*m/s*^{2}

3. Correlation analysis

Correlation analysis of the collected data was performed to find their inter-relationships and eliminate the redundant ones from further studies. The correlation analysis was performed on all training datasets, and strong correlations were observed between similar signals generated by different drivers. Correlation analysis revealed that the output torque demand ($\tau_{request}$), throttle position (α_d) and axle torque (τ_{axle}) are strongly correlated. Also, since throttle percentage is a good reflection of the axle torque (τ_{axle}), throttle (or accelerator) pedal can be used as a representative signal for the three signals mentioned above. It was also observed that the steering wheel angle and vehicle speed are not strongly correlated with any of the other signals, and hence these can form a very good component of the classifier. Using correlation analysis, we were able to reduce the feature space from 9 to 7. The signals were shortlisted to steering wheel angle (θ), vehicle speed (β_v), vehicle acceleration (α_v), accelerator pedal (α_d), driver requested brake torque (τ_B), lateral acceleration (α_{Lat}), and longitudinal acceleration (α_{Long}). Next, principal component analysis was undertaken to determine the most important signals for classification.

4. Principal component analysis

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Principal Component Analysis (PCA) transforms an original set of variables into a substantially smaller set of uncorrelated variables, while retaining most of the information present in the original set of variables. Thus, PCA can be used to reduce the dimensionality of the original data set.. According to Dunteman [7], PCA can also be used to select a subset of variables from a larger set of variables by selecting only those variables that have a high correlation with the principal components. PCA was performed on the variables shortlisted from the correlation analysis, and the results are shown in Table 2 below.

Table 2: PCA Results

Principal Component	*Percentage Contribution*	*Major Contributors*	*Attribute Description*
PC1	37%	α_v,α_d, α_{long} and $1/(\tau_B)$.	Linear Acceleration of the Vehicle
PC2	24%	θ, β_v, τ_B, and α_{lat}	Vehicle Acceleration during turns
PC3	14%	θ, β_v, α_d, and α_{lat}	Lateral Acceleration
PC4	12%	β_v, α_d and τ_B	Speed Variations in the vehicle

Based on the results of correlation analysis and PCA, the signals selected for feature extraction include lateral acceleration (α_{lat}), vehicle acceleration (α_v), vehicle speed (β_v), and accelerator pedal percentage (α_d).

5. Feature extraction and selection

The following features were extracted from the signals identified at the end of the previous section for driver classification.

Feature 1: Feature extracted from lateral acceleration, α_{Lat}

From the lateral acceleration signal, we extract information for two types of maneuvers, namely, cornering maneuvers for $|\theta| > \theta_{Th}$, and non-cornering maneuvers for $|\theta| < \theta_{Th}$, where θ_{Th} is a threshold dependent on the minimum wheel angle that a vehicle needs to make with the longitudinal axis and is determined from the relationship between the steering wheel angle and the wheel angle. The features extracted from these two types of maneuvers are mean (α_{Lat}) for cornering maneuver and max (α_{Lat}) for non-cornering maneuver. The mean value computed during cornering maneuvers describes the aggressiveness of the driver during turns, whereas the maximum value computed during non-cornering maneuvers describes the aggressiveness of the lane change maneuvers.

Feature2: Mean vehicle acceleration/deceleration, α_v

This feature computes the mean acceleration of the vehicle when it accelerates from a certain threshold velocity, β_{vTh} to 80% of the posted speed limit or until the brake is applied. Similarly, it computes the mean vehicle deceleration when the brake is applied and the speed is between 80% of the posted speed and β_{vTh}, or the brake pedal is released.

Computational Logic:

$If\ [[\beta_{vTh} < \beta_v < (0.8\beta_P)]\ \ \&(\alpha_d \geq \alpha_{dTh})\&(\tau_B = 0)]$, compute $mean\ (\alpha_v)$

$else\ If\ [(0.8\beta_P > \beta_v > \beta_{vTh})\&(\alpha_d < \alpha_{dTh})\ \&(\tau_B > \tau_{BTh})]$, compute $mean\ (\alpha_v)$,

where β_{vTh}, α_{dTh} and τ_{BTh} are the empirically determined minimum speed, minimum accelerator pedal value and the minimum brake torque threshold.

Feature3: Standard deviation of vehicle speed, β_v

Standard deviation of the vehicle speed is measured for the time interval during which the vehicle speed is above 70% of the posted speed limit and ends when either the brake pedal is pressed, or the vehicle speed drops below 70% of the posted speed limit, or when the vehicle is on a turn as detected by the steering wheel angle measurement from the earlier feature. This feature indicates the speeding index of the driver.

Computational Logic:

$If\ [(\beta_v \geq (0.7\beta_P))\&(\tau_B \leq 40)\&\ (|\theta| < \theta_{Th})]$, compute $std(\beta_v)$

Feature4: Throttle activity index (TAI)

This feature characterizes the driver's confidence level by measuring the change in the magnitude of the accelerator pedal relative to the frequency of change in the accelerator pedal percentage. It is measured when the vehicle speed is above 70% of the posted speed limit and the accelerator pedal percentage is greater than 10%. The throttle activity index is computed as follows.

1. For a given time window $t_{feature4}$, measure the standard deviation of accelerator pedal with respect to the moving ideal accelerator pedal percentage required to maintain the vehicle speed at a given posted speed limit and road gradient. Ideal accelerator pedal position, $\alpha_{d_{calculated}}$, can be calculated from the pedal-to-torque mapping of the vehicle once the tractive

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force requirements are known for a given speed and grade. The vehicle torque demand is essentially the tractive force which is a function of road load, aerodynamic drag, rolling resistance and the acceleration component.

2. The frequency of pedal change is determined using an instantaneous frequency estimator [14]. Next, the normalized standard deviation was calculated as follows.

$\alpha_{d\_std} = \left|\frac{std(\alpha_d) - \alpha_{d_{nTh}}}{\alpha_{d_{nTh}}}\right|$, where $\alpha_{d_{nTh}}$ is the normalization threshold.

The normalized pedal frequency was calculated as:

$\alpha_{d\_freq} = \left|\frac{\hat{F}(n) - f_{nTh}}{f_{nTh}}\right|$, where f_{nTh} is the normalization threshold.

Computational Logic:

$If\ [(\beta_v \geq 0.7\beta_P)\&(Drive\ Segment = True)\ \&(\alpha_d > 5)]$ compute $TAI = \frac{2 \times Pedal\_Deviation \times DCC}{(Pedal\_Deviation + DCC)}$

The throttle activity index, as illustrated in Fig. 1, is a fuzzy number ranging between 0 and 1, where 0 represents a steady and conservative driver, while a 1 represents an extremely aggressive driver showing significant movement in the accelerator pedal in both magnitude and pedal movement for the given window.

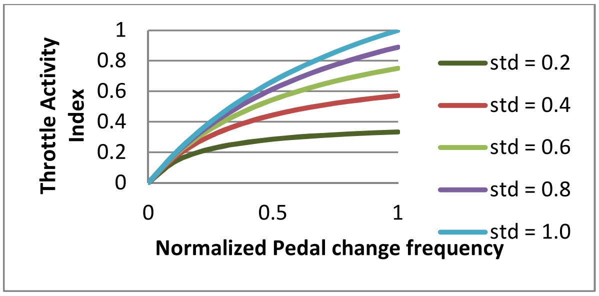

Figure 1: TAI as a function of STD and DCC

6. Classifier Design

A generalized bell function [14] is used to describe the probability density function of each of the features and its classification into one of the three categories, aggressive, moderate and conservative. The function is defined as:

$$f(x, a, b, c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}.$$

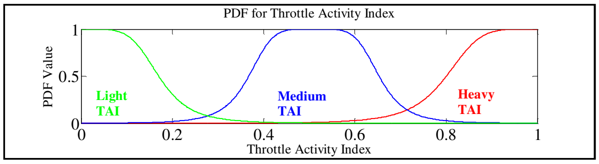

Figure 2: Sample PDF for Throttle Activity Index

The PDF parameters for each feature are determined empirically, and they allows us to partition the whole training set into discrete individual feature spaces. During the classification phase, when a new sample is encountered, the PDFs of the extracted features are determined and then only those training datasets (pre-classified samples) that have at least 75% of the extracted features with non-zero values are chosen for analysis. The classification is done based on a simple majority criterion. This classifier does not need to compute the Euclidean distance between every new feature sample and the samples in the training data set. Also, if there is a repetition observed in the pre-classification stage, where the training data set is being classified, the dimensions can be reduced by simply eliminating one of the training data sets. This will occur only when all the extracted features of both the samples have the same individual PDFs and also are classified in the same category. Given an unknown sample, its nearest neighbours need not be sought in the entire feature space but only in a region surrounding it. This method

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calls for the exploration of the concept of partitioning the feature space into cells. The downside is that this method leads to approximate nearest neighbours, which is adequate in most situations. For driver classification, three classes are considered, aggressive, moderate and conservative.

Let $\omega = \{\omega_1, \omega_2, \dots \omega_c\}$ be the finite set of classes and let F be the feature vector containing all the extracted features from a given time window such that $F = \{F_1, F_2, \dots, F_k\}$. A general assumption is made that the data is bounded and partitioned into three categories, i.e., aggressive, moderate and conservative. Let $P(F_k|\omega_j)$ be the state conditional probability density function (PDF) for F_k and $P(\omega_j)$ describe the prior probability that the class is ω_j. $P(\omega_{jk})$ is the prior probability that the class is ω_{jk} for the feature F_k. The posterior probability is then computed as

$$P(\omega_{jk}|F_k) = \frac{P(F_k|\omega_{jk}) \times P(\omega_{jk})}{\sum_{j=1}^{c} P(F_k|\omega_{jk}) \times P(\omega_{jk})}, c = 3$$

Using Bayesian decision theory further, for a class vector $\omega = \{\omega_{agg}, \omega_{mod}, \omega_{cons}\}$, the class of the feature F_k is now determined by finding the class that has the maximum probability. Thus we obtain the class for each individual feature in the feature vector.

Next, to determine the posterior probability of a class for the entire feature vector, we use the following equation:

$$P(\omega_{ji}|F) = \frac{\sum_{i=1}^{k} P(F_i|\omega_{ji})}{\mathrm{k}}.$$

The final class for the feature vector sample is determined by finding the class that has the maximum probability.

Since a driver cannot be judged by just a few bad actions, hysteresis was built into the classifier by incrementing the appropriate bin counter for each class at the end of each sample window in the drive cycle and then using the following equation to estimate the driver characteristic for the entire drive cycle. The classes have been assigned numerical values for computational ease with conservative=1, moderate=2 and aggressive=3. If during the drive cycle, the driver's actions are classified as conservative *'k'* times, as moderate *'m'* times and aggressive *'n'* times, then their mean is given by:

$$Mean\ Class = \frac{\sum_{i=1}^{n}(3) + \sum_{i=1}^{m}(2) \sum_{i=1}^{k}(1)}{(n+m+k)}$$

The above equation gives us an index of the driver's aggressiveness as compared to a discrete classification into one of the three classes.

7. Experimental Results

From the raw data collected, the threshold values used in the feature extraction phase were empirically determined to be as follows:

Table 3: Threshold Values for Experimental Variables

Threshold Variable	*Value*
θ_{Th}	*100°*
β_{vTh}	*3 Km/hr.*
α_{dTh}	*5%*
τ_{BTh}	*40 Nm*
α_{dnTh}	$0.1 \times \alpha_{d_{calculated}}\%$
$t_{feature4}$	*10 sec.*
f_{nTh}	*0.35 Hz*

From the data that was obtained from different drivers, approximately 75% was used for initial training whereas the remaining 25% was used for validating the accuracy of the classifier.

The classifier was initially trained based on the observed samples in the training set. Training samples that were observed to meet at least 80% of the PDF domains in the features from any of the previous samples were discarded as the classification would have resulted in the same class and to reduce the size of the data bank. However all samples (with new feature PDF combinations) were kept. This process ensured that the training and observation set is diverse and that repetitions are avoided. Features that had a value of zero in a given time window for a given feature vector was not considered in the analysis. The PDFs belonging to any feature were denoted by L (light), M (medium) and H (heavy). Since we had 4 features and each feature had 3 PDFs, there were a total of $3^4 = 81$ combinations possible. The classification was performed based on the technique explained

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above. For the sample instantaneous classifier, the classification is shown in the last column of table 4 (training set). Table 5 shows the validation set in which the classifier was able to classify with 100% accuracy. In the overall datasets collected, the classifier was able to classify with an overall accuracy of 77%.

Table 4: Example of Training Set

Sr. No.	*Feature 1*	*Class*	*Feature 2*	*Class*	*Feature 3*	*Class*	*Feature 4*	*Class*	*Classification*
1	0.1063	L	-0.200	M	0.4578	L	0.3350	L	Conservative
2	0.0	X	0.13	L	0.3742	L	0.4107	M	Conservative
3	0.0	X	-0.140	L	0.1358	L	0.6093	M	Conservative
4	0.0	X	0.21	M	0.7130	M	0.0150	L	Moderate
5	0.0	X	-0.25	M	0.5351	L	0.7015	M	Moderate
6	0.1800	M	0.18	M	0.6959	M	0.5113	M	Moderate
7	0.34	H	-0.331	H	0.8261	M	0.8111	H	Aggressive
8	0.0	X	0.3099	H	0.7930	M	1.0000	H	Moderate
9	0.0	X	-0.26	M	0.8130	H	0.9899	H	Aggressive

Table 5: Example of Validation Set

Sr No	*Feature 1*	*Class*	*Feature 2*	*Class*	*Feature 3*	*Class*	*Feature 4*	*Class*	*Classification (Supervised)*	*Classification (Classifier based)*	
										Matching Indices (50%)	Majority based Classification
1	0.1859	M	-0.3276	H	0.753	M	0.4858	M	Moderate	4, 5, 6, 8	Moderate
2	0.1271	L	0.1201	L	0.4986	L	0.745	H	Conservative	1, 2, 3	Conservative
3	0.2116	M	-0.288	M	0.8342	H	0.6762	M	Moderate	4,5,6, 8	Moderate
4	0.2648	H	0.2099	M	0.0.896	H	0.7999	H	Aggressive	7, 9	Aggressive
5	0	X	0.2469	H	0.7089	M	0.6928	M	Moderate	4, 5, 6, 8	Moderate

8. Conclusion

This paper presents a new technique for driver classification for optimization of energy usage in a vehicle. The classifier uses features extracted from the vehicle's powertrain signals. Experimental results show that the classifier is able to classify a driver's driving style based on the power demands placed on the vehicle powertrain with an overall accuracy of 77%. The classifier is computationally more efficient compared to conventional KNNs as it does not need to compute the Euclidean distance of every new sample with respect to other samples in the training dataset. The achievable savings in computational cost and a powertrain optimization strategy that can achieve better fuel economy based on the information provided by the classifier are currently under investigation.

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