Driver's Style Classification Using Jerk Analysis

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Abstract— **This paper presents an innovative approach to classifying the driver's driving style by analyzing the jerk profile of the driver. Driving style is a dynamic behavior of a driver on the road. At times a driver can be calm but aggressive at others. The information about driver's dynamic driving style can be used to better control fuel economy. We propose to classify driver's style based on the measure of how fast a driver is accelerating and decelerating. We developed an algorithm that classifies driver's style utilizing the statistical information from the jerk profile and the road way type and traffic congestion level prediction. Our experiment results show that our approach generates more reasonable results than those generated by using other published methods.**

I. Introduction

DRIVING patterns exhibited in a real world driver are the product of the instantaneous decisions of the driver to cope with the (physical) driving environment. Research has shown that driver style, roadway type, and traffic congestion levels have various degrees of impacts on fuel consumption and emissions [1, 2]. Research has also shown that by incorporating the knowledge of driving environment into power management, fuel consumption can be significantly reduced [3, 4, 5, 6, 7]. During real world driving, the driving patterns need to be predicted accurately in real time so the results can be used by the online power controller [5, 6, 7]. However prediction and classification of roadway types and driver styles are not trivial. In a previous paper, we presented our research in road way type prediction and the power management algorithm that incorporates the roadway type and traffic congestion predictions to find the optimal power distribution [7]. The classification of driving style will be to serve as the database that will be used for training of Neural Networks. The goal is to make an intelligent prediction of the future as our research in the road way prediction for power management has proven successful. With the future knowledge of the drivers style, power management techniques can be further refined, but that topic is out of the scope of this discussion. We will focus on generating a data set that is mathematically and logically coherent.

In this paper we present our research on the automatic classification of dynamic driving style of a driver on the road. Driving style is a dynamic behavior of a driver on the road. At times a driver can be calm but aggressive at others. The knowledge about driver style can be used in real time vehicle power control to minimizing fuel consumption in hybrid electric vehicles. For example if it's predicted that the driver is being aggressive at the current drive cycle, more battery power may be used instead of engine power to help minimize the fuel consumption.

There is not much research being done on this particular topic. Langari, R.; Jong-Seob Won [5, 6] attempted the driver style classification by using the ratio of the standard deviation and the average acceleration extracted from the acceleration profile within a specified window. If the ratio is greater than 100%, the driver style is classified as aggressive, if it is between 50% and 100%, the driver style is normal, if it is less than 50%, the driver style is calm. Then Langari and Won incorporated the predicted driver style into their power management strategy.

We present in this paper an innovative approach to dynamically classifying driver's style by analyzing the online jerk profile of the driver combined with the statistics of driver styles specific to different roadway types. We also propose a quantitative method to assess the performance of driver style classification. We conducted experiments on a number of drive cycles and the results will show that our driver style classification approach generates better results than those generated by the published method in [5, 6]. All these experiments were conducted within the PSAT (Powertrain System Analysis Toolkit) environment. PSAT[8] is a vehicle simulation program developed by Argonne National Laboratory under the direction of and with contributions from Ford, General Motors, and DaimlerChrysler. PSAT is a "forward-looking" model that simulates fuel economy and performance in a realistic manner — taking into account transient behavior and control system characteristics

In this paper we attempt to classify driving style into four different categories:

- *Calm driving:* a driver that anticipates other road user's movement, traffic lights, speed limits, and avoiding hard acceleration. This driving style should be most fuel efficient.

- *Normal driving :* a driver that drives with moderate acceleration and braking. This driving style is less fuel efficient.

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- *Aggressive driving:* a driver drives with sudden acceleration and heavy braking. This driving style is the least fuel efficient.

- *No Speed:* the vehicle is not moving.

We consider the driving style as a transient behavior: a driver can be aggressive at one time period but normal at others. We propose to classify the driver's driving style by utilizing the statistical information from the jerk profile combined with the knowledge of road-type classification.

II. Driver Style Classification

A. *Jerk Feature Based Driver Style Classification*

In principle, driver's aggressiveness should be measured by how fast the driver accelerates and decelerates. Jerk is defined, in physics, as the rate of change in acceleration or deceleration. Therefore we consider jerk is a more effective feature than acceleration in driver style classification. Jerk is calculated as the derivative of the acceleration/deceleration or the second derivative of the velocity. While an acceleration profile shows how a driver speeds up and slows down, a jerk profile shows how a driver accelerates and decelerates, which is more important in determining the driver's aggressiveness. Fig. 1 presents a comparison between the velocity, acceleration, and jerk profile of the well-known UDDS drive cycle. The jerk profile clearly depicts how the acceleration changes over time in the UDDS driving cycle and the spikes in the jerk profile occur only when there are big changes in the acceleration, negative or positive. By using the features extracted from jerk, a very robust algorithm can be developed to classify the driver's style.

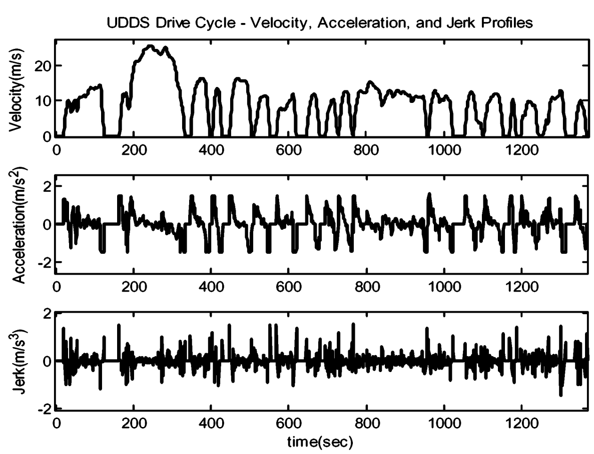

Fig. 1. Comparison between Velocity, Acceleration & Jerk Profile for UDDS Drive Cycle

We propose a quantitative measure of ground truth for driver style classes: fuel rate measured in grams per second. The aggressive drivers tend to have highest fuel rate, calm drivers have the minimum fuel rate, and normal drivers are in the middle. Figure 2 depicts the correlation between the fuel rate of conventional vehicle simulated using PSAT software on the UNIF01 drive cycle and the respective jerk profile. These variables do not correlate extensively due to the braking influence. However, it is noticeable that as the variation in the jerk profile increases, so does the fuel rate.

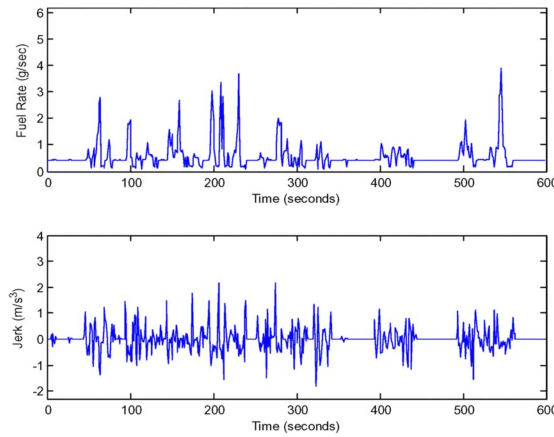

Fig. 2. Correlation between Fuel Rate & Jerk Profile for UNIF01 Drive Cycle

We classify driver styles on a window by window basis in a drive cycle. A drive cycle is usually represented as the speed function of time t, i.e. DC(t), t=0, …, t_e. The jerk function, J(t), can be derived by taking the second derivative of speed, DC(t), i.e. J(t) = $\frac{d^2DC(t)}{dt^2}$. The current driver's driving style at time t is classified based on the following jerk features extracted within time period t $\in [(t_c - \omega), t_c)$: the ratio of the standard deviation of the jerk profile and the typical jerk while driving on that particular road type, where t_c is the current time and ω is the window size. Mathematically, the jerk feature is calculated as $\gamma = \frac{SD_J}{\bar{J}}$, where SD_J is the standard deviation of the jerk over a specified window, and $\bar{J}$ is the jerk of the normal driving style on the road-type the driver is currently on.

The ratio being used, standard deviation divided by the mean, is a useful measure that is referred to as the coefficient of variation. It is often used to compare the amount of variance between populations with different means. This would be the ideal ratio to use in our case, due to the fact that the average jerk is based on the predicted road-type. Whenever the road-type changes, so does the average jerk used in this ratio, thus we can better compare the variation at different points in the drive cycle by using this ratio.

The reason we use $\bar{J}$ as a feature in the classification is that we believe a driver's driving style is strongly influenced by the roadway type and traffic congestion level the driver is on. On a freeway with no traffic congestion, even an aggressive driver does not accelerate and decelerate that much. However on a local road with heavily congested traffics, even a calm driver has to make many brake-acceleration moves. Therefore it is important to incorporate the driving statistics of roadway types into the driver style classification.

We use the speed profile of 11 standard drive cycles developed by Sierra Research [9] as the standard normal driver's driving style on the different roadway types and traffic congestion levels. This set of 11 drive cycles represents passenger car and light truck operations over a range of facilities and congestion levels in urban areas. The 11 drive cycles are divided into four categories of roadways, freeway, freeway ramp, arterial, and local, and the two categories, freeway and arterial are further divided into subcategories of traffic congestion levels characterized by a qualitative measure called level of service (LOS) that describe operational conditions within a traffic stream based on speed and travel time, freedom to maneuver, traffic interruptions, comfort, and convenience. Six types of LOS are defined with labels, A,…, F, with LOS A representing the best operating conditions and LOS F the worst. Each level of service represents a range of operating conditions and the driver's perception of those conditions; safety is not included in the measures that establish the service levels [10,11]. The complete list of the facility specific drive cycles is denoted as fs-dc = {freeway A, freeway B, freeway C, freeway D, freeway E, freeway F, freeway ramp, arterial A-B, arterial C-D, arterial E-F, local road way}. Table I shows the average jerk calculated from all 11 standard drive cycles.

TABLE I
AVERAGE JERK OF 11 SIERRA RESEARCH DRIVE CYCLES

Drive Cycle	Average Jerk (m/s^3)
Freeway A	0.2131
Freeway B	0.2126
Freeway C	0.2258
Freeway D	0.2075
Freeway E	0.2401
Freeway F	0.3096
Ramps	0.2925
Art-AB	0.2580
Art-CD	0.2825
Art-EF	0.2460
Local	0.2439

These average jerks from Table I are calculated by averaging the absolute value of each entire sierra research jerk profile. The absolute value of the jerk is used since it is desired to obtain the 'total' amount of jerk throughout the cycle. The average jerk has significant difference among different traffic congestion levels and different roadway types. In freeways, the most congested levels E and F have higher jerk average than A~E; in arterial road way, the jerk averages for CD and EF are higher than AB; arterial, the local and ramps have higher jerk average than freeway in average. These jerk average values are used in the driver style classification algorithm, DS_Classification algorithm described in the next subsection, to represent a 'normal' driver on the respective roadway and the LOS. This means if the standard deviation of the jerk exceeds the average jerk of the road-type, then the driver will be classified as aggressive. On the contrary, if the standard deviation of the jerk is much lower than the average jerk of a normal driver; it will be classified as calm, unless the velocity is zero.

B. DS_Classification: A Driver Style Classification Algorithm

We We model a driving trip as a time series of speed profile over a sequence of different road types such as local, freeway, arterial/collector, etc. augmented with different traffic congestion levels. As we stated above that the driver's driving style classification is conducted on a window by window basis. At any given time t_c, the classification algorithm extracts the standard jerk within the time window $[(t_c - \omega), t_c)$ and uses the average jerk of the predicted the roadway type to make the classification decision. The next driver's style classification is made at time $t_c + \Delta t$. We refer to ω as window size and Δt as time step. The effect of these two parameters on the classification process will be discussed in the next section. The classification algorithm, DS_Classification, is executed at every time step to perform online driver style classification. The DS_Classification algorithm relies on the output of a roadway type prediction program that predicts the current roadway type and traffic congestion level. The description of the roadway type prediction algorithm we developed can be found in [12].

The following describes the computational steps in DS_Classification, the proposed driver's driving style classification algorithm.

Step 1. Calculate jerk profile within the window, J(t), t $\in [(t_c - \omega), t_c)$.

Step 2. Calculate the standard deviation of the jerk during the entire window.

Step 3. Detect the current road type and traffic congestion level using the roadway type prediction algorithm presented in [12].

Step 4. Calculate jerk ratio $\gamma = \frac{SD_J}{\bar{J}}$, where $\bar{J}$ is the average jerk of the predicted current road-type.

Step 5. If Velocity = 0 m/s then No Speed
Elseif $\gamma < norm_{threshold}$ then DS = Calm
Elseif $norm_{threshold} < \gamma < agg_{threshold}$ then DS = Normal
Elseif $agg_{threshold} < \gamma$ then DS = Aggressive

Two thresholds are used, $norm_{threshold}$ and $agg_{threshold}$. Based on trial and error in experiments, we suggest to take $norm_{threshold}$ = 0.5 and $agg_{threshold}$ = 1.0. Fig. 3 shows an example result of the classification for 250 seconds of the UDDS drive cycle. The color code for the labeling should be interpreted as follows: Red lines denote no speed, Magenta calm, Green normal and blue aggressive. The result was generated by the DS_Classification Algorithm with a 9 second window and the time step of 6 seconds, which allowed a 3 second overlap between the two adjacent windows. The overlap is necessary in order to give a smooth transition between adjacent windows. For the purpose of display, the classification output that is identical to the last adjacent window is not shown. The classification result is shown only when it is different from the result of the previous window. Thus, if there is a gap between two labels, every label in between is the same as the last one illustrated in the graph. For examples, the first pair of Blue and Green line represents the aggressive driving style from 160sec to 192sec; the first pair of Magenta and Green lines represents the calm driving style within the time interval of 210sec to 265sec; the first pair of Green and magenta lines represents the normal driving style within the time interval of 280sec and 308sec. This example shows that the segments classified as aggressive have strong jerk features, the calm segments have weak jerk features, and the normal segments have the jerk features stronger than the calm segments but less than the aggressive segments.

III. Experiment Results

A number of experiments have been conducted to evaluate the proposed driver's driving style classification algorithm, DS_Classification. We first address the issue of the proper window size that can be used to extract effective jerk features, and then we compare the classification results generated by the DS_Classification algorithm with the acceleration based classification algorithm by authors of [4, 5].

A. Comparison of Different Window Sizes

This subsection discusses the effects of window sizes used to extract jerk features for driver's driving style classification. Because the driver style is measured by the transient behavior, jerk, which is captured in a short time interval, i.e. within a window of time, window size is closely related to the classification results. A good window size allows to accurately capturing this transient behavior. If the window size is too small, it may not give enough time to capture the entire acceleration and deceleration event. However if the window size is too big, it may capture multiple events. For example if a driver drives in a relative steady speed for about 20 second and then suddenly accelerates hard for about 10 seconds. A window with a size of 30 seconds will not be able to capture the aggressive event sufficiently since most features in the window are not reflecting this event. The aggressiveness may be detected at a later time, but this delay makes power management less efficient since by the time the aggressiveness is recognized the driver is no longer in the aggressive state.

The driving classification results using different window sizes for approximately 200 seconds of the US06 drive cycle are shown in Fig. 4. The classification results generated by the window sizes of 15, 9, 6, and 3 seconds are superimposed on the speed profile of the drive cycle. The classification at time *t* is displayed only when there is a change in the previous label and the same color scheme as Fig. 3 is used to denote different driving styles. When window size 3 was used, the driver's driving styles changed rapidly. When window size 15 was used, a number of events were missed. For example, the no speed segment between 125 to 150 seconds was missed, and the two segments marked as aggressive between 200 and 250 are more likely to be normal drive style. It appears that the window size 9 and 6 give better results for this drive cycle. Note only window size 6 and 3 detected the stop period, i.e. no speed period between 125sec and 150sec.

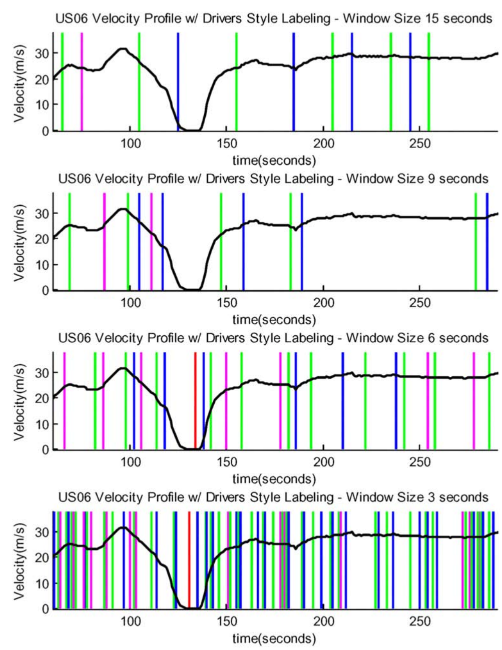

Fig. 4. US06 velocity profiles with Driver's Style classification results using different window sizes

In general, there is some trade-off between using larger and smaller window sizes. Smaller ones capture every bit of aggressiveness of the driver, but produce many transitions in driving styles. Whereas larger windows may cause miss some aggressiveness, but produce considerably less transitions in driving styles. Based on our experience a window size of 6 or 9 is recommended for driving style classification.

B. Comparison of Driver's Style Classification Using Jerk & Acceleration

In this section, we present a comparison of the driver's driving style classification results generated by the proposed DS_Classification algorithm and the acceleration based driving style classification algorithm proposed by Langari and Won in [5]. Fig. 5 and Fig. 6 will show the two examples of driver's style classification results generated by DS_Classification algorithm and the acceleration based algorithm. In both figures the classification results using the acceleration features are shown in the upper graph, and the classification results generated by the DS_Classification algorithm are shown in the lower graph. The results shown in Fig. 5 were generated from the UDDS drive cycle. The DS_Classification algorithm successfully detected the aggressive style between 10 seconds and 50 seconds, but the acceleration based algorithm considered it as normal driving style. The DS_classification algorithm detected the sudden deceleration between 100sec and 125sec, but the acceleration based algorithm output three different styles between the same time interval: aggressive, calm and normal. The DS_Classification algorithm also successfully detected the aggressive style between at about 400 seconds, but the acceleration based algorithm generated many driver styles with the same time period.

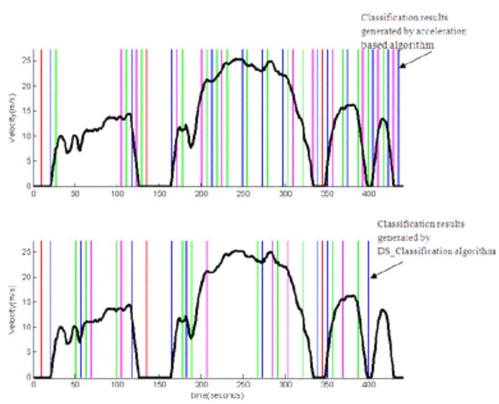

Fig. 5. Comparison of classification results using UDDS drive cycle

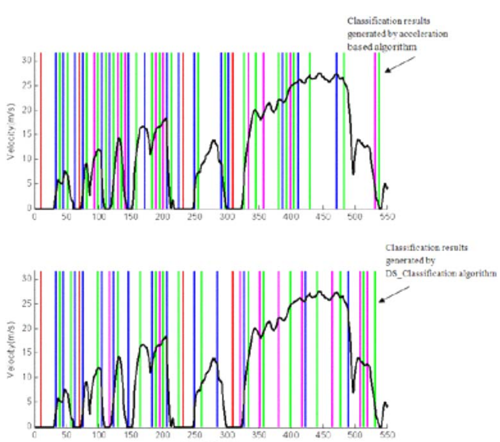

Fig. 6. Comparison of classification results using LA92 drive cycle

The classification results shown in Fig. 6 were generated from the LA92 drive cycle. The DS_Classification algorithm detected the aggressive style between about 20 second and 120 second, but the acceleration based algorithm detected many transitions of driving styles at the same time period. Another example is that the DS_Classification detected an aggressive style at around 200 second, but the acceleration based algorithm detected the same segment as calm style.

One quantitative performance measure of driver style classification is to calculate the fuel rate with a given time segment. We expect to have the following relationship between fuel rate and driving styles:

FR_{ave}(calm) < FR_{ave} (normal) < FR_{ave}(aggressive), where FR_{ave} (*) is the average fuel rate with a given segment that is classified as *, where * represents either calm, normal or aggressive style. Fig. 7 shows the fuel rate curves for three 20-second drive cycle segments that were classified by the DS_Classification algorithm as calm (magenta curve), normal (green curve), and aggressive (blue curve). For the most time, the fuel rates within the aggressive segment are higher than the normal and calm segments, and the fuel rates within the normal segment are higher than the calm segment. Table II shows the average fuel rates for these three driving styles, which satisfies the relationship, FR_{ave} (calm) < FR_{ave} (normal) < FR_{ave} (aggressive).

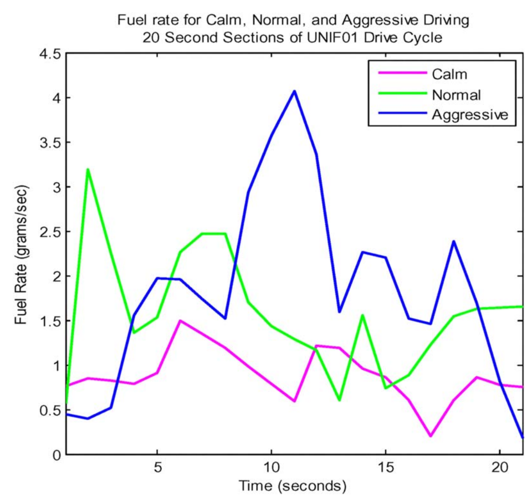

Fig. 7. Fuel-Rate of different driver's style classified by DS_Classification algorithm

TABLE II
AVERAGE FUEL-RATE COMPARISONS BETWEEN CALM, NORMAL, AND AGGRESSIVE DRIVING FOR UNIF01 DRIVE CYCLE

Start Time (sec)	End Time (sec)	Driver Style	Average Fuel-Rate (gram/sec)
1615	1635	Calm	0.8808
1570	1590	Normal	1.5780
225	245	Aggressive	1.8170

Another useful quantitative measure of classification accuracy for driving style classification is fuel mileage measured in miles per gallon (MPG). We expect the correlation between the fuel mileage and the driving style as follows: MPG(calm) > MPG(normal) > MPG (aggressive).

We ran both algorithms, DC_Classification and the acceleration based algorithm, on 9 driving cycles provided in the PSAT library [9] using the same window size (9) and the same time step (6 seconds). Table III shows the MPG for each drive style classified by the DS_Classification and the acceleration based algorithm on all 9 drive cycles. Within each of the 9 drive cycle, we calculate the average mileage over all segments classified in the same class.

TABLE III
AVERAGE MILES PER GALLON
FOR CALM, NORMAL, AND AGGRESSIVE DRIVING:
COMPARISON BETWEEN TWO ALGORITHMS

Drive Cycle	DS_Classification			Acceleration Based Algorithm		
	Calm	Normal	Aggressive	Calm	Normal	Aggressive
UDDS	29.38	17.18	10.85	15.95	20.13	15.66
HWFET	31.94	27.37	8.99	29.36	30.24	37.29
US06	16.22	22.65	10.60	14.40	17.34	13.36
SC03	24.76	23.45	10.24	17.25	19.56	10.26
LA92	23.65	19.37	10.23	16.22	16.97	15.84
REP05	24.25	23.24	12.00	15.83	20.41	26.96
HL07	32.16	17.39	7.64	32.56	12.63	12.13
UNIF01	24.62	20.01	11.10	17.82	20.08	15.45
ARB02	21.16	21.25	10.95	14.82	19.35	11.10

For all drive cycles, the segments classified by the DS_Classification algorithm as "calm" or "normal" have much better fuel mileage than those segments classified as "aggressive". The average mileage for the "calm" segments are all greater than the "normal" segments on all drive cycles except for the two drive cycles, US06 and ARB02. The average mileage for the "calm" segments is almost the same as the "normal" segments in ARB02. But in US06 the average mileage for "calm" segments is much less than the "normal" segments. We consider this as a classification error between "calm" and "normal" classes of driving styles. The classification results generated by the acceleration based algorithm showed that segments classified as "calm" or "normal" in two drive cycles (HWFET and REP05) have less fuel mileage than the "aggressive" segments. This implies serious classification errors. 8 out of the 9 drive cycles showed that average fuel mileages of "calm" segments are less than the "normal" segments, which again implies serious classification errors between "calm" and "normal" on these 8 drive cycles.

IV. CONCLUSION

We presented an innovative algorithm for online classification of driver's driving styles for application to vehicle power management. The algorithm, DS_Classification, extracts jerk features from the current vehicle speed within a short window, and classifies the current driver style into three classes, calm, normal and aggressive, by comparing the extracted jerk feature with the statistics of the driver styles on the current roadway.

Through experiments conducted in the PSAT simulation environment, the DS_Classification algorithm has shown to be effective in classifying the driver's style: (a) the fuel-rate of a conventional vehicle has a positive correlation with spikes in the jerk profile of the cycle, (b) the fuel rates within the aggressive segments are higher than the normal and calm segments, (c) the fuel mileages of "calm" and "normal" segments are much greater than the "aggressive segments, and in most cases, the fuel mileages of "calm" segments are greater than "normal" segments.

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