SYSTEMATIC DATA-DRIVEN APPROACH TO REAL-TIME FAULT DETECTION AND DIAGNOSIS IN AUTOMOTIVE ENGINES

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Abstract – The competitive businesses' desire to provide "smart services" and the pace at which the modern automobiles are increasing in complexity, are motivating the development of automated intelligent vehicle health management systems. Current On-Board Diagnosis (OBD II) systems use simple rules and maps to perform diagnosis, and significant human intervention is needed to troubleshoot a problem. More research is needed on developing innovative, easy-to-use automated diagnostic approaches for incorporation into the OBD systems. In addition, developing intelligent remote diagnosis technology, building a bridge between on-board and off-board diagnosis are open areas of research in the automotive industry.

Here, we propose a systematic data-driven process that utilizes knowledge from signal-processing and statistical domains to detect and diagnose faults in automotive engines. The proposed approach is applied to a Toyota Camry engine, and the experimental results are presented in detail. The experimental system consists of an engine running with manual transmission on a dynamometer test-stand. For our experiments, the data for five faults (three sensor faults and two physical faults) with different severity levels under various operating conditions (e.g., different throttle angles, engine speeds, etc) is collected from the engine, and the application of a data-driven diagnostic process is examined.

INTRODUCTION

Currently, the automotive industry is undergoing a fast-paced transformation in producing more complex automobiles than ever before due to the need for better fuel economy and lower pollutant emissions, while maintaining vehicle performance and drivability. Many mechanical systems have been replaced by electronic systems in modern cars with the advent of cheap and reliable computer systems. It was estimated by IC Insights, a semiconductor-market research company, that electronic content of an automobile will constitute 40% of the total price by year 2010 [20]. With advances in automobile technology, after-market maintenance services are playing a significant role in the continuous healthy operation of a vehicle, and consequently on the profitability of automobile manufacturers.

Current On-Board Diagnostic (OBDII) systems perform a great job in assisting technicians to trouble-shoot faulty components in the vehicle. However, with the increasing complexity of newer automobiles, the average technicians are facing challenges in understanding the interactions between components, resulting in longer time to diagnose faults, more service costs, increased warranty costs, and, more importantly, customer dissatisfaction. Hence, these factors necessitate the development of intelligent and easy-to-use automated diagnosis tools for troubleshooting automotive problems.

Fault detection and diagnosis (FDD) has mainly evolved upon three major paradigms, viz., model-based, data-driven and knowledge-based

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approaches. Over the years, many researchers [4 - 14] have investigated vehicle fault diagnosis, especially those related to the engine. Model-based technology is widely used in the automotive industry for control system development. However, to derive dynamic relations for model-based fault diagnosis application poses many challenges due to the system complexity. In this vein, a data-driven approach can provide a more systematic solution, if monitored sensor data is available over a period of time for analysis.

Paul Baltusis [16] provided an excellent overview of current on-board vehicle diagnosis technology. Performing complex analysis onboard a vehicle was once limited by memory and speed constraints of embedded processors. Introduction of telematics into current automotive technology provides a way to monitor vehicle data continuously, and the application of advanced classification algorithms enhances the accuracy of fault diagnosis. Remote diagnosis has received considerable attention recently [17][18][19] [21].

Here, we propose a data mining approach that utilizes the knowledge from signal-processing, statistical and pattern recognition domains. This process has been successfully applied to an engine simulator system in [1] [2]. In this paper, we show its applicability to FDD in a real automotive engine, and comment on its practical application. The rest of the paper is organized as follows. In section 2, we describe the engine experimental system under consideration. Section 3 provides a detailed description of the proposed data-driven FDD procedure. In section 4, we present our experimental results, along with a discussion. The paper concludes in section 5 with future research directions.

EXPERIMENTAL SYSTEM DESCRIPTION

The target system considered here is a Toyota Camry engine with manual transmission installed on a dynamometer test-stand. The engine is controlled by a rapid-prototyping electronic control unit (RType ECU). Data is collected in real-time from stock sensors installed on the engine.

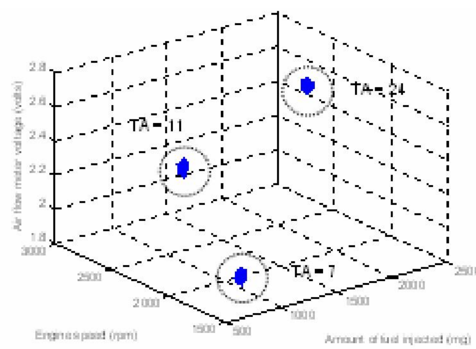
Faults and Monitored Variables

The engine is operated under various scenarios, and the data is collected for FDD analysis. Three representative operating conditions of the engine are considered in our experiments, as shown in Table 1. The three conditions represent cruising around town, highway cruising, and hill climbing or towing on the highway, respectively. The approximate operating regions for the three conditions are shown in Figure 1 in the (reduced) space of three monitored quantities: the amount of fuel injected, engine speed, and air flow meter voltage.

Table 1. Operating Conditions of the Engine

Pedal Angle (deg.)[1]	Throttle Angle (TA) (deg.)	Engine Speed (rpm)	Gear +TCC	Vehicle Speed (km/h)	Grade (deg.)	Airflow (g/s)
7 ± 2	7	1800	4 + lock	68	0	10.1
9 ± 2	11	2500	4 + lock	96	0	18.3
16 ± 1	24	2300	4 + lock	88	4.8	37.5

Figure 1. Three Operating Regions of the Engine



Five fault cases with different severity levels are considered in each of the operating conditions. The faults considered include: three sensor faults and two physical faults. Since inducing sensor faults physically would involve tampering with the engine wiring harness, we modified the production control software to introduce the faults artificially. The two physical faults, namely, air intake leakage and blockage of air filter are introduced by removing caps from intake manifold ports and by covering the inlet of the air filter by a piece of rubber sheet, respectively. The data is collected from eight stock sensors installed on the test bed. The list of faults along with the number of severity levels considered, and the monitored variables, are provided in Table 2.

[1] A range of pedal angles is defined, since there is not a one-to-one correspondence between pedal angle and throttle angle.

Table 2. Engine Faults and Monitored Variables

FAULTS			MONITORED VARIABLES		
Name	Notation[2]	No of severity levels	Name	Notation[3]	Units
Air flow sensor	MAF_f	4	Amount of fuel injected	FC	mg
Air to fuel ratio	AFR_f	4	Exhaust air to fuel ratio	AFR	-
Coolant temperature	ECT_f	1	Engine speed	RPM	rpm
Leakage in air intake system	AIS_Leak	3	Air flow meter	MAF	volts
Blockage of air filter	AF_Blockage	3	Engine coolant temperature	ECT	deg. C
			Secondary oxygen sensor	O2S2	volts
			Variable valve timing	VVT	deg.
			Actuator spark timing	SPKT	deg.

FDD PROCESS OVERVIEW

Model-based design is widely adapted in automotive industry for control design. However, for FDD design, one needs an extensive expertise and knowledge to derive the dynamic relations of the system, especially those related to faulty conditions. The vehicle operating conditions keep changing in realistic scenarios, such as, acceleration, deceleration, cruising, idling, etc. Developing an accurate mathematical model/ simulator for residual generation in real-time is a cumbersome task. Due to the increasing complexity of modern automobiles, data-mining is gaining importance for FDD because it obviates the need for detailed system models.

Figure 2 depicts our proposed approach for automatically detecting and diagnosing faults in automotive engines. It is a generic approach applicable to any engineering system, and we have applied it successfully to an engine simulator in [1][2]. It requires only sensor data, and does not need detailed system models. The following subsections describe the process in detail.

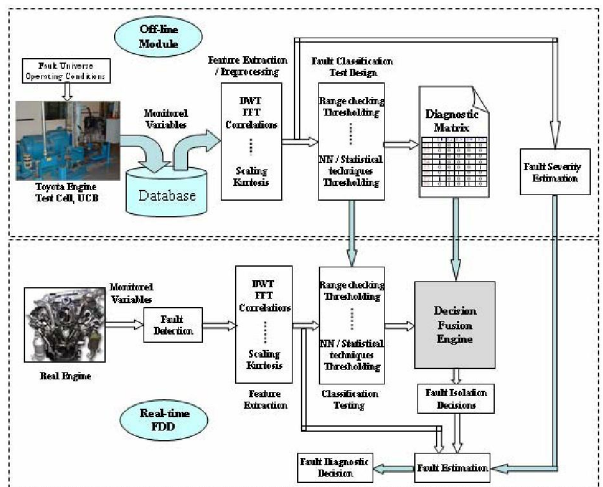
Off-line Module

In the off-line module, the sensor data is collected from the engine test bed. The engine is operated at the pre-defined operating conditions, faults are injected, and sensor data is collected for analysis. The collected data is processed and analyzed to achieve good diagnostic accuracy. The following sub-sections provide the glimpse of each block in the off-line phase.

Feature Extraction/Preprocessing

Salient feature extraction plays a major role in achieving good diagnostic performance. In the feature extraction block of Figure 2, several signal processing, and statistical data analysis techniques are employed to extract relevant information for diagnosing faults.

Figure 2. Generic Data-Driven FDD Approach



This block explores all possible methods to preprocess the data, and provides a way to compare the impact of preprocessing on diagnostic performance. The extracted features are input to the fault classification block.

Fault Classification

Fault classification/isolation is an important step in root-cause identification. Test design plays a critical role in achieving better classification accuracy. Here, the tests are designed to uniquely detect pre-defined faults, and generate a D-matrix (Diagnostic matrix) for on-line inference. If large amount of data is available from a pre-defined fault set, pattern recognition techniques have proven to be very useful in achieving good classification. In this block, depending on the nature of fault, tests are designed by applying pattern recognition techniques, various signal-processing and statistical tools (wavelets, filters,

[2] These are referred to as Faults 1 - 5 in later sections.
[3] These are referred to Sensors 1 - 8 in later sections.

kurtosis, etc.). The test outcomes are input to the on-line inference block for real-time classification of faults.

Fault Severity Estimation

Determination of the severity of faults, followed by appropriate remedial actions can prevent the system from further damage. This can also assist the user by providing information such as how long the vehicle can run safely even in the presence of a fault, and when the vehicle needs to be brought to service, etc. In the next block, the severity of the fault is estimated by applying regression techniques on extracted features. The weights are imported by the on-line module for real-time estimation.

On-line Module

In the on-line module, the operational engine is monitored continuously for real-time FDD. The sensor data is passed through the detection block for real-time fault detection. Statistical tests such as generalized likelihood ratio test (GLRT), cumulative sum (CUSUM), etc., are used to detect the abnormal events. The next steps are the same as in the off-line module. In the decision fusion block, the test decisions are fused using sequential fault diagnosis algorithms to provide a classification decision [3] [21]. In this paper, we examined the applicability of this FDD process on a Toyota Camry Engine. The data is collected from a real-engine operating at five pre-defined fault scenarios, and is analyzed to generate a D-matrix for classifying the faults.

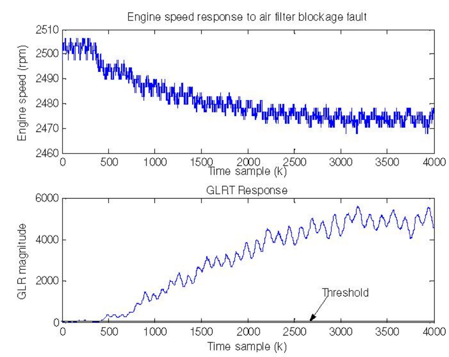
EXPERIMENTAL RESULTS AND DISCUSSION

As discussed earlier, several experimental runs are carried out on the engine and pre- and post-fault data is collected. The data sampling time is 5ms. The total number of patterns constitute 45 from five faults collected under three operating conditions. We faced some problems in conducting the experiments on actual engine, such as engine shaking, and reaching unstable conditions for certain severity of faults. So, we limited our test runs to a few scenarios. The following sub-sections discuss the results in detail.

Fault Detection

The three sensor faults are introduced at 2.5sec. The data is collected for 10 seconds or 2500 time samples. As it is not possible to control the exact onset time for the two physical faults, we collected 4000 time samples to allow a proper window for pre- and post-fault data. GLRT is applied on the speed sensor signal to detect the faults. As shown in the figure, proper threshold on the GLRT amplitude achieved 100% fault detection. Some signal amplitudes are too low to detect an abnormality. In those cases, GLRT aids in achieving proper detection by amplifying the change. Speed signal is chosen for detection, as it was found to respond to all faults.

Figure 3. GLRT Response on Speed Sensor Signal to Air Filter Blockage Fault

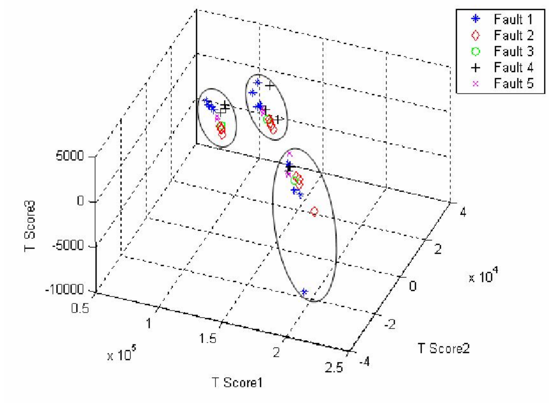


Feature Extraction/Preprocessing

Principal Component Analysis (PCA) is an excellent tool to cluster the data into different regions, and we also used it for classification successfully in [15]. Here we used it to show how the fault clusters are distributed in all three operating regions. 1000 fault time samples are used from each scenario, and PCA is applied to extract the first three scores which capture most of the variation in the data. As we can see from Figure 4, it is difficult to distinguish the five faults just from the raw data.

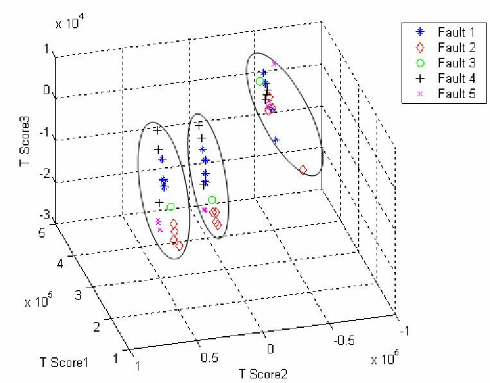
Wavelets have proven to be very useful in extracting fine-grained information from irregular and noisy signals [8][9]. We employed wavelets on the sensor signals to retrieve salient features from the data. Daubechies 2 mother wavelet is used to transform the raw data, and level 10 approximate coefficients provided relevant information for diagnosis.

Figure 4. PCA Score Plot on Faulty Raw Data



Pre- and post-fault data is used for extracting the wavelet features as they capture the transient characteristics very well and hence we can significantly reduce the time delay for fault isolation. We applied PCA on the extracted approximate coefficients, and the plot of first three scores is shown in figure 5. As we can see, the five faults are well separated in each operating condition. However, we need a testing strategy to classify the faults into pre-defined classes. The following sub-section provides the testing strategy and the classification results.

Figure 5. PCA Score Plot on Extracted Approximate Wavelet Coefficients



Fault Isolation

Pattern recognition techniques require large amount of data to train for achieving good classification accuracy. The diagnosis strategy is more efficient, if we could detect and isolate the faults irrespective of the operating conditions in which they occurred. Testing on extracted features proved to be very promising in achieving mode-invariant diagnosis, even with sparse training data [1][3][8].

Figure 6a. Response of Amount of Fuel Injected to Air Flow Sensor Fault and the Corresponding Wavelet Coefficients in three Operating Conditions

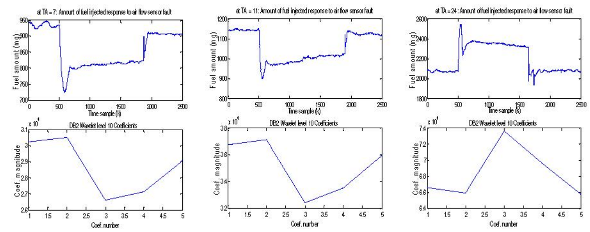


Figure 6b. Response of A/F Signal to A/F Sensor Fault and the Corresponding Wavelet Coefficients in three Operating Conditions

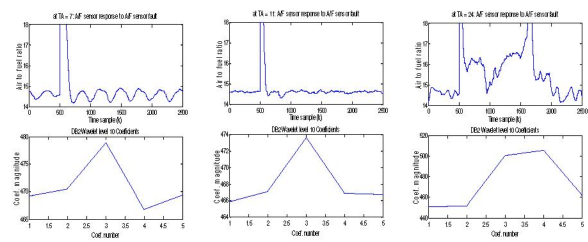
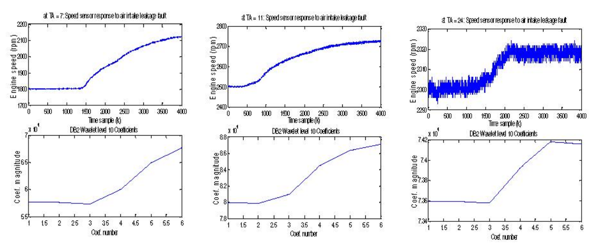


Figure 6c. Response of Engine Speed to Air Intake Leakage Fault and the Corresponding Wavelet Coefficients in three Operating Conditions



In the current engine application, we observed that the sensor signals are very irregular, and have no unique trends to distinguish the faults. Figures 6a-6c show response of amount of fuel injected, air to fuel ratio, engine speed and the response of their corresponding wavelet coefficients to air flow sensor fault, air to fuel ratio sensor fault, and air intake leakage fault respectively. As can be seen, it is not possible to apply a trend/threshold test here.

We applied the following test strategy on the wavelet coefficients to derive a D-matrix.

Define $\{d_i\}_j$, $i=0,1,2,3,...$. as the set of level 10 approximate coefficients (obtained via Duabechies mother wavelet) associated with sensor j. The decision that the sensor j responds to fault is made if

$$max\{d_i\} - min\{d_i\} > b \quad (1)$$

where, b is a threshold (we determined it via observation of the values of ($max\{d_i\} - max\{d_i\}$) from all scenarios. The d-matrix obtained via the above testing is shown in Table 3.

Table 3. Fault Diagnostic Matrix

FAULTS\TESTS	S1T	S2T	S3T	S4T	S5T	S6T	S7T	S8T
Fault 1	1	0	1	1	0	1	1	1
Fault 2	1	1	1	0	0	1	0	0
Fault 3	0	1	1	0	1	1	1	1
Fault 4	0	1	1	0	0	1	0	0
Fault 5	0	1	1	0	0	0	0	0

Table 4. Fault Confusion Matrix

TRUTH\CLASSIFIED AS	FAULT1	FAULT2	FAULT3	FAULT4	FAULT5
Fault1	**12/12**	0/12	0/12	0/12	0/12
Fault2	0/12	**12/12**	0/12	0/12	0/12
Fault3	0/3	0/3	**3/3**	0/3	0/3
Fault4	1/9	3/9	0/9	**3/9**	2/9
Fault5	0/9	0/9	0/9	0/9	**9/9**

Each row in Table 3 represents a fault and the column represents the test given by equation 1. Here S1T, S2T… represent the test on sensor 1, test on sensor 2, so on. As we can see from the table, each fault has a unique row resulting in zero ambiguity group. We can use sequential testing algorithms to obtain an optimal test suite [21]. We also evaluated this matrix on the data we collected. The tests are applied on the 45 patterns and we achieved a classification accuracy of 82.22%. The classification performance is shown in the form of a confusion matrix in Table 4. We can observe that except for air intake leakage all other faults achieved 100% classification.

While performing these mathematical experiments we observed that some of the signals respond to some fault severity levels in only few operating conditions. It is interesting to see the relation between fault severity levels and engine operating regions and this is leading us to formulate a reasoning problem which we will explore in near future.

CONCLUSION

In this paper, we proposed a systematic data-driven approach for performing fault detection and diagnosis in automotive engines and showed its applicability to Toyota Camry engine. Pre- and post - fault data is collected from the engine under various scenarios, and the proposed approach is applied to generate a D-matrix to uniquely isolate the faults into pre-defined fault classes.

Our future works involve generating multi-valued D-matrices for fine-grained classification, collecting data for additional faults from the test-bed, and applying the proposed data-mining approach to comprehensive engine FDD. We also plan to develop intelligent testing strategies to deal with transient data, and develop a demo system illustrating the application of proposed approach on a realistic road scenario.

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