Signal Interpretation for Monitoring and Diagnosis, A Cooling System Testbed

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Abstract

This paper discusses our method for monitoring and diagnosis of dynamic systems. A key aspect in our approach is the interaction between a qualitative diagnosis engine that requires symbolic input data and a monitoring component that performs a signal to symbol transformation on the observed signals. We have applied the methodology to the cooling system of an automobile engine on which we have installed thermocouples and pressure sensors. Faults can be introduced into the cooling system in a controlled manner. We show that a combination of linear approximation techniques and statistical signal processing can provide robust symbolic signal values for the diagnosis algorithm.

1 Introduction

Diagnosis in engineering systems is the process of detecting anomalous system behavior and then isolating the cause for this behavior. The problem may be a faulty control setting or a faulty sensor or component. We adopt a model based approach, where the model of the process relates observed variables to model component parameters. Deviations in the parameter values imply faults. We distinguish between incipient faults and abrupt faults. Our work concentrates on the detection and isolation of abrupt faults in system components.

An abrupt fault causes transients that can be attributed to the system dynamics. These transients help differentiate among different faults. But, fault transients may not persist because of interactions and feedback, so we must track and analyze system behavior before transient manifestations disappear. A fault that is not detected and acted upon in a timely manner may lead to catastrophic failure before the system reaches a new steady state. Therefore, the ability to identify faults based on transients may be crucial in dynamic systems.

However, transients are difficult to analyze and require complex dynamic models. Several difficulties can be readily identified. The model may contain deficiencies in that significant higher order phenomena may not be included, and parameter estimates may lack sufficient accuracy. In addition, quantitative parameter estimation techniques may not work well for complex systems because it is difficult to invert functions either by analytic or numeric methods. Finally, measured signals are typically noisy and sensor response is a function of environmental conditions and characteristics which may drift over time.

We have developed a comprehensive framework for monitoring and diagnosis of physical systems. Our methodology is intended to overcome the difficulties associated with quantitative techniques. The emphasis of our past work has been on the modeling and diagnosis tasks. We have evaluated our algorithms in simulated environments using simplified lumped parameter models [6, 7]. In this paper we focus on the monitoring aspects of our framework. We also describe our testbed, built around a Chevrolet V8 internal combustion engine. We are currently focusing on diagnosis of faults in the cooling system for this engine. The testbed allows us to demonstrate the feasibility of our approach on a real system.

The organization of this paper is as follows. Section 2 reviews the monitoring and diagnosis framework and then discuss the signal analysis task in more detail. Section 3 describes our testbed and the experiments we have conducted. Section 4 presents results of our fault isolation experiments. Discussion and conclusions appear in Section 5.

2 Method

2.1 Framework for monitoring and diagnosis

Figure 1 illustrates our diagnosis system architecture. The input to the physical process is the input vector u, and the observations are indicated by vector y. An observer system uses a model of dynamic system behavior in the form of ordinary differential equations (ODEs) to generate the expected behavior, $\hat{y}$, given u. The observer scheme tracks the residuals, $r = y - \hat{y}$, and uses a standard gain matrix scheme to correct small discrepancies in the system state vector x [3].

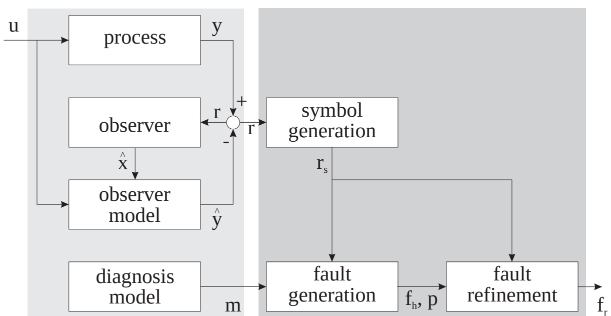

Figure 1. Diagnosis of dynamic systems.

The residuals are also input to the signal analysis module for discrepancy detection in the measured signals. Once discrepancies are detected, the symbol generation unit reports the values of a set of symbols to the fault generation and fault refinement units. These symbols represent (i) discontinuous changes, (ii) magnitude deviations, (iii) slope deviations, and (iv) steady state behavior.

The diagnosis model captures qualitative dependency relations between component parameters and the observed variables. The fault generation unit uses this information, m and the symbolic residuals, r_s, to generate hypothesized faults from observed deviations, f_h, and to predict their future transients and steady state behavior, p. A fault is hypothesized as a parameter value deviating above (+) or below (−) nominal. A monitoring scheme compares actual observations against the predicted transients for each hypothesized fault, $f \in f_h$. Only those faults whose transients agree with the observations are retained in the refined set f_r. The goal is to continue monitoring until the true fault is isolated.

Transient characteristics at the time of failure change over time as other phenomena in the system affect the measured variables. For example, a fault in the system may have no effect on the initial magnitude of a variable, but it may affect the first derivative. Immediately after the fault occurs the variable value will be observed to be normal, but as time progresses the magnitude will follow the direction of the first derivative. When an observed variable does not match a predicted *normal* value, the comparison is extended to predicted higher order derivatives in the signature. If the higher order derivatives match the observed value the hypothesized fault is still retained. We refer to this mechanism as *progressive monitoring* [5]. Predictions of magnitude deviations that have a high or low value before progressive monitoring is applied indicate abrupt changes, which correspond to discontinuities in the model. The diagnosis is thus enhanced if discontinuities can be reliably detected.

Therefore, the primary functionality of the monitoring component is the extraction of qualitative magnitude and slope values and to detect abrupt changes. We view this as a signal interpretation problem, and we usually refer to it as the *signal to symbol transformation*.

2.2 Signal to symbol transformation

2.2.1 Signal analysis for diagnosis

Two key issues affect the signal to signal analysis steps: (i) the discrete time representation of signals, and (ii) noise contamination of signals.

Continuous time signals must be discretized in time for data capture and analysis on digital systems. The sampling rate required to correctly sample a bandlimited continuous time signal is given by the Nyquist theorem. However, this is a theoretical lower bound that applies to reconstruction of the signal from its samples by a method that cannot actually be implemented. When we wish to do signal *analysis*, and in particular on-line feature extraction, we are interested in local signal behavior, i.e., signal behavior around a point in time. For this problem, the sampling theorem can at best be a starting point to select a sampling rate. This problem has been identified in a variety of signal analysis applications (e.g., [9]). Typically we must use oversampling, that is, a sampling rate that exceeds the Nyquist rate to obtain a signal representation that is more robust for local signal analysis techniques. Empirical studies are required to determine an appropriate oversampling factor. In the case of fault detection and isolation, just establishing the bandwidth of the system is non trivial. The highest frequency component derived from the system model is an approximation that depends on the level of detail included in the model.

Noise in data leads to a compromise between speed of feature extraction and confidence in the derived result. For feature extraction it is not so much required to attenuate the noise in the data, as it is to use feature extraction methods that are robust for noisy signals. Noise is often assumed to have a Gaussian distribution. A noise model that is not completely realistic with respect to the data does not necessarily invalidate a feature extraction method. However, measurement data often contains *outliers*, sparse samples with values very different from the assumed distribution. Removing outliers is almost always desirable, and can be achieved through nonlinear filtering such as a median filter of short length.

2.2.2 Magnitude changes and discontinuities

Discrepancy detection is a crucial component of the monitoring system. We trade sensitivity to changes in the signal for robustness to reach a compromise between false alarms and missed alarms. The detection process implies the use of a threshold to make the decision whether a change has occurred or not. A naive approach is to compare the measured signal value to the nominal value directly. This, however, would give a poor performance in the presence of noise, and requires further analysis to label the nature of the change as well. So usually a normal band that is a multiple of the standard deviation is set around the data.

As we have indicated, the ability to detect abrupt changes in the data contributes greatly to the discriminative powers of the fault identification scheme. We have investigated three sophisticated approaches for the detection of abrupt changes: signal reconstruction using splines, statistical signal processing, and the discrete wavelet transform [8]. Here we discuss only the statistical signal processing approach because it is most relevant to the results discussed later.

The detection process computes an innovation function based on the likelihood ratio between several hypotheses. Each hypothesis corresponds to a different statistical signal model. The detector used here is the Generalized Likelihood Ratio (GLR) which makes no assumption about the magnitude of the change. The decision function is made by applying a threshold on the innovation function. Much work has been done in developing a systematic framework using this method and it can be shown to be the optimal detector [1]. However, it does require a statistical model of the data.

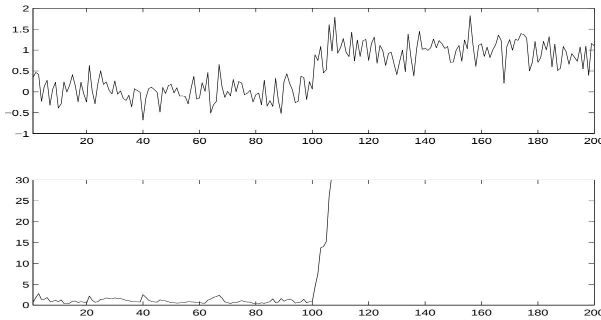

Figure 2. Abrupt change detection in a unit step function with Gaussian noise ($\sigma = 0.3$). The step occurs at x = 100.

2.2.3 Slope estimation

The second component of signature derivation is estimation of the slope of the signal after an initial change. The simplest way to do this is a discrete approximation using a difference operator. This approach is extremely sensitive to signal noise because the difference operator acts as a high pass filter (e.g., see [2]). In the presence of noisy signals, it is unrealistic to assume that successful diagnosis using first order derivatives can be based on two samples in time. A more reliable method for estimating derivatives is to use statistical model fitting methods. A simple example of this approach is the estimation of slopes from piecewise linear approximations of the signal.

3 Experiment Design and Testbed Implementation

3.1 Selection of the device under test

Our experimental studies require a 'device under test' that exhibits dynamic behaviors and for which we can construct a well defined energy-based dynamic model. For practical reasons, introduction of sensors should not affect system operation, and faults introduced should be controlled without causing catastrophic failures. We have selected a Chevrolet V8 internal combustion engine as the device under test, and focus on the engine cooling subsystem for our diagnosis studies.

An automotive cooling system uses a liquid coolant that circulates through the engine block and radiator at pressures that can reach 15 (psi). The temperature of the coolant can exceed 100 (°C). A detailed description of the cooling system operation and the model is presented in [4]. Since we are dealing with a combined thermal and fluid flow problem it is important to collect temperature and pressure values at various points in the cooling system circuit.

Several faults can be introduced into the cooling system without damaging the engine, provided the temperature of the engine block does not exceed certain limits:

- Thermostat failure. This causes a mode switch to happen or not. Failure may occur either in the open or closed position.
- Belt failure. This results in the fan and pump no longer being driven in which case the coolant becomes too hot.
- Punctured hose. This causes coolant to leak quickly.
- Leaking radiator. This is typically a slow leak.
- Clogged radiator. Metal deposits in the coolant may clog the radiator outlet.
- Water pump failure. This can be a gradual or catastrophic failure.

3.2 Experimental Setup

The Chevrolet V8 engine was chosen because of available expertise and parts. The testbed consists of the engine, bolted on a steel frame, and a PC based instrumentation system made up of an Intel Pentium workstation running the Microsoft Windows NT operating system. This machine is equipped with a data acquisition board with 8 differential inputs, and a maximum acquisition rate of 333kS/s (Data Translation, DT3001-PGL). An external enclosure holds a screw terminal interface to the data acquisition board and is fitted with connectors for the sensors. The enclosure can also house additional signal conditioning, although none is in place at this time. The screw terminal itself provides cold junction compensation (CJC) for thermocouples. To eliminate interference from the ignition system, all wiring from the sensors to the enclosure is shielded.

Discriminating ability and ease of installation were the criteria used by our expert to choose sensor locations. Figure 3 shows the location of these measurement points on the engine and Table 1 relates them to the list of faults.

Figure 4 shows a detail of the engine with the installed sensors. A probe style thermocouple (T1) has been installed in the thermostat housing, immediately downstream from the thermostat. A second probe style thermocouple (T2) is just upstream from the thermostat in the intake manifold. This location is very close to the cylinder heads, where the coolant reaches its maximum temperature. The sensor is installed in an existing opening in the intake manifold, normally used for the coolant outlet connected to the heat exchanger for heating the car interior. Both thermocouples are immersed in engine coolant. One amplified voltage output pressure transducer (P1) is directly installed in the intake manifold in an existing opening next to the thermostat housing. This places the pressure measurement immediately downstream of the thermostat. A second pressure transducer (P2) of the same type is installed in the lower radiator hose. This measures pressure close to the radiator outlet.

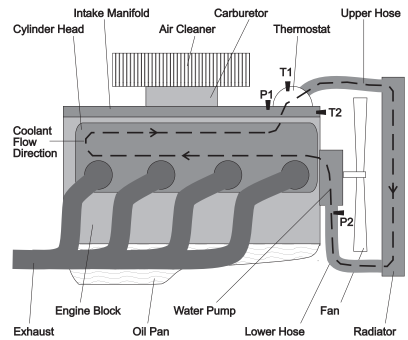

Figure 3. Engine schematic with suggested sensor placement.

The testbed is set up to run the engine in steady state operation, then to introduce a fault and collect data for diagnosis. Because the system is assumed to be in steady state during normal operation, we did not use an observer for this experiment. Nominal values were measured during steady state operation, and an accurate estimate of system parameters was not required. The sampling time used in the cooling system experiments was 0.02 (s). All signals were filtered with a median filter of length 5 to remove outliers.

Thermostat failure: open	T1
Thermostat failure: closed	T2, P1
Belt failure	T2, T1
Punctured hose (fast leak)	P1, P2
Radiator leak (slow leak)	T1, T2, P1
Radiator obstruction	P1, P2
Waterpump failure: gradual	T1, T2, P1
Waterpump failure: abrupt	T2, T1

Table 1. Faults in the cooling system and implicated transducers.

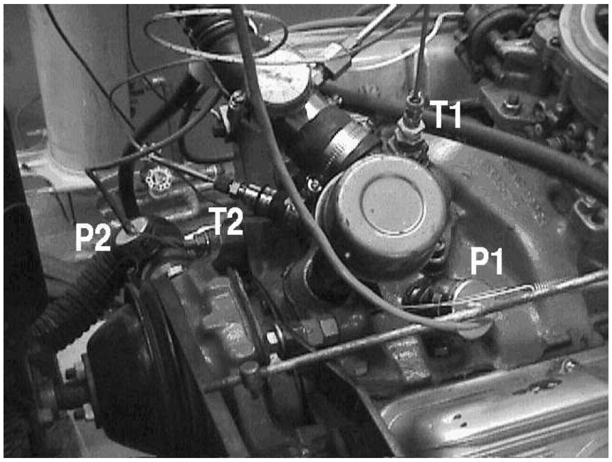

Figure 4. Engine detail with sensors. The fan is on the bottom left, the carburetor on the top right (the air cleaner has been removed).

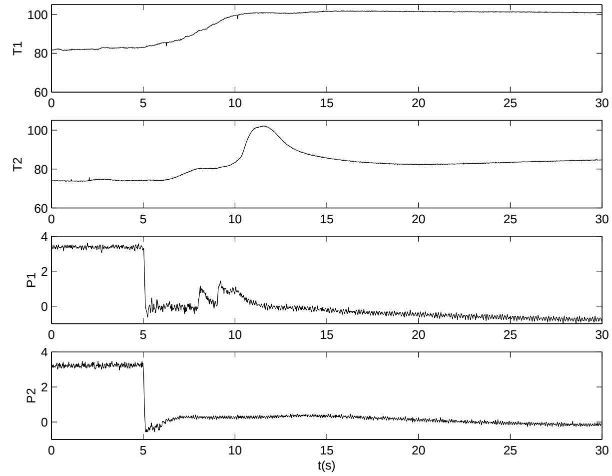

Figure 5. Abrupt loss of coolant through punctured lower radiator hose at t = 5(s).

Time	T1	T2	P1	P2
4	(0,.)	(0,.)	(0,.)	(0,.)
5	(0,.)	(0,.)	(0,.)	(0,.)
6	(0,.)	(0,.)	(-,.,*)	(-,.,*)
7	(+,+)	(+,+)	(-,-)	(-,+)
8	(+,+)	(+,+)	(-,-)	(-,0)

Table 2. Results of the signal to symbol transformation on the data around the occurrence of the fault.

4 Results

We analyze a coolant leak fault in the system. To simulate the leak, we have inserted a T-split coupling in the lower radiator hose which allows us to drain coolant from the system by attaching a valve to the open end of the coupling. To simulate a large hose puncture a lever operated gate valve is attached to the coupling. This valve can be switched from closed to open almost instantaneously. The valve is included in the model as a parameter, R_{leak}. A complete description of the model and all model parameters can be found in [4].

Figure 5 shows the resulting signals after introducing the fault. The valve is opened at t = 5(s) and remains open for several seconds. In this interval a large amount of coolant is drained from the system. We do not drain all the coolant from the engine but instead close the valve again after a few seconds to avoid damage to the engine. As a result we also see some spurious transients, but they can be ignored in the analysis. The very fast transients in the pressure signals and slower transients in the temperature signals can clearly be seen.

We compute the symbolic feature values every second, using 50 samples for the least squares linear approximation of the signal to determine the slope. A monitoring diagnosis step is thus made every second. Abrupt change detection using the GLR algorithm is applied to the pressure signals only. We exploit the fact that abrupt changes cannot occur in the temperature data. This type of domain knowledge can and will be built into the framework in a structured manner.

Table 2 shows the output of the signal to symbol transformation from time t = 4(s) through t = 8(s). the format for the computed features is an '+/−/0' pair for magnitude deviation and slope, and a '$\star$' to indicate if an abrupt change was detected during a step. The slope values aren't computed until *after* the initial discrepancy has been detected. This is indicated with the symbol '·'.

Figure 6 shows the results of the fault isolation process. The format for the predicted symbol values is similar to that of the computed ones. It is a '+/−/0' tuple for the magnitude deviation and derivatives from first order up to the predicted order. A '·' means that the prediction is unknown. It turns out that T1 does not contribute to the fault isolation for this particular fault and it has been removed from the results. For this model, derivatives are predicted up to second order.

The initial discrepancy detection generates the candidate set at step 0. Detection of abrupt changes results in the elimination of a large number of hypothesized faults at step 1. At step 2 the $R_{hy-blk}-$ (input fluid flow resistance of the engine block) fault is step 0

actual	P1:	−	0	
	P2:	−	0	
	T2:	0	0	
$C_{hy-blk}-$	P1:	−	·	·
	P2:	+	·	·
	T2:	0	+	·
g_f-	P1:	−	·	·
	P2:	+	·	·
	T2:	0	+	·
m_1+	P1:	−	·	·
	P2:	+	·	·
	T2:	0	+	·
$R_{leak}-$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	+	·
$I_{rad-out}+$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	·	·
$I_{tstat}+$	P1:	0	−	·
	P2:	0	+	·
	T2:	0	·	·
$R_{l-hose}+$	P1:	0	−	·
	P2:	0	−	·
	T2:	0	0	·
$C_{hy-rad}+$	P1:	0	−	·
	P2:	0	−	·
	T2:	0	0	·
$R_{tstat}+$	P1:	0	0	−
	P2:	0	0	+
	T2:	0	0	·
$R_{hy-blk}-$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	−	·
g_f+	P1:	+	·	·
	P2:	−	·	·
	T2:	0	−	·
m_1-	P1:	+	·	·
	P2:	−	·	·
	T2:	0	−	·
$C_{hy-blk}+$	P1:	+	·	·
	P2:	−	·	·
	T2:	0	−	·
$I_{tstat}-$	P1:	0	+	·
	P2:	0	−	·
	T2:	0	·	·
$R_{tstat}-$	P1:	0	0	+
	P2:	0	0	−
	T2:	0	0	·

step 1

actual	P1:	−	−	
	P2:	−	+	
	T2:	+	+	
$R_{leak}-$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	+	·
$I_{rad-out}+$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	·	·
$R_{hy-blk}-$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	−	·

step 2

actual	P1:	−	−	
	P2:	−	0	
	T2:	+	+	
$R_{leak}-$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	+	·
$I_{rad-out}+$	P1:	−	·	·
	P2:	−	·	·
	T2:	0	·	·

Figure 6. Fault detection and isolation for a punctured lower hose fault ($R_{leak}-$).

eliminated by applying the progressive monitoring algorithm. The predicted *slope* is negative for measurement e30, which does not match the observed magnitude deviation. Without abrupt change detection, $R_{l-hose}+$ (flow resistance of the lower hose) cannot be eliminated at step 1 nor at any later time step and would have stayed in the set of hypothesized faults. The final result at step 2 shows that the diagnosis is *accurate* because it includes the actual fault $R_{leak}-$. One spurious candidates is generated. $I_{rad-out}+$ (radiator outflow inertia) can not be distinguished from $R_{leak}-$ given this set of observations.

5 Conclusions

The development of a suitable testbed is vital to demonstrate utility of research results for monitoring and diagnosis of real systems. The comparisons of symbolic feature values computed from the real data with the predictions generated by the model lead to new insights on the model building as well as provide guidelines on the type of signal analysis algorithms to use. The results so far indicate that the combination of qualitative diagnosis with sophisticated signal to symbol transformation methods is promising.

Acknowledgments

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