

Driving Pattern Recognition for Adaptive Hybrid Vehicle Control

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ABSTRACT

The vehicle driving cycles affect the performance of a hybrid vehicle control strategy, as a result, the overall performance of the vehicle, such as fuel consumption and emission. By identifying the driving cycles of a vehicle, the control system is able to dynamically change the control strategy (or parameters) to the best one to adapt to the changes of vehicle driving patterns. This paper studies the supervised driving cycle recognition using pattern recognition approach. With pattern recognition method, a driving cycle is represented by feature vectors that are formed by a set of parameters to which the driving cycle is sensitive.

The on-line driving pattern recognition is achieved by calculating the feature vectors and classifying these feature vectors to one of the driving patterns in the reference database. To establish reference driving cycle database, the representative feature vectors for four federal driving cycles are generated using feature extraction method. The quality of representative feature vectors with different feature extraction methods is evaluated by examining the separation of feature vectors in the feature space and the success rate of the pattern recognition. The performance of the presented adaptive control strategy based on driving pattern recognition is evaluated using a powertrain/propulsion simulation and analysis software - Autonomie.

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1. INTRODUCTION

A hybrid electric vehicle (HEV) has better fuel economy and less emission than a conventional internal combustion engine vehicle due to the existence of electric powertrain. The introduction of additional powertrain components, however, makes the HEV control more challenging and the performance of HEVs is more sensitive to their control strategies. To achieve maximum fuel economy and minimum emissions, researchers in the automotive community have made significant effort to investigate the major factors impacting fuel efficiency and develop optimal power management strategies for hybrid vehicles [1,2,3,4,5]. Research results showed that, in addition to vehicle and fuel characteristics, driving patterns have a strong impact on the fuel consumption and exhaust emissions [6, 7]. To optimize vehicle performance, multi-mode driving control method has been proposed for the adaptive vehicle control [8, 9]. The multi-mode driving control is defined as the control strategy which is able to switch a current control algorithm to the one that is optimized to the recognized driving pattern [8]. The ability to dynamically select control algorithms based on identified driving patterns leads to adaptive vehicle control,

improved energy efficiency, and reduced green gas emissions.

A driving pattern is typically defined as the driving cycle of a vehicle in a particular environment [10]. To recognize driving patterns, it is necessary to identify a list of characteristic parameters which can be used to describe driving patterns. Although there is no consensus among researchers about what parameters can be used for driving pattern recognition, several studies have attempted to find such a list of parameters. Ericsson [6] investigated the impact of 62 driving pattern parameters on fuel economy and emissions using a large amount of testing driving cycles. The study showed that nine driving pattern parameters (four associated with power demand and acceleration, three with gear changing behavior, and two with speed level) had an important effect on fuel consumption and emissions. Lin *et al.* [9] selected power demand related parameters and stop time for hybrid electric truck driving pattern recognition. In addition to vehicle parameters, Jeon *et al.* [8] incorporated road grade parameters in the driving pattern recognition. For pattern classification method, neural network [8], support vector machine (SVM) [11], and learning vector quantization

network [12] were applied for the driving pattern classification. However, most existing driving pattern recognition methods are based on binary classification, which may cause losing of information.

The importance of driving patterns to the fuel economy and emission justifies a systematic study of driving pattern recognition. In this paper, supervised pattern recognition approach is studied for the classification of a real-world driving cycle to a similar driving cycle in the representative driving cycle group. Four federal driving cycles, Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Driving Schedule (HWFET), a high acceleration aggressive driving schedule (US06), and an air conditioning driving schedule (SC03), are selected as representative driving cycles. These driving cycles represent different street types, driver behavior, and weather condition. With pattern recognition method, driving cycles and environmental information for various driving patterns are represented by corresponding features vectors. The classification is based on the distance of a test feature vector (test driving cycle) to the representative feature vectors (representative driving patterns). The test driving pattern is classified to one of representative driving pattern with which the test driving pattern has the smallest distance. The identified driving pattern information is then used to implement adaptive control strategies. The performance of adaptive control is evaluated in a powertrain/propulsion simulation and analysis software - Autonomie.

The rest of the paper is structured as follows. Section 2 introduces driving cycle classification based on the pattern recognition method. Section 3 presents the classification of real-world driving cycles using representative feature vectors of four federal driving cycles. Section 4 studies the impact of dissimilarity measures and feature extraction methods on the performance of driving cycle pattern recognition. Section 5 discusses adaptive vehicle control based on driving cycle pattern recognition. Section 6 concludes the presented work.

2. PATTERN-RECOGNITION-BASED DRIVING CYCLE RECOGNITION

2.1. CONCEPT OF PATTERN RECOGNITION

Pattern recognition is a scientific discipline whose goal is to classify objects into a number of meaningful categories or classes [13]. In pattern recognition, the patterns to be classified are usually the groups of measurements, defining points in an appropriate multidimensional space [13]. The measurements used for the classification are described by features. If p features are used $f_i, i=1, 2, \dots, p$, these p features can form a feature vector $F = (f_1, f_2, \dots, f_p)^T$, where T denotes transposition. A feature vector is a point in P dimensional space R^P . The process of supervised pattern recognition consists of feature extraction and classification two steps. In

the feature extraction stage, a number of feature members are selected from the measurement data of the pattern. These feature members are used to form feature vectors to represent the pattern. In the pattern classification stage, the dissimilarity of the test pattern with the representative patterns is evaluated. The dissimilarity of two patterns is defined as a function of the distance between the corresponding feature vectors of the patterns. Usually, the shorter distance means higher similarity and the longer distance means lower similarity. As such, the test pattern is classified to one of representative pattern with which the test pattern has the smallest distance. Different types of distance definitions can be used in pattern recognition. The Euclidian distance is one of the most commonly used distances. Let $X = (x_1, x_2, \dots, x_n)^T$ and $Y = (y_1, y_2, y_3, \dots, y_n)^T$ denote two feature vectors. The Euclidian distance between these two feature vectors is defined below:

$$d_{XY} = \sqrt{\left(\sum_{i=1}^n (x_i - y_i)^2 \right)} \quad (1)$$

2.2. FEATURE SELECTION FOR DRIVING CYCLE PATTERN RECOGNITION

Feature selection is application dependent. The rule of thumb for feature extraction is that the selected features can replicate most information of the original measurement data and separate feature vectors for different patterns in the feature space. To classify driving cycles, thirty-nine characteristic parameters were initially chosen based on Jeon and Ericsson's work [6, 8]. The high dimension of feature vectors, however, impedes practical application of driving cycle pattern recognition in real-time. To reduce the dimension of feature vectors, numerous simulation tests were performed to find a reduced set of feature members and the weighting factor for each feature member. The selection of the feature members and their weighting factors are based on if the representative feature vectors of individual driving cycles are clearly separated in the feature space. The simulation work finally identified fifteen feature members and corresponding weighting factors, listed in Table 1, to form feature vectors for driving cycles as shown below:

$$f = (k_1 \times a_1, k_2 \times a_2, \dots, k_i \times a_i, \dots, k_{15} \times a_{15})^T, \quad i \in [1, 15] \quad (2)$$

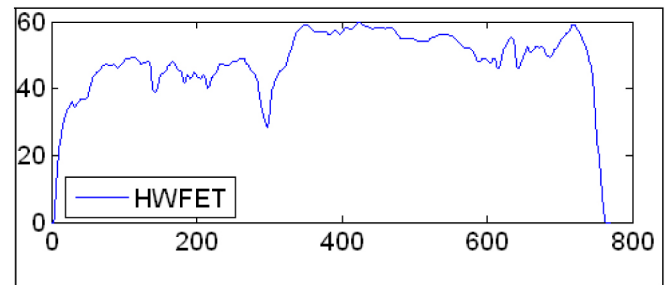
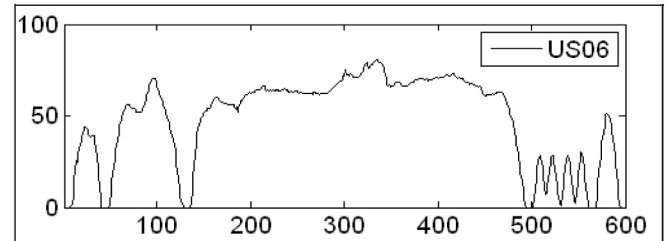
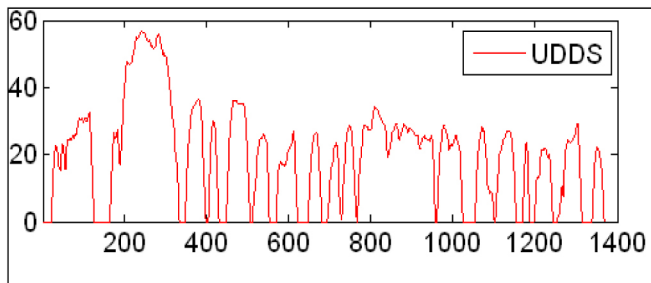
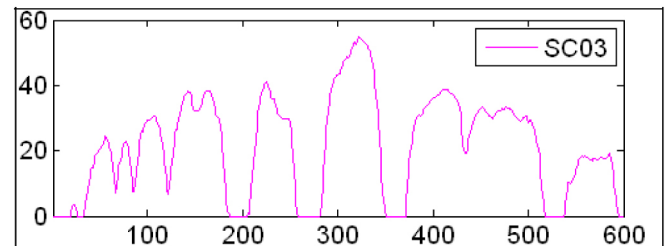
Where a_i is a feature member and k_i is a weighting factor

Table 1. Driving cycle feature members and corresponding weighting factors.

Index Number (i)	Feature Parameters (a)	Weighting Factor (k)
1	Average Cycle Speed (m/s)	10
2	Positive Average Acceleration ($a > 0.1 \text{ m/s}^2$)	1
3	Low Speed Time (15-30 Km/h)/Total Time (%)	10
4	Mid High Speed Time (70-90 Km/h)/Total Time (%)	100
5	High Speed Time ($> 90 \text{ Km/h}$)/Total Time (%)	10
6	Extreme Deceleration Time ($a < -2.5 \text{ m/s}^2$)/Total Time (%)	1000
7	High Deceleration Time ($a < -2$ & $a > -2.5 \text{ m/s}^2$)/Total Time (%)	1
8	Maximum Cycle Acceleration (m/s^2)	100
9	Maximum Cycle Speed (Km/h)	6
10	Standard Deviation of Cycle Speed (Km/h)	1
11	Mid Deceleration Time ($a < -1$ & $a > -1.5 \text{ m/s}^2$)/Total Time (%)	1000
12	Mid High Deceleration Time ($a > -2$ & $a < -1.5 \text{ m/s}^2$)/Total Time (%)	1000
13	Mid Acceleration Time ($a > 1.5$ & $a < 2 \text{ m/s}^2$)/Total Time (%)	1
14	High Acceleration Time ($a > 2$ & $a < 2.5 \text{ m/s}^2$)/Total Time (%)	1000
15	Extreme Acceleration Time ($a > 2.5 \text{ m/s}^2$)/Total Time (%)	1000

2.3. REPRESENTATIVE FEATURE VECTORS FOR SELECTED DRIVING CYCLES

As discussed previously, a driving pattern is determined by multiple factors, including road type, driver behavior, and weather and traffic conditions. To form a good representative driving cycles base which are able to reflect aforementioned features, four federal driving cycles, UDDS, HWFET, US06, SC03, are selected as representative driving cycles. UDDS and HWFET are two driving cycles representing two road types. US06 represents the driver's behavior of aggressive driving. SC03 is chosen to represent the influence of humid weather. The profiles of these four driving cycles are shown in Figure 1, Figure 2, Figure 3, Figure 4. HWFET is a typical highway driving cycle featuring high speed and short stop time, while UDDS has the features of low average speed and long stop time. US06 has the highest average speed and presents extreme acceleration ($a > 2.5 \text{ m/s}^2$). SC03 is similar to UDDS but its acceleration is milder than that of UDDS due to the usage of air conditioner.

**Figure 2. The driving cycle of HWFET.****Figure 3. The driving cycle of US06.****Figure 1. The driving cycle of UDDS.****Figure 4. The driving cycle of SC03.**

A feature vector of a driving cycle is calculated based on partial data points of a driving cycle for the quick recognition of driving cycle patterns, which is especially valuable in real-time applications. The number of data points is defined by the size of a sample window as shown in [Figure 5](#). In this paper, the window size is set to 450 sample points. To speed up the recognition of driving cycle patterns, the technique of sequential processing of measurement is applied. As such, the next feature vector is calculated by advancing the sample window by 50 sample points. During real-time driving cycle pattern recognition, vehicle controllers collect a number of data points defined by the size of the sample window and calculate a feature vector for the current sample window using parameters defined in [Table 1](#). The real driving cycle is then classified to one of four representative driving cycles using classification algorithms and calculated feature vector. Once the driving cycle is recognized, the control algorithm/parameters are switch to the one that is optimal to recognized driving pattern. The time between one control decision points to the next control decision point is 50 seconds in this study if the sample rate is 1 Hz.

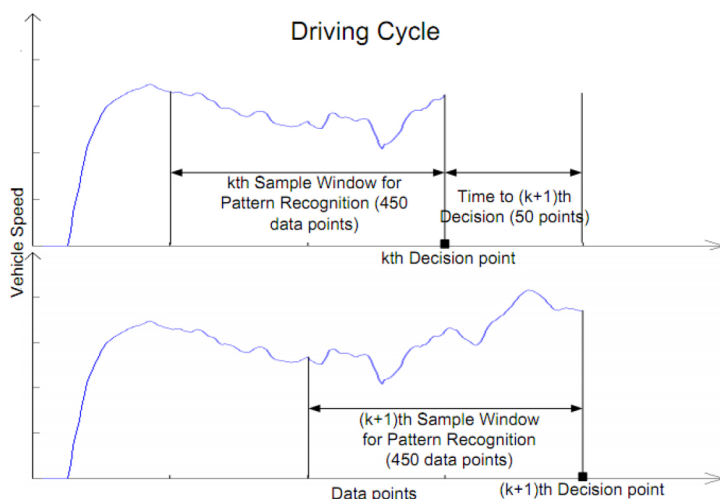


Figure 5. The definition of sample window and sequential processing of measurements.

To generate the representative feature vectors for the UDDS, HWFET, US06, and SC03, the velocity data for these driving cycles were downloaded from the U.S. Environmental Protection Agency website[14]. By comparing the speed profiles, the beginning part of the UDDS and US06 are similar to each other. To correctly distinguish UDDS and US06 driving cycles, the most representative data segments were used to generate feature vectors for the corresponding driving cycles. For the UDDS, velocity data starting from 347th second to the end of the driving cycle were used since this segment contains frequent stops, which is the major feature of the UDDS. For the US06 cycle, velocity data starting from 134th second to the end of the driving cycle were used. This segment differs from UDDS and represents the aggressive feature of driving (large accelerations). Since

these representative segments have different lengths, a common data length of 2000 data points was specified to ensure the same number of representative feature vectors for each driving cycle. The representative segment for each driving cycle was repeated to form a data set with a length of 2000. In each data set, the first 450 data points were used to form the first sample window and find the first feature vector using [equation \(2\)](#). The second feature vector was calculated by advancing the sample window by 50 data points. From [equation \(2\)](#) we can see that the dimension of feature vectors is 15. To display high dimensional driving cycle feature vectors, the Principal Component Analysis (PCA) algorithm was applied to the generated representative feature vectors. The first and second principal components were then used to plot representative feature vectors in 2-dimensional space. [Figure 6](#) shows the distribution of representative feature vectors for the selected four driving cycles.

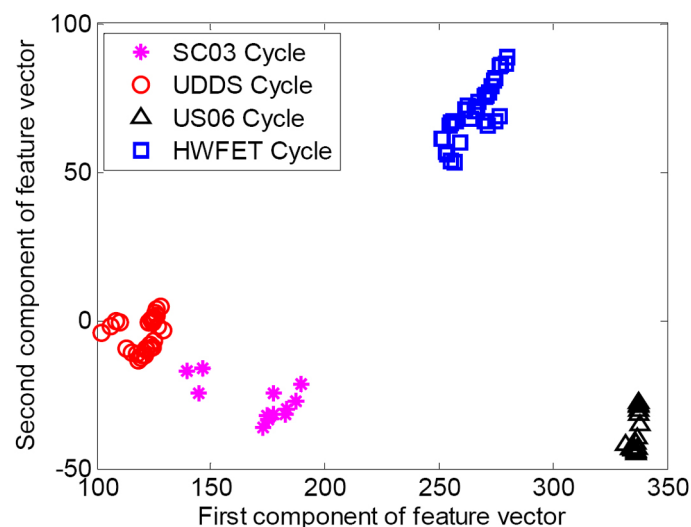


Figure 6. The distribution of the feature vectors of selected four driving cycles.

3. CLASSIFY REAL WORLD DRIVING CYCLES USING REPRESENTATIVE FEATURE VECTORS

To validate the effectiveness of representative feature vectors for real-world driving cycle pattern recognition, two real-world driving cycles were adopted for the performance test. The two real-world driving cycles were collected by a mild-hybrid Chevy Malibu driven in the urban and suburban area near the downtown Hancock. The routes of real-world city cycle (RW-CC) and real-world highway cycle (RW-HC) are shown in [Figure 7](#) and [Figure 8](#). The speed profiles for these two driving cycles are shown in [Figure 9](#) and [Figure 10](#). To classify real-world driving cycles to one of the selected four driving cycles, the feature vectors for the RW-CC and RW-HC were generated using the feature extraction method