10.3: Vehicle Fault Diagnostics Using a Sensor Fusion Approach

Steven E. Muldoon
Delphi
Technical Center Brighton
Brighton, MI USA
s.muldoon@ieee.org

Mark Kowalczyk
Cosworth Technology
Dearborn, MI, USA
mkowalc1@ford.com

John Shen
University of Michigan - Dearborn
Dearborn, MI 48128, USA
Johnshen@umich.edu

Abstract
Vehicle electronics and mechanical systems continue to become more complex and interdependent. Automotive electronic control units (ECUs) used in vehicle sub-systems execute high performance algorithms requiring robust fault detection and diagnostics. Our technical approach begins by presenting an overview of several techniques used for processing information from multiple input sources (sensors in particular) in the context of ECU fault detection and diagnostic schemes. We assert that inter-relationships between groups of sensors can be exploited through sensor fusion for signal integrity estimation, and present two vehicle application examples (chassis and powertrain). We propose a virtual fusion / estimation technique which provides basic signal redundancy and fault tolerance. Dynamic vehicle sensor information was used to develop an uncompounded fusion-processing algorithm, expressed through a Matlab/Simulink model. The results of these modeling experiments are presented to the reader and subsequent conclusions are drawn regarding the implementation of a sensor fusion-based or sensor fusion-enhanced ECU algorithm as part of a more comprehensive diagnostic, control and service methodology. The potential increase in vehicle system functionality and utility realized from sensor fusion-based or sensor fusion-enhanced ECU fault diagnostics has significant implications for the sensor designer, control algorithm architect, vehicle systems integration engineer, and automotive service community.

Keywords
Sensor Fusion, Vehicle Diagnostics, Automotive Sensors.

I. INTRODUCTION

The current use of automotive diagnostic tools and sensors can be directly traced to the introduction of microprocessors in vehicle applications, and more specifically the introduction of emissions control systems for the engine. Proliferation of microprocessor based vehicle sub-systems such as Electronic Engine Control (EEC), Anti-Lock Brakes (ABS) and Electronic Suspension Control has led to a situation where a multitude of sensors, actuators, inputs, outputs and application specific diagnostic schemes are found in automobiles. The demands for increased performance and robustness have resulted in algorithm improvements, optimization and intra-vehicle system integration.

Vehicle data communication infrastructures and protocols were created to perform information exchange between the vehicle and the service community (i.e. OBD parameter monitoring). The creation of this communication infrastructure was (in part) driven by the mandates and regulations created by the California Air Quality Board (CARB) and the United States Environmental Protection Agency (EPA). Today, in addition to providing the means for exchanging detailed ECU information with the service community, this data bus is also utilized for exchanging particular data between ECUs, including information from and related to vehicle sensors. Any straightforward effort to design automotive diagnostics must attempt to determine the constantly changing states of both the ECU hardware as well as the application software utilized in these systems.

A. Vehicle Fault Diagnostics

Fault Diagnosis can be generally defined as the process that identifies the root cause of a failure. Vehicle level fault diagnostics should be considered an important area of study for several reasons, including the following:

- Failure diagnosis adds directly to the cost of vehicle parts – software is not "free" and warranty part returns cost money.
- Failure diagnosis is a large contributor to the labor time involved in vehicle servicing – once a problem is identified, a solution is typically swift.
- Improper fault diagnosis can lead to an incorrect repair action – this leads to opportunity costs and fosters the perpetuation of inefficient problem solving (unsatisfied customers tend not to return).

There are several levels of vehicle diagnostics. The first level of diagnostics may be a simple reminder to the driver that standard maintenance (i.e., replacing filters and fluids) is required. The next level of diagnostics is targeted for the service technician, using more sophisticated tools and techniques. And, there is a level or levels of tools and methods used by the system architects and engineers who develop the sub-system hardware and software. A well-planned diagnostic strategy fully comprehends the relationships between these levels. [1, 2]

0-7803-7454-1/02/$17.00 ©2002 IEEE

B. Sensor Fusion

In the case of multiple sensor faults, highly interactive components or subsystems, information from a single sensor does not provide enough intelligence to accurately diagnose all of the possible faults. A better approach is to exploit the use of multiple sensors to provide additional information to the diagnostic algorithm. Using this approach, observers can be selected such that they provide complementary and/or redundant information about the component or subsystem behavior. The additional information provided by this scheme can be used to broaden the number and scope of potential faults that the diagnostic algorithm detects and reduces the probability of misdiagnosing a failure. [3]

By fusing two raw signals together and processing the resulting information, improved characterization of the input signals can be obtained. Further, by combining a number of fused input signals with a simple voting or decision making algorithm, improvements in fault classification accuracy can also be obtained. [3]

II. TECHNICAL APPROACH

A. Diagnostic Methodologies

Vehicle diagnostics will play a significant role in the automotive markets of 21st century. Therefore, there is a strong need for the development of strategies that can diagnose, predict, and perhaps prevent system failures. A brief overview of some of the basic concepts and methods used in fault detection are presented here.

A general dynamic system block diagram and fault representation is shown below in Figure 1 [2].

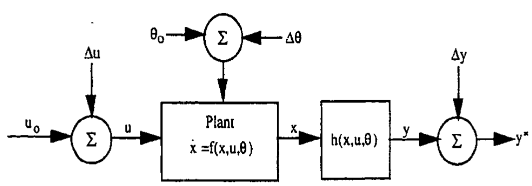

Figure 1. General Dynamic System Block Model [2]

The relationship between the variables of this system can be described as follows: [2]

$$\dot{x} = f(x, u, \theta)$$

$$y = h(x, u, \theta)$$

where $u = u_o + \Delta u$, $\theta = \theta_o + \Delta\theta$, $y^* = y + \Delta y$.

The variables for the block diagram and expressions shown are defined in Table 1.

Table 1. General Dynamic System Variables [2]

Variable	Description
u_o	Input vector
Δu	Input fault vector
θ_o	Nominal parameter vector
$\Delta\theta$	Parameter (component) fault vector
x	State vector
$f(\cdot,\cdot,\cdot)$	State evolution vector field
$h(\cdot,\cdot,\cdot)$	Output measurement function
y	Actual output vector
Δy	Output fault vector
y^*	Measured output vector

B. Neural Networks

A neural network is a (sometimes very large) parallel computational structure. Neural networks consist of a very large number of simple processing elements called neurons, with each neuron connected to a large number of other neurons.

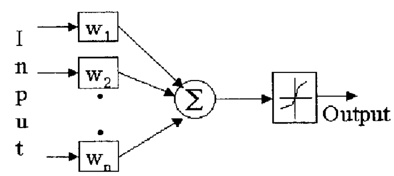

Figure 2. Diagram of a Simple Neuron [4]

Figure 2 shows a simple neuron that receives inputs from the external inputs, or from other neurons. The inputs are multiplied by connection weights, and summed to form the activation of the neuron. The neural network has an input side where stimuli are presented to the network, and an output side where the results of neural network's results can be obtained. These results are commonly referred to "residuals", particularly when used as feedback for control and diagnostic purposes. [4] The neural network can be effectively used as the basis of a multi-sensor fusion implementation, which will be shown in greater detail using our model example.

C. Fuzzy Logic

Fuzzy logic is a process designed to deal with ambiguous or non-crisp situations. It was developed to represent and reason with knowledge, expressed in terms of linguistic quantities, e.g., "hot", "warm", "cold", rather than in terms of crisp numbers. A fuzzy logic controller attempts to emulate the qualitative knowledge of an operator or expert of the process concerned. An expert of a particular procedure can easily express knowledge about the process in terms of linguistic rules, rather than in crisp rules. [5] In the context of this paper, fuzzy logic can be used as a complementary or alternate approach in designing sensor fusion algorithms. Figure 3 shows an example of how fuzzy logic can implemented for fault detection.

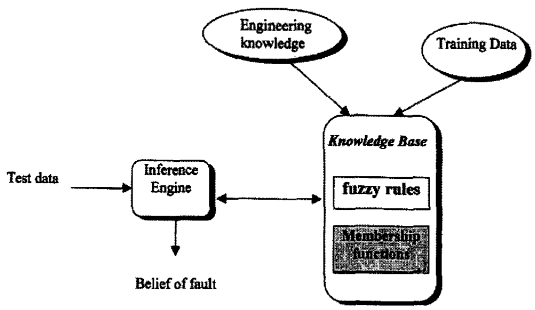

Figure 3 – Fuzzy Model for Fault Diagnosis [5]

C. Observer Based Residual Generation

The use of the Dedicated and General Observer schemes for sensor fault diagnosis are explored and discussed in detail by Kim in [1]. In these methods, each observer uses measurements from different sensors to provide an estimate of the system output. Again, the results of these observers are also typically referred to as "residuals". These schemes allow for individual or multiple sensor faults to be isolated and identified when used in conjunction with threshold or logic algorithms. A diagram of this approach is shown in figure 4.

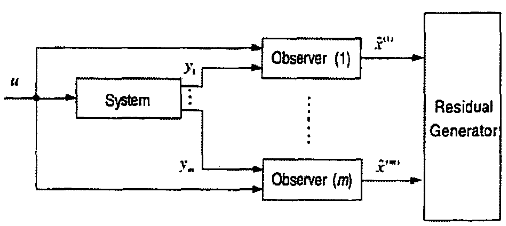

Figure 4 – Dedicated Observer Scheme [1]

If all sensors are operating in a normal condition, the estimated output value of the observers will be the same as the sensor being evaluated. Similarly, by evaluation of the individual observer outputs, a sensor fault can be identified since only the observers using that particular sensor input will deviate from the measurement made by the collective observer system. By further comparison of the deviant observer, sensor fault isolation can be obtained.

D. Model Based Diagnostics

The basic concept of model based fault detection is the design of theoretical redundancy using system or process models, which may be mathematical descriptions of known physical laws, or descriptions obtained using system identification techniques. With these models, the user can generate sensor signal residuals. Fault detection then takes place by evaluation of residual signals combined with a logic decision. It is widely accepted that the main difficulty of using the model-based fault detection schemes is the model uncertainty. [6] This problem becomes accentuated in model based fault detection used for automotive based systems, since the process of "car driving" is influenced by many unknown factors. Some of these factors can only be partially modeled, modeled with uncertain fidelity or, in some cases, cannot be mathematically described.

Since many new sensors will be introduced into passenger cars in the near future due to the desire for additional features and functions, the model based redundancy concept offers a general purpose approach to sensor monitoring. Figure 4 shows a generic example of a model based diagnostic scheme. In this example, the inputs to the system (sensors for our purpose) are processed in parallel through the control system and the associated model of the control system. Then, a comparison is made between the system and system model outputs, generating multiple residuals. Fault conditioning and logic (which may be implemented using fuzzy logic) determine the final system output and error signals.

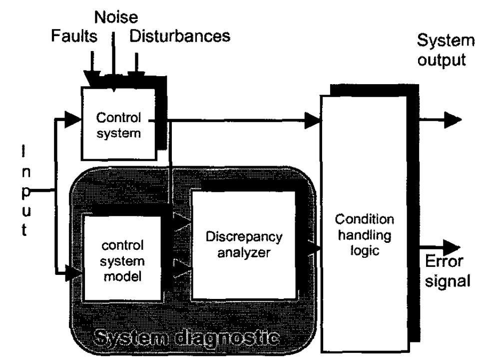

Figure 4 – Model Based Diagnostic Scheme [6]

III. SENSOR FUSION APPLICATION EXAMPLES

A. Chassis Sensor Fusion / Diagnostic

Since the beginning of chassis control systems, it has been necessary to implement condition monitoring of the electrical and electronic components being used. For sensors and actuators, the use of signal reasonability criteria and electrical circuit monitoring is common practice. For this purpose, several vehicle sensors and control system inputs were monitored and captured, including steering angle, vehicle speed, yaw rate, and lateral acceleration.

In a generic stability control system, one popular method of providing input to the control algorithm is through the use of yaw rate, lateral acceleration and steering angle information. As the vehicle is driven, the driver indicates the desired direction of travel through positioning of the steering handwheel. The static and dynamic relationships between the various sensor signals determine the need and/or level for controlled brake intervention to physically correct the directional path of the vehicle. In a simplified example, if the difference between the yaw rate signal and steering angle signal become greater than a predetermined threshold level, stability system intervention takes place. Therefore, the importance of the signal integrity from various sensor inputs to the system, in both magnitude and phase, becomes obvious. The control system can set a Diagnostic Trouble Code (DTC) based on the results of sensor electrical and correlation testing. Once a DTC is set, the features provided by the system are typically degraded or disabled, and may require vehicle service depending on the severity of the sensor failure detected.

Using the data collected from the vehicle, we later performed sensor fusion diagnostic modeling using three chassis control parameters, yaw rate, lateral acceleration, and steering angle. These signals were selected based on the observation that they demonstrate systematic inter-relationship.

B. Powertrain Sensor Fusion / Diagnostic

The intake air system provides clean air to the engine, optimizes air flow and reduces unwanted induction noise. The intake air system consists of an air cleaner assembly, resonator assemblies and hoses. The mass air flow (MAF) sensor is attached internally or externally to the air cleaner assembly and measures the quantity of air delivered to the engine combustion chamber. The MAF sensor can be serviced or replaced as an individual component. The air intake subsystem is used to provide increased intake airflow. This improves torque, emissions and performance. The throttle body controls the overall quantity of air delivered to the engine.

We collected real vehicle data from several sensor and engine control inputs, including RPM, LAMBSE, throttle position, mass air flow, and other powertrain diagnostic information. This information would later be used as input data for the sensor fusion modeling activity.

One engine parameter that can give insight into the overall condition of the engine system is the desired air/fuel flow "Lambda" (λ). There are many factors that can influence the air/fuel ratio in the engine. If there is MAF sensor malfunction, air entering an engine is not being measured correctly. If the sensor fails, a false indication of larger or smaller amount of air entering the intake will cause an imbalance to the air / fuel ratio, resulting in the engine running leaner or richer. [7] The LAMBSE signal is compared with a calibratable max and min, and an error code is set if the signal is out-of-range for a given number of sampling periods. Once an error code is set, the vehicle must either be serviced to clear the DTC, or (if the fault is deemed less severe) the DTC will automatically clear from the ECU memory after a preset number of driving cycles are completed without the fault condition reoccurring.

Using the data collected from the vehicle, we later performed sensor fusion diagnostic modeling using three engine parameters, MAF, throttle position, and engine RPM. These signals were selected based on the observation that they have some degree of systematic inter-relationship.

IV. SENSOR FUSION MODELING

A conceptual model of a multi-sensor fusion fault diagnosis algorithm for a vehicle sensor application was inspired by work being pursued in the areas of control system algorithm development and fault detection and identification (FDI) research. The implementation discussed here was modeled using the Matlab / Simulink software package. Figure 5 shows a high level view of the Simulink model created. The data is processed through what the authors call a direct, empirical system identification transfer function. These transfer functions were developed using the ARMAX (Auto Regressive Moving Average) system identification algorithm found in the Simulink System Identification Toolbox. By processing each sensor input as a system output of the other two available sensor inputs, six unique 3rd degree transfer functions describing the mathematical relationship between the sensor signals were established.

By using two transfer function outputs derived from two sensors that describe the input signal of a third sensor, an elementary sensor fusion estimation signal (representative of the third sensor input) was obtained. The combination of these transfer functions was obtained by a single, equally weighted, summing neural node. The output of the neural node is then filtered again using the ARMAX algorithm to provide a final forcing function for each "estimated" sensor signal.

Simultaneous to the signal fusion operation, a fuzzy logic control algorithm implements a fault detection feature in the model. Based on a limited rule set, the fuzzy logic algorithm monitored the sensor input signals for deviation from a predefined dynamic operating range. This threshold level fault detection scheme is discussed in many of the reference sources. When no faults are detected by the fuzzy processing unit, the sensor inputs are passed straight through to the output ports.

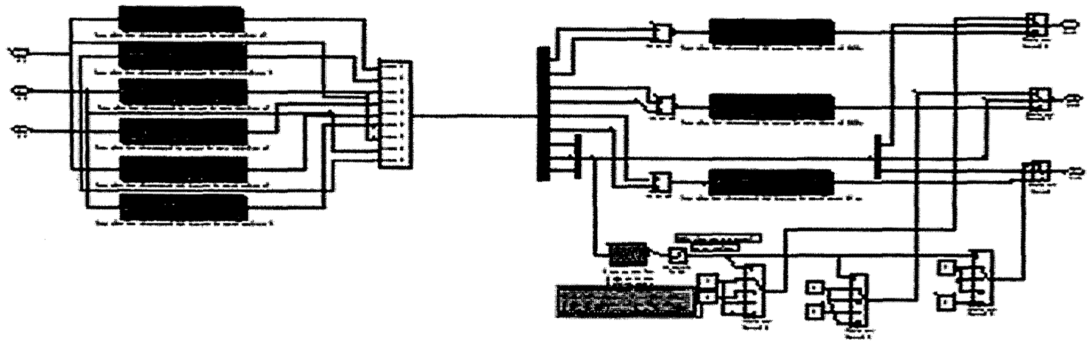

Figure 5. Simulink Sensor Fusion Model

A switching network was developed that allows the estimated sensor signal to be passed to the output port of the model when a fault on the original signal is detected. This is an on-line process that operates in real time. If the fuzzy controller no longer detects the fault, the original sensor signal is again passed through to the output of the model. In this sense, a fault tolerant sensor module is represented by the model, providing both a sensor fusion estimate of the original signal, and a means to detect signal faults and switch signal paths dynamically in response to those faults using fuzzy logic.

Generally, it is proposed by the authors that the end user of the output from this type of sensor fusion processing algorithm take into consideration the lowered fidelity of the estimated signal provided during a fault condition and take appropriate actions to adjust the system control or diagnostic response, with the advantage being the ability to continue operation, rather than disabling a function due to the faulted sensor condition. Additionally, the authors suggest that the fuzzy logic cross correlation features could ultimately be refined to provide automated "parameter of interest" selection and triggering for an enhanced diagnostic datalogging, providing a source of valuable information to the service technician.

V. RESULTS AND DISCUSSION

Several assumptions were made in developing this simulation model: First, the model and methodology used are acknowledged to have limitations in application and practical use. Second, it is beyond the scope of this paper to fully define mathematical relationships between the sensor signals, our intent is to demonstrate that the interrelationships exist, and can be exploited to enhance system robustness and fault diagnostics. Last, the assumption is made that the sensor signals used have a mathematical relationship, which may or may not be linear and which may have discontinuities across their dynamic range that invalidate this modeling algorithm. Methods to address these concerns are discussed in other research literature and are not presented here. With that said, our data showed positive results supporting the feasibility of this sensor fusion concept as applied to an automotive sensor set.

Figure 6 shows an example of the results from the Simulink sensor fusion model described in the previous section. The upper graph in the figure shows the actual signal and the modeled signal. The lower graph shown in figure 6 and Figure 7 shows the relative error between the actual and modeled signals. As can generally be seen in this figure, the sensor fusion algorithm employed in this model was very responsive and followed the actual input signal well. Initial calculations show that error was about 10 to 20% for the signal estimation with some local maximums and minimums performing slightly better or worst.

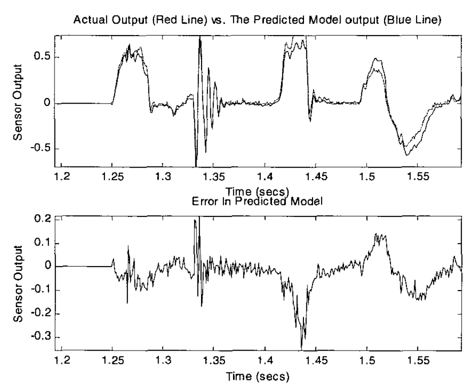

Figure 6 – Chassis Fusion Results

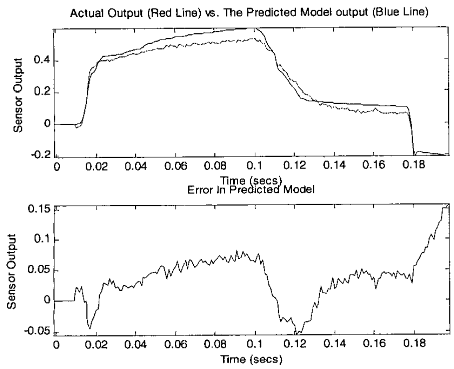

Figure 7 – Powertrain Fusion Results

Figure 7 shows an example of processing the powertrain sensor signals in the same fashion as the chassis sensors with the only difference being the transform function equations and threshold levels used. Note that the same algorithm and model was used to process both the chassis and powertrain data. The differences were dealt with in the transform functions and threshold levels, which in a more sophisticated implementation of the model could be made calibratable. It can easily be seen that the concept of sensor fusion for signal estimation and/or fault detection in a vehicle application is a valid concept worthy of further exploration.

VI. CONCLUSION

This paper reviews the technology related to sensor fusion and vehicle fault diagnostics to provide the reader with a better understanding of the methodologies and concepts used for correlation of vehicle sensor / diagnostic data, as well as to demonstrate the trends and needs for future vehicle diagnostic strategies. Improvements and optimization of existing systems, system integration, and the demands for more performance and features from future vehicle systems and diagnostic schemes are inevitable. Fusing two raw signals together and processing the information with a fusion algorithm can improve characterization of the input. Furthermore, by combining a number of fused input signals and adding a simple voting or decision making algorithm, improvements to fault classification accuracy can also be obtained.

One area of research directly related to this topic is the application of sensor fusion techniques to enhance the capabilities of the automotive service community. The authors allude to this by stating that the fuzzy voting or diagnostic algorithm could be easily modified to accommodate an output provision to be used for fault isolation datalogging. This selective captured information would be available to the service technician for more effective fault analysis.

The number of sensors in automobiles has risen dramatically in the last decade. Current vehicles can contain from 40 to 50 sensors costing in excess of $1000. [8] The technique of sensor fusion has been presented here as a potential tool for automotive sensor parameter estimation problems, and optimization of sensing resources. The benefits of sensor fusion for vehicle diagnostics will include new functions that enable a cleaner environment, increased fuel economy, and greater vehicle safety and reliability. Automobiles of the future will require unique, complex and reliable diagnostic schemes, as they become more integrated with advanced technologies for safety, features, and performance. Continued study and development of sensor fusion techniques (especially as applied to automotive applications) will provide additional technical momentum towards accomplishing these goals.

ACKNOWLEDGMENTS

The authors wish to thank Delphi, Cosworth Technology, Ford Motor Company, and the University of Michigan – Dearborn for generously allowing access to resources used to conduct research and experiments related to this paper.

REFERENCES

[1] Y.W. Kim, "A Methodology for Integration of Control and Fault Diagnostics", Ohio State University, PhD Dissertation, UMI Microfilm 9931629, 1999

[2] Ahmed A. Soliman, "The Application of Fuzzy Logic to the Diagnosis of Automotive Systems", Ohio State University, PhD. Dissertation, 1997

[3] Claudio A. Hernandez, Alois J. Adams, "Application of Mathematical Models to Detect and Diagnose Reciprocating Compressor Valve Leakage", SAE 2001-01-1724

[4] Sameer M. Prabhu, "An Overview of Neural Network and Fuzzy Logic Applications to Earthmoving Machine Systems Control", SAE 1999-01-1880

[5] Carlo N. Grimaldi and Francesco Mariani, "OBD Engine Fault Detection Using a Neural Approach", SAE 2001-01-0559

[6] Fredrik Gustafsson, Stefan Ahlqvist, Urban Forssell and Niclas Persson, "Sensor Fusion for Accurate Computation of Yaw Rate and Absolute Velocity", SAE 2001-01-1064

[7] Yi Lu Murphey, "Fuzzy Diagnostic Systems for Automotive Engineering", University of Michigan-Dearborn, Technical Project Report 1995/9, 1999

[8] D. Sparks, T. Noll, D. Agrotis, T. Betzner and K. Gschwend, "Multi-Sensor Modules with Data Bus Communication Capability", SAE 1999-01-1277