Application of an Effective Data-Driven Approach to Real-time Fault Diagnosis in Automotive Engines

*Setu Madhavi Namburu, *Shunsuke Chigusa, *Danil Prokhorov, *Liu Qiao, +Kihoon Choi & +Krishna Pattipati
*Toyota Motor Engineering & Manufacturing North America, 1555 Woodridge, RR # 7, Ann Arbor, MI 48105, USA.
+Dept. of ECE., Univ. of Connecticut, 371 Fairfield Road, U-2157, Storrs, CT 06269, USA.
E-mail: setumadhavi.namburu@tema.toyota.com

Abstract—A dominant thrust in modern automotive industry is the development of "smart service systems" for the comfort of customers. The current on-board diagnosis systems embedded in the automobiles follow conventional rule-based diagnosis procedures, and may benefit from the introduction of sophisticated artificial intelligence and pattern recognition-based procedures in terms of diagnostic accuracy. Here, we present a mode-invariant fault diagnosis procedure that is based on data – driven approach, and show its applicability to automotive engines. The proposed approach achieves high-diagnostic accuracy by detecting the faults as soon as they occur. It uses statistical hypothesis tests to detect faults, a wavelet-based preprocessing of the data, and pattern recognition techniques for classifying various faults in engines. We simulate the Toyota Camry 544N Engine SIMULINK model in a real-time simulator and controlled by a prototype ECU (Electronic Control Unit). The engine model is simulated under several operating conditions (pedal angle, engine speed, etc), and pre- and post-fault data is collected for eight engine faults with different severity levels, and a database of cases is created for applying the presented approach. The results demonstrate that appealing diagnostic accuracy and fault severity estimation are possible with pattern recognition-based techniques, and, in particular, with the support vector machines[1 2].

TABLE OF CONTENTS

1. INTRODUCTION

The Fault Detection and Diagnosis (FDD) has been an active area of research for the past four decades. This research has mainly evolved upon three major paradigms, viz., model-based, data-driven and knowledge-based approaches. As the modern systems' complexity is increasing at a faster pace, fault diagnosis and prognosis (FD&P) is gaining significant attention for advanced system maintenance and for improving customer satisfaction. The FDD involves three steps: fault detection, classification, and fault severity estimation. Accurate root-cause identification is an important attribute in safety-critical and high-availability systems, such as automobiles and aerospace vehicles. Although we present an FDD application targeted at automotive systems, in particular, the automotive engine, it has direct applications to aerospace engines [25]. The current on-board diagnosis systems in vehicles follow simple maps, rule-based systems, and technicians' expertise to diagnose faults. The future automobiles are expected to be equipped with more than 150 ECUs, and this content could constitute 40% of the total price [15]. These advances require smarter service systems to assist the technicians in an interactive way to troubleshoot the failed components in less time and reduce the customers' wait time.

If sufficiently accurate dynamic models of the system to be diagnosed are available, a model-based approach is desirable because it can outperform the other two approaches. However, with the increasing sophistication of modern automobiles, it has become a difficult task to generate complete and accurate models of systems. The ever-growing communication technology is prompting the automotive industry to incorporate web-based services in modern vehicles. Several automotive companies have already produced cars that are equipped with telematic equipment to provide enhanced services to customers. Remote diagnosis is one of the services that could be offered by telematics, and has received considerable attention recently [11][12][13][14]. This capability provides a means to collect large amount of data and perform data-mining to diagnose system components remotely. In this vein, we are investigating various FDD approaches, and testing their practical feasibility and applicability in hardware-in-the-loop simulations [1][3][4].

There exists significant amount of literature on automotive diagnosis. Luo et al. [4] proposed an intelligent diagnostic process that is generic, and can be applied to any system. Nyberg [20], Gertler [21] and Struss [22][23] have developed model-based techniques for automotive diagnosis. Several researchers have applied signal-based approaches to automotive diagnosis [5-10]. Here we present a data-driven approach that effectively preprocesses the data for achieving high diagnostic accuracy via several pattern recognition techniques, notably the support vector

1

[1] 1-4244-0525-4/07/$20.00 ©2007 IEEE.
[2] IEEEAC paper # 1646, Version 7, Updated December 15, 2006

machines. Though it is illustrated on a data set of modest size, the approach presented can in principle be used for large-scale data-mining.

The paper is organized as follows. In section 2, we describe the FDD problem in automotive engines and the model we considered in our experiments. Section 3 explains the FDD process in detail. In section 4, we present the experimental results with a discussion. We conclude the paper in section 5 with a summary and future research directions.

2. Problem Description

The system under consideration is a SIMULINK model of the Toyota Camry 544N Engine. This is a highly non-linear, complex system consisting of five primary sub-systems, namely, air dynamics, fuel dynamics, torque generation, rotational dynamics, and the exhaust system [4]. The model is simulated in a real-time simulator CRAMAS® (ComputeR Aided Multi-Analysis System), and is controlled by a prototype ECU (Electronic Control Unit). Figure 1 depicts the HIL (Hardware-In-the-Loop) system set-up for simulating the engine model to achieve real-time performance. Here, our goal is to test the viability of our proposed data-driven FDD approach based on data collected on the monitored variables of the engine under nominal and faulty scenarios, and in different operating conditions.

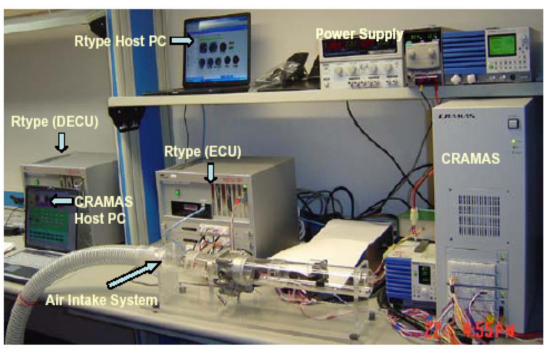

Figure 1: CRAMAS HIL set-up for engine model simulation

Engine Fault Universe and Monitored Variables

We investigate eight engine faults, namely, four sensor faults (red), three plant faults (blue), and one actuator fault (black), as shown in Table 1. The model is simulated under three steady-state operating conditions, namely, pedal angle *(PA)* = 15, 18 and 20 degrees, respectively. The monitored data consisted of seven monitored variables from the engine (Table 1). In each operating condition, all the eight faults are simulated at ten severity levels ranging from 6-15% with a step size of 1% (from its nominal value), and pre- and post-fault data is collected for 10sec with fault on-set time set at 2.5sec. Figure 2 shows well separated operating regions of the nominal data through a 3-D plot of engine speed, throttle angle and air pressure signals. The following section outlines the procedure by which faults are detected and diagnosed irrespective of the operating region in which they occur.

Table 1: Fault universe and monitored variables list

Fault List		Monitored Variables	
Name	Notation	Name (Units)	Notation
Air Flow Sensor Fault (F1)	AFS	Air Pressure (KPa)	P_m
Leakage in AIS (F2)	AIS_leak	Amount of Fuel Injected (mg)	FC
Blockage of Air Filter (F3)	AF_blockage	Air to Fuel Ratio	A/F
Throttle Angle Sensor Fault (F4)	TAS	Engine Speed (rpm)	NE
Less Fuel Injection (F5)	LFI	Vehicle Speed (km/h)	SPD
Added Engine Friction (F6)	AEF	Throttle Angle (deg)	TA
Air/Fuel Sensor Fault (F7)	AFuel_S	Air Flow Meter (Volts)	VG2
Engine Speed Sensor Fault (F8)	ESS		

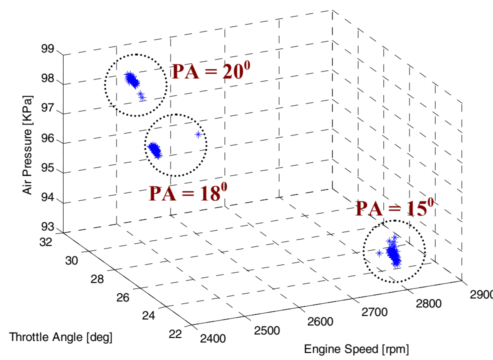

Figure 2: 3D-plot of nominal data from three monitored variables (NE, P_m, TA) showing the clusters associated with the three operating conditions

3. Fault Detection and Diagnosis Process Overview

Model-based design is widely adapted in automotive industry for control design purposes. However, for the FDD design, one needs extensive expertise and knowledge to derive dynamic relations of the system under nominal and faulty conditions. The vehicle's operating regions often change depending on the driving conditions, such as acceleration, deceleration, cruise control, etc. Consequently, developing an accurate model/simulator for residual generation in real-time is a cumbersome task. Due to the increasing complexity of modern automobiles, data-driven approach is gaining importance because it is flexible and does not need a detailed system model. Of course, this assumes that ample monitored data is available.

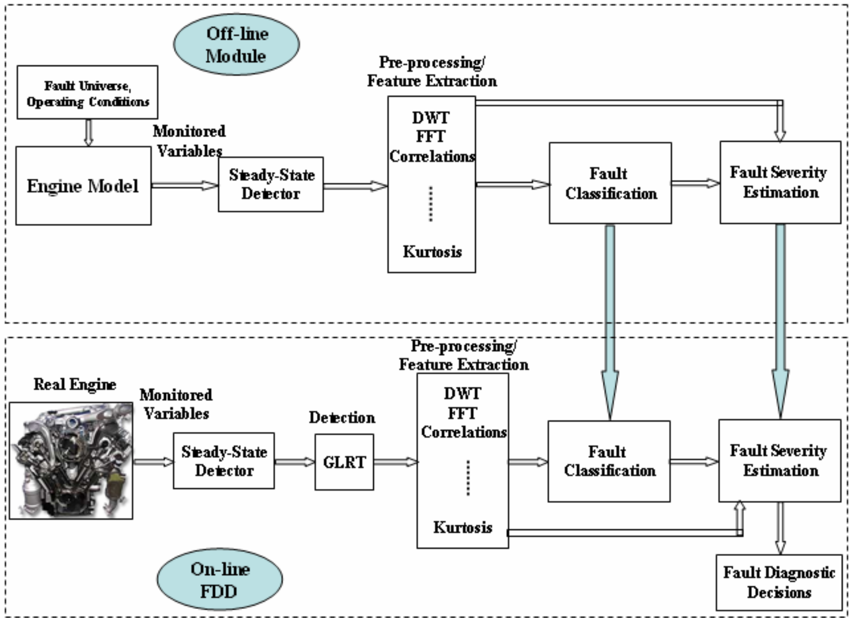

Figure 3: Fault Detection and Diagnosis Process

Figure 3 depicts our proposed approach for automatically detecting and diagnosing faults in automotive engines. It is a generic approach applicable to any engineering system. It consists of off-line and on-line modules. The following subsections describe the process in detail.

Off-line Module

In the off-line module (the top half of Figure 3), the sensor data is collected from a Simulink model running in CRAMAS®. The model is simulated at the specified operating conditions and fault scenarios, and the database of cases is created for analysis. This could be a model/HIL simulator/test bed/remotely acquired data. The description of each block of the off-line module is provided below.

Steady-state Detector — Here, we performed our analysis on steady-state data. Since the operating conditions change depending on the driving condition, it takes considerable amount of time for the system variables to reach steady-state. We used time-derivative estimation over a moving window for detecting the steady-state condition.

Feature Extraction/Preprocessing — Feature extraction plays a critical role in the performance of a diagnostic algorithm. In the feature extraction block shown in figure 3, several signal processing algorithms, and statistical techniques are employed to extract fine-grained information for diagnosing faults. In our experiments, the preprocessing is done via wavelet transformation of the original signals.

Wavelets have proven to be extremely useful feature extractors in recovering fine-grained mode-invariant information from the data [2][5][7][8]. They not only reduce

the data size, but also aid in capturing salient events in a signal such as trends, discontinuities, breakdown points, self similarity, etc., and this results in the generation of a strong feature set for classification. The processed signals are fed to the fault classification block.

Fault Classification — Fault classification/isolation is an important step in identifying the root-cause. In this block, several classification techniques are used to classify faults. We used five well-known pattern recognition techniques [3] for comparing the classification performance on the experimental data, namely,

- Support Vector Machines (SVM)
- Linear Descriminant analysis (LD)
- K-Nearest Neighbor (KNN)
- Probabilistic Neural Network (PNN)
- Gaussian Mixture Model (GMM)

The trained parameters (weights) of these classifiers are imported by the on-line module for real-time FDD.

Fault Severity Estimation — Estimating the damage level and providing appropriate remedial actions to the driver in real-time can prevent further damage to the system. 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, when the vehicle needs service, etc. In the next step, the severity of the fault is estimated by the SVM regression technique. The trained weights/parameters are imported by the on-line module for real-time estimation.

On-line Module

In the on-line FDD module (the bottom half of Figure 3), the system is continuously monitored. The sensor data is processed by a statistical hypothesis test (generalized likelihood ratio test, GLRT) for real-time fault detection. In the next step, once the fault is detected, the reference feature set (from training) over a moving window of data is extracted. Then, the classification and severity estimations blocks classify faults and estimate the severity levels respectively and they use parameters from training to perform these tasks. The fault diagnostic decision block provides the user with all the information necessary, such as, the fault component name, fault on-set time, severity level, and remedial action. In this paper, we divided the data into training and test sets, and used them in the off-line and on-line modules, respectively.

4. Experimental Results and Discussion

As described in section 2, the engine model is simulated under various scenarios, and the collected data constituted 240 patterns. The data matrix *X* has dimensions 240x7x2000 where the number of patterns from eight faults is 240, the number of monitored variables is 7, and the time series data from pre- and post-fault conditions consisted of 2000 samples. The faults are inserted as step changes at 2.5 seconds in each simulation. The following subsections provide the experimental results in detail.

Fault Detection

The faults are detected via the application of a Generalized Likelihood Ratio test (GLRT) [24] on the monitored variables. The decision function of GLRT computed over a window of size *w(j-i)* is given by

$$g_j = \frac{1}{2\sigma_0^2} \max_{1 \le i \le j} \frac{1}{j-i+1} \left[\sum_{n=i}^{j} \left(x(n) - \mu_0 \right) \right]^2 \qquad (1)$$

where $\mu_0, \& \sigma_0$ are known mean and variance of the sensor signal before change. The fault detection thresholds are set dynamically depending on the operating condition. Figure 4 shows the detection of blockage of the air filter by the GLR test on the air pressure signal. Perfect fault detection is achieved in all fault conditions via the GLRT on monitored variables. Variation in some of the raw signals due to faults is not noticeable (e.g., refer to Figure 6). However, the GLRT function amplifies these changes and aids in the proper detection of the fault.

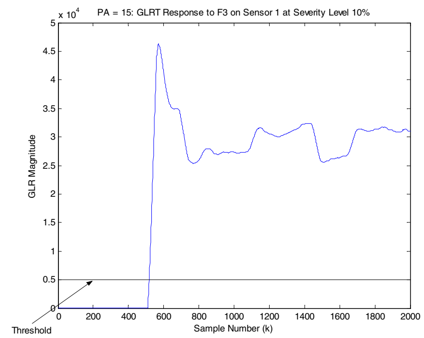

Figure 4: Detection of AF_blockage fault with severity 10% inserted at sample k=500 via the application of GLRT on the air pressure signal

Feature Extraction

Discrete Wavelet Transform (DWT) is a good alternative for effective signal pre-processing. In DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. It analyzes the signal at different frequency bands with different resolutions and decomposes the signal into coarse approximate and detailed information (refer to Figure 5). The basic formula for Continuous Wavelet Transform (CWT) of a signal *x(t)* is given by

$$W_x(a,b) = a^{-1/2} \int_{-\infty}^{\infty} \overline{\psi}\left(\frac{t-b}{a} \right) x(t)\,dt \qquad (2)$$

For Discrete Wavelet Transform (DWT), the two parameters *a* and *b* are for scaling and translating, respectively, and can be defined as functions of level *j* and position *k*

$$a = 2^{-j} \;\; j \in Z, b = a.k \;\; k = 0,\ldots,n-1 \qquad (3)$$

The analyzing function ψ is given by

$$\psi_{j,k} = 2^{j/2} \psi\left(2^j t - k \right) \qquad (4)$$

Where ψ is called the *mother wavelet* and $\psi_{j,k}$ is called the *daughter wavelet [26]*.

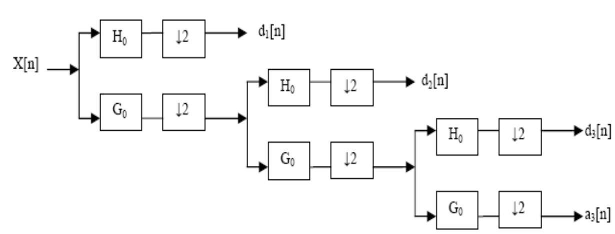

Figure 5: Example wavelet decomposition tree

.

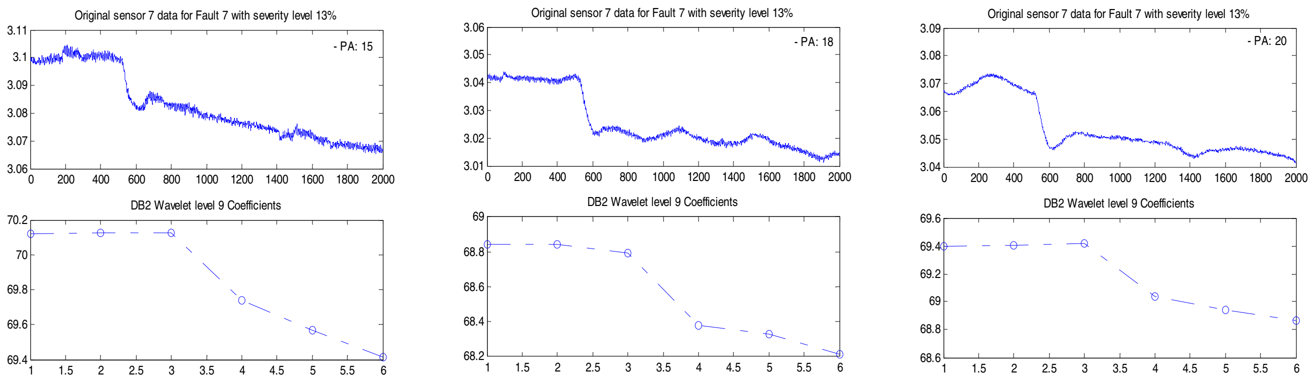

Figure 6: The air flow meter voltage and it's wavelet approximate coefficients response to 13% AFuel_S fault inserted at k=500

Daubechies wavelets constitute the most popular wavelet family among others for capturing sharp changes, transient effects in a signal. Here, the approximate level 9 Daubechies 2 (DB2) wavelet coefficients are extracted for each pattern of the data matrix X, for improving the accuracy of the classification algorithms. Figures 6 present the mode invariant trends of air flow meter voltage signal to Afuel_S fault. Here we can observe that the wavelet coefficients captured the trend information irrespective of vehicle's operating condition (such as PA = 15, 18, and 20 degrees). What is more important is that this pre-processing also helped in reducing the data size tremendously (6 coefficients as opposed to 2000 time samples of a raw signal). The coefficients are scaled in order to achieve uniformity of the data from various scenarios

Fault Classification Results

Initially, SVM is applied on raw sensor time-series data after the system reaches its steady-state. We got an accuracy of 80.21%. Then, we applied five pattern recognition techniques on preprocessed wavelet coefficients to classify faults into pre-defined classes. We used a 5x2 (5 times 2-fold) cross-validation for training and testing the classifiers, and for reporting the average diagnostic accuracies. Figure 7 presents the bar plot of total classification accuracy achieved by each of the individual classifiers. As can be observed, except for GMM, all other classifiers achieved classification accuracies of greater than 90%. Table 2 presents the individual classification accuracies of each classifier for each fault. It is seen that SVM performed best by achieving greater than 97% accuracy on each fault with an overall accuracy of 99.25%. The bad performance of GMM compared to less sophisticated techniques (LD & PNN) is suspicious here, and we will investigate it further.

Wavelet preprocessing/ feature extraction helped in reducing the data-size substantially (26.88MB raw data size to 80.64KB reduced data) and in capturing trends from both pre- and post-fault data, irrespective of the operating conditions of the engine.

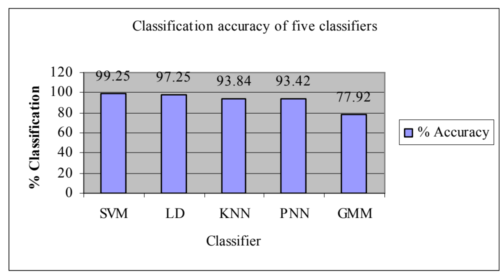

Figure 7: Overall classification accuracy of classifiers

Table 2: Classification accuracy of each classifier for each fault

Fault \ Classifier	SVM	LD	KNN	PNN	GMM
F1	100	96	96	96	100
F2	97.33	97.33	92	92	60.67
F3	99.33	94.67	94.67	94.67	66
F4	99.33	98	92.67	92.67	53.33
F5	100	95.33	92	92	97.33
F6	100	100	96.67	96.67	61.33
F7	99.33	100	94	94	99.33
F8	98.67	96.67	92.67	89.33	85.33

Wavelet feature extraction not only aided in boosting the classification accuracy, but also reduced the memory requirements significantly. If data-reduction is not done, it is infeasible to use some of the classification techniques (LD, PNN, GMM) on raw time-series data directly.

Fault Severity Estimation

After the faults are classified into one of the pre-defined eight classes, their severities are estimated via SVM regression. Table 3 presents the estimation errors of fault severities in terms of their percentage average error and root mean square error (RMSE). We randomly used 60% of the data for training and 40% for testing and repeated the procedure for 20 times. The results presented are the average over 20 runs. The faults are estimated quite accurately with the average errors never exceeding 10%, except for Added Engine Friction, AEF fault.

Table 3: Fault severity estimation errors

Fault	Average Error (%)	RMSE
AFS (F1)	7.13	0.76
AIS_leak (F2)	7.71	0.85
AF_blockage (F3)	7.02	0.84
TAS (F4)	8.01	1.04
LFI (F5)	5.76	0.76
AEF (F6)	19.7	2.42
AFuel_S (F7)	6.61	0.70
ESS (F8)	7.73	0.89

The sample of faults and signals considered in this paper are to test the viability of the presented approach. It is necessary to explore more realistic scenarios, such as actual driving conditions, road scenarios, a variety of faults, etc. and validate the proposed approach. Our preliminary experimental results are promising. We also observed a relationship between fault severity levels and operating conditions, i.e., at large size faults the model entered into unstable conditions. This information can be fed back to control system designers.

5. Conclusion and Future Research

In this paper, we presented a flexible and effective data-driven FDD approach, and showed its applicability to automotive engines. It uses a statistical hypothesis test for fault detection, wavelet feature extraction for effective preprocessing of the data, and several pattern recognition techniques for fault isolation, followed by severity estimation via SVM regression. In fact, the SVM results are best in isolating each of the faults F1-F8. The approach presented here demonstrated high accuracy in terms of diagnosis and fault severity estimation, and has a potential for real-time application in automotive engines due to effective data reduction techniques employed.

Our future work will involve exploring a variety of faults, such as abrupt faults, spikes, slow degradation faults, etc., and developing a demonstrator system. We also plan to investigate other data reduction techniques (both linear and nonlinear), and classifier fusion techniques for dealing with data from a wide-variety of operating and transient conditions.

REFERENCES

[1] Namburu, S. M., Chigusa, S., Qiao, L., Azam, M., and Pattipati, K., “Application of Signal Analysis and Data-driven Approaches to Fault Detection and Diagnosis in Automotive Engines”, In *Proceedings of the IEEE SMC conference*, Taipei, Taiwan, October, 2006.

[2] Azam, M., Pattipati, K., Allanach, J., and Patterson-Hine, A., “In-flight Fault Detection and Isolation in Aircraft Flight Control Systems”, *Proceedings of the IEEE Aerospace Conference*, Big Sky, Montana, March, 2005.

[3] Choi, K., Luo, J., Pattipati, K., Namburu, S. M., Qiao, L., and Chigusa, S., “Data Reduction Techniques for Intelligent Fault Diagnosis in Automotive Systems”, *Proceedings of the IEEE Autotestcon*, Anaheim, CA, September, 2006.

[4] Luo, L., Pattipati, K., Qiao, L., and Chigusa, S., “An Integrated Diagnostic Development Process for Automotive Engine Control Systems” Accepted for publication in *IEEE Transactions on Systems, Man, Cybernetics*, Part – C, March, 2006.

[5] Crossman, J. A., Guo, H., Murphy, Y. L., and Cardillo, J., “Automotive Signal Fault Diagnostics – Part I: Signal Fault Analysis, Signal Segmentation, Feature Extraction and Quasi–Optimal Feature Selection”, *IEEE Transactions on Vehicular Technology*, Vol. 52, No. 4, July, 2003.

[6] Murphy. Y. L, Crossman, J. A., Chen, Z., and Cardillo, J., “Automotive Fault Diagnostics – Part II: A Distributed Agent Diagnostic Systems”, *IEEE Transactions on Vehicular Technology*, Vol.52, No. 4, pp. 1076 – 1098, July, 2003.

[7] Guo, H., Crossman, J. A., Murphy, Y. L., and Coleman, M., “Automotive Signal Diagnostics using Wavelets and Machine Learning”, *IEEE Transactions on Vehicular Technology*, Vol. 49, No.5, September, 2000.

[8] Zhang, J. Q., and Yan, Y., “A Wavelet-Based Approach to Abrupt Fault Detection and Diagnosis of Sensors”, *IEEE Transactions on Instrumentation and Measurement*, Vol. 50, No.5, October, 2001.

[9] Kimmich, F., Schwarte, A., and Isermann, R., “Fault Detection for Modern Diesel Engines using Signal- and Process Model-based Methods”, *Control Engineering Practice*, Vol.13, pp.189-203, 2005.

[10] Capriglione, D., Ligouri, C., and Pietrosanto, A., “On-Line Sensor Fault Detection, Isolation, and Accommodation in Automotive Engines”, *IEEE Transactions on Instrumentation and Measurement*, Vol.52, No.4, pp.1182-1189, August, 2003.

[11] Baltusis, P., "On Board Vehicle Diagnostics", *Proceedings of the SAE*, Detroit, MI, 2004.

[12] Carr, B. J., "Practical Application of Remote Diagnostics", *Proceedings of the SAE*, Detroit, MI, 2005.

[13] Hilger, J. E., Ford, E. J., and Flaherty, M. M., "Diagnostic Challenges in the Automotive Workshop", *Proceedings of the SAE*, Detroit, MI, 2004.

[14] The Hansen Report on Automotive Electronics, "Remote Diagnostics – the Next OEM Frontier", *A Business and Technology Newsletter*, Vol. 16, No.0, Dec. 2003/ Jan. 2004.

[15] Cravotta, R., "Making Vehicles Safer by Making them Smarter", *EDN Magazine*, June 2006.

[16] Qualtech Systems Inc. : www.teamqsi.com

[17] Sangha, M. S., and Gomm, J. B., "Steady State Fault Diagnosis of an Automotive Engine Air Path", *GERI Annual Research Symposium*, GARS 2005.

[18] Radwan, A., Soliman, A., and Rizzoni, G., "Model-Based Component Fault Detection and Isolation in the Air-Intake System of an SI Engine Using the Statistical Local Approach", *Proceedings of the SAE*, 2003.

[19] Console, F., Console, L., Guagliumi, M., Osella, M., Pnati, A., Sottano, S., and Dupre, D. T., "Generating On-board Diagnostics of Dynamic Automotive Systems Based on Qualitative Models", *AI Communications*, 12, 33-43, (1999).

[20] Nyberg, M., "Automatic Design of Diagnosis Systems with Application to an Automotive Engine", *Control Engineering Practice*, 7, 993-1005, 1999.

[21] Gertler, J., Costin, M., Fang, X., Kowalczuk, Z., Kunwer, M., and Monajemy, R., "Model Based Diagnosis for Automotive Engines – Algorithm Development and Testing on a Production Vehicle", *IEEE Transactions on Control Systems Technology*, Vol.3, No.1, March, 1995.

[22] Struss, P., and Price, C., "Model-based Systems in the Automotive Industry", *American Association for Artificial Intelligence*, 2003.

[23] Struss, P., Sachenbacher, M., and Carlen, C., "Insights from Building a Prototype for Model-based On-board Diagnosis of Automotive Systems", *11th International Workshop on Qualitative Reasoning (DX'00)*, Morelia, Mexico, 2000.

[24] Basseville, M., and Nikiforov, I. V., *Detection of Abrupt Changes: Theory and Application*, Prentice-Hall Inc., 1993.

[25] Donat, W., Choi, K., An, W., Singh, S., and Pattipati, K.R., "Visualization, Data Reduction and Classifier Fusion for Intelligent Fault Detection and Disgnosis in Gas Turbine Engines," submitted to *GT2007*, Montreal, Canada.

[26] Engin, S. N., Gulez, K., "A Wavelet Transform – Artificial Neural Networks (WT-ANN) based Rotating Machinery Fault Diagnostics Methodology", Proceedings o the IEEE Nonlinear Signal and Image Processing, Turkey, 1999.

BIOGRAPHY

Setu Madhavi Namburu received B.Tech degree from Jawaharlal Nehru Technological University, India in 2002 and M.S degree from the University of Connecticut, USA in 2006, both in Electrical Engineering. Currently she is working as a Research Engineer at Toyota Motor Engineering and Manufacturing North America, USA. Her research interests include data-mining, knowledge-discovery, systems analysis, simulation, fault diagnostics and prognostics.

Shunsuke Chigusa is Senior Principal Research Scientist of Technical Research Department at Toyota Motor Engineering & Manufacturing North America,Inc. He started his automotive career as autonomous vehicle control system scientist and later as intelligent diagnosis scientist in Toyota Motor Corporation (Japan). He received the master's degree in electrical engineering from Osaka University in Japan.

Danil V. Prokhorov (SM'02) received the M.S degree with Honors from the State Academy of Aerospace Engineering (former LIAP), St. Petersburg, Russia in 1992, and the Ph.D. in Electrical Engineering from Texas Tech University, Lubbock, in 1997. He was with Ford Research Laboratory, Dearborn, MI, from 1997 till 2005. He has been engaged in application-driven studies of neural networks and training algorithms. He is currently a research manager of Technical Research Department at Toyota Motor Engineering & Manufacturing North America, Inc. His research interest is in machine learning algorithms and their applications to decision making under uncertainty. Dr. Prokhorov was awarded the INNS Young Investigator in 1999. He was the IJCNN 2005 General Chair and IJCNN 2001 Program Chair. He has been a reviewer for numerous journals and conferences, a program committee member for many conferences, and a panel expert for the NSF every year since 1995. He has authored 80 technical publications including several patents.

Liu Qiao is General Manager and Chief Technologist of Technical Research Department at Toyota Motor Engineering & Manufacturing North America, Inc. Switching from a university faculty position, Dr. Qiao started his automotive career as an advanced automotive control system expert, advanced technology manager, eBusiness manager and research manager. Dr. Qiao successfully led Canadian hybrid vehicle project and its market introduction. Dr. Qiao received his Bachelor of Engineering from Beijing University of Technology, Master and Ph.D of Electrical Engineering from Tohoku University in Japan. He is an active member/supporter of many academic associations.

Kihoon Choi is a Ph.D candidate in the Electrical and Computer Engineering at the University of Connecticut. His research interests are in the areas of fault diagnosis of complex systems, system real-time fault diagnosis, and analysis and optimization of large-scale systems. He won the best technical paper award at the 2004 IEEE AUTOTEST Conference.

Krishna Pattipati is a Professor of Electrical and Computer Engineering at the University of Connecticut, Storrs, CT, USA. He has published over 340 articles, primarily in the application of systems theory and optimization techniques to large-scale systems. Prof. Pattipati received the Centennial Key to the Future award in 1984 from the IEEE Systems, Man and Cybernetics (SMC) Society, and was elected a Fellow of the IEEE in 1995. He received the Andrew P. Sage award for the Best SMC Transactions Paper for 1999, Barry Carlton award for the Best AES Transactions Paper for 2000, the 2002 NASA Space Act Award, and the 2003 AAUP Research Excellence Award, and the 2005 School of Engineering Teaching Excellence Award at the University of Connecticut. He also won the best technical paper awards at the 1985, 1990, 1994, 2002, 2004 and 2005 IEEE Autotest Conferences, and at the 1997 and 2004 Command and Control Conferences. Prof. Pattipati served as Editor-in-Chief of the IEEE Transactions on SMC-Cybernetics (Part B) during 1998-2001.