# Signal Interpretation for Monitoring and Diagnosis, A Cooling System Testbed

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## Abstract

*We present our framework for monitoring and diagnosis. The framework is based on interaction between a qualitative diagnosis engine and a monitoring component that performs a signal to symbol transformation on the signals. We have applied the methodology to a real system, 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 algorithms.*

## 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 in the system. Diagnosis typically requires a model of normal operation of the system and a number of observable variables. The model relates functionally redundant observed variables and hypothesizes model changes when inconsistencies arise. The model changes may correspond to a fault. We distinguish three types of faults, intermittent faults, incipient (gradually evolving) faults and abrupt faults. Our work concentrates on the detection and isolation of abrupt faults in system components.

The occurrence of an abrupt fault results in transients caused by system dynamics. These transients contain important discriminating information about which fault may have occurred. Due to feedback effects of the system, a fault manifestation may not persist, so we must track and analyze system behavior before the transient effects disappear. Additionally, 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 observed here. The model may contain modeling deficiencies such as significant higher order phenomena and system parameters may not be estimated accurately enough. This makes it difficult to interpret system behavior. In Addition, quantitative techniques such as parameter estimation 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.

Our model-based diagnosis group at Vanderbilt University has developed a comprehensive framework for monitoring and diagnosis of physical systems that attempts to overcome the difficulties associated with such quantitative techniques. So far, the emphasis has been on the diagnosis algorithms and system modeling. A number of different simulations using lumped parameter models have been built to evaluate the approach [7, 8, 9].

This paper focuses on the monitoring aspects. We discuss critical signal analysis issues that must be addressed to make the methodology work with real world signals and actual systems. We also describe our testbed, which has been built around an internal combustion engine as the device under test. We are cur-

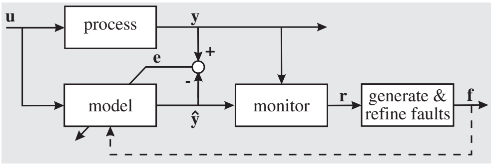


**Figure 1. Diagnosis of dynamic systems.**

rently focusing on the cooling system for this engine. The testbed allows us to demonstrate the feasibility of our framework operating on a real system.

The organization of this paper is as follows. In section 2 we review the monitoring and diagnosis framework and then discuss the signal analysis aspects in more detail. In section 3 we describe the real world experiment we have designed and the testbed we have built. Section 4 shows results based on faults introduced in our engine. We close with a discussion and conclusions in section 5.

# 2 Method

## 2.1 Framework for monitoring and diagnosis

Figure 1 illustrates a generic model based approach to fault detection and isolation [3, 4]. A set of variables, called *measurements*, are monitored at frequent intervals during normal operation. Dynamic behaviors from system models are utilized to predict operating values for a chosen set of system variables in a given mode of operation. The diagnosis system maps these measurements, $\mathbf{y}$, that deviate from predicted normal behavior, $\hat{\mathbf{y}}$, onto a system model. Analysis of discrepancies or residuals, $\mathbf{r}$, in the context of the model helps to *generate* one or more hypothesized *root-causes*, $\mathbf{f}$, that explain the measured deviations. Hypothesized faults suggest modifications to the system models which are then employed to predict future system behavior. The goal is to continue the monitoring, comparison, and refinement process until the set of faults occurring in the system is isolated.

Our framework for monitoring and diagnosis uses bond-graphs as the modeling paradigm. We exploit systematic methods for generating temporal causal graphs for behavior propagation from the bond-graph representation. Bond-graphs are suited for both quantitative and qualitative analysis. Our diagnosis algorithms process system parameter values based on their qualitative behavior, that is, magnitude and temporal effect. Magnitude deviations are predicted in terms of *low (-)* or *high (+)* values with respect to normal operating values. The temporal effect is introduced by energy storing elements (related to state variables) and is applied to predict first order behavior, whether signal slope is *positive (+)* or *negative (-)*. If the behavior of multiple energy storage elements accumulates, the prediction may be in terms of higher order derivatives. Because in time these higher order derivatives propagate into lower order effects, their qualitative prediction may overrule nondeviating predictions of lower order time derivatives and even magnitude predictions. This is referred to as *progressive monitoring* [6].

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. A discontinuity must not be confused with a magnitude deviation. A magnitude deviation emerges over time and is identified by the progressive monitoring scheme. As mentioned earlier, the diagnosis is enhanced if they 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 as the signal to symbol transformation.

## 2.2 Signal to symbol transformation

### 2.2.1 The realities of real data

There are two significant issues in dealing with real data in monitoring and fault isolation tasks: contamination of signals by noise, and the discrete time representation of signals.

Noise in data leads to a fundamental tradeoff between speed and confidence in analytic results. On the one hand, additional measurement points lead to higher reliability in estimates made on the data. On the other hand, using additional measurement samples leads to delay before feature values become available to the diagnostic algorithms. The attenuation of noise with an FIR filter thus should be considered in the light of this tradeoff.

Since the signal to symbol transformation is concerned with extracting features from the data the nature of any noise attenuation also needs to be taken into account. A linear low pass filter distorts the signal the least, but will also affect the location of features in the data. The objective in signal analysis is to preserve the features of interest, not necessarily to minimize possible distortion. A Nonlinear filter may provide a solution if we wish to preserve high bandwidth features while at the same time attenuate noise. Statistical order filters (the median filter being the most familiar example) and morphological filters are well known examples.

Continuous time signals must be discretized before we can apply any analysis or processing. The Nyquist theorem defines the sampling rate required to reconstruct a signal from its samples. However, this is a theoretical lower bound, that cannot be used in a real system. In addition, it only applies to signal reconstructing. When we wish to do signal analysis, the sampling theorem can at best be a starting point for selecting a sampling rate. Typically we must use oversampling, that is, sampling at a rate that exceeds the Nyquist rate. This results in a more robust description of the signal in causal systems.

#### 2.2.2 Discrepancy detection and Slope estimation

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.

The second component of signature derivation is estimation of the slope of the signal after the 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. Moreover, the use of higher order derivatives is almost always impossible (unless dedicated transducers such as accelerometers are available). A more reliable method for estimating derivatives is to use statistical model fitting methods. A simple example of this is to apply piece wise linear approximation of the signal.

#### 2.2.3 Abrupt change detection

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 [10]. Here we discuss only the statistical signal processing approach because it is most relevant to the results discussed later.

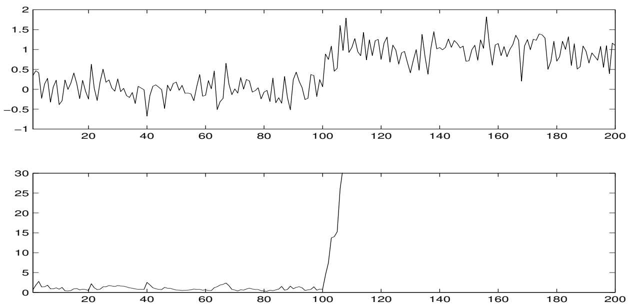


**Figure 2. Abrupt change detection in a unit step function with Gaussian noise ($\sigma = 0.3$). The step occurs at x = 100**

The statistical signal processing method is based on hypothesis testing and the notion of likelihood ratio. The detection process computes an innovation function based on the likelihood ratio between several hypotheses, each corresponding with a different signal model. The detector used here is called 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.

## 3 Experiment Design and Testbed Implementation

### 3.1 Selection of the device under test

A suitable 'device under test' should satisfy the following requirements: 1) it should exhibit dynamic behaviors, 2) there should be a well defined dynamic model of the system based on energy exchange between components that captures behaviors of interest, 3) we must be able to introduce faults that do not damage the testbed, and 4) sensors can be introduced where needed without affecting operation. We have selected an internal combustion engine from an automobile as the device under test. As the initial project, we have taken on the task of modeling, monitoring and fault isolation of the engine cooling system.

An automotive cooling system uses a liquid coolant that circulates through the engine block and radiator at

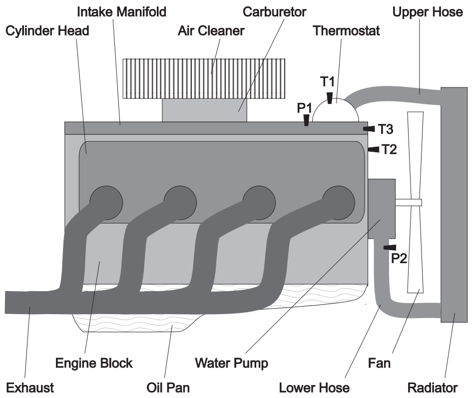


**Figure 3. Engine schematic with suggested sensor placement**

pressures that can reach 15 (psi). The temperature of the coolant can exceed 100 (°C). A detailed description of the cooling system and corresponding bond-graph model is presented in [5]. 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.

- The thermostat may fail. This causes a mode switch to happen or not. Failure may occur either in the open or closed position.
- The belt may fail. This results in the fan and pump no longer being driven in which case the coolant becomes too hot.
- A hose may get punctured, causing coolant to leak quickly.
- The radiator may start leaking. This is typically a slow leak.
- Metal deposits in the coolant may clog the radiator outlet.
- The water pump may fail, either catastrophically or gradually through wear.

### 3.2 Experimental Setup

The actual engine is a Chevrolet V-8. We selected this because of available expertise as well as readily available peripheral components. It also offers several subsystems for experimentation. The testbed consists of the engine, bolted on a steel frame, and a PC based instrumentation system.

The instrumentation system consists of an Intel Pentium microprocessor based computer running the Microsoft Windows NT operating system. This machine is equipped with a PCI bus data acquisition board from Data Translation (DT3001-PGL) with 8 differential inputs, and a maximum acquisition rate of 333kS/s. An external enclosure houses 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. All wiring from the sensors to the enclosure is shielded.

We have installed sensors at expert selected measurement points. The selection was made based on the discriminating ability and the possibilities for ease of installation on the engine. 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. Thermocouples are used for temperature measurements. A probe style thermocouple (T1) has been installed in the thermostat housing, immediately downstream from the thermostat. A second probe style thermocouple (T3) 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 loop that is connected to the car heat exchanger. Both probe style thermocouples are immersed in engine coolant. A 'bolt-on' type thermocouple (T2) is fixed to the cast iron engine block but the measurement is not currently used in the model or diagnosis. 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

| | |
|---|---|
| Thermostat failure: open | T1 |
| Thermostat failure: closed | T3, P1 |
| Belt failure | T3, T1 |
| Punctured hose (fast leak) | P1, P2 |
| Radiator leak (slow leak) | T1, T3, P1 |
| Radiator obstruction | P1, P2 |
| Waterpump failure: gradual | T1, T3, P1 |
| Waterpump failure: abrupt | T3, T1 |

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

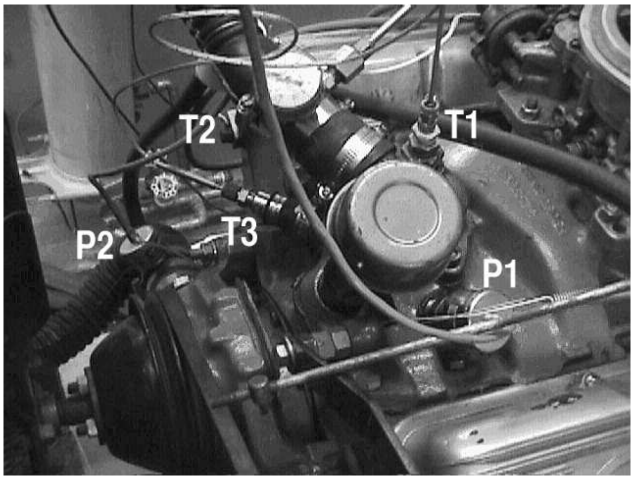


**Figure 4. Engine detail with sensors. The fan is on the bottom left, the carburetor on the top right (the air cleaner has been removed)**

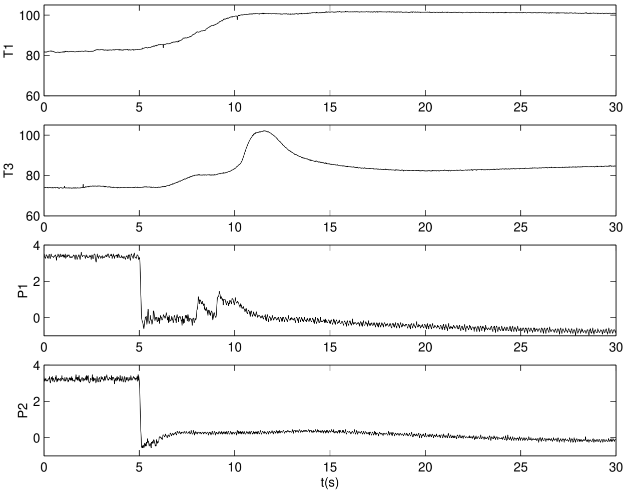


**Figure 5. Abrupt loss of coolant through punctured lower radiator hose**

in the lower radiator hose, where pressure is close to the pressure at the radiator outlet.

### 3.3 Introducing Faults

At the present time we are investigating coolant leakage faults. In order to simulate a leak we have inserted a T-split coupling in the lower radiator hose which makes allows us to drain coolant from the system by attaching a valve to the open end of the coupling. The coupling has a large inner diameter to enable high outflow.

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. We do not drain all the coolant from the engine but instead close the valve again. This helps prevent damage to the engine. As a result we also see some spurious transients, but they can be ignored in the analysis.

To create smaller and more controlled leaks we use a different valve type with control of the outflow. A small leak in the lower radiator hose is very close in behavior to a small leak in the radiator.

## 4 Results

Figure 5 shows an example of a hose puncture experiment. The engine is running stationary and the system has reached steady state (actually, a tiny amount of temperature gradient is still noticeable in the temperature data). The sampling time is 0.02 (s). All signals are filtered with a median filter of length 5. This removes the few outliers that can be seen in the otherwise very clean temperature data. From the figure it can be seen that the steady state pressure is quite low. this is caused by the fact that the gate valve is leaking slightly, even when closed. 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. The closing of the valve gives results in transients in both pressure and temperature data that will be ignored. The very fast transients in the pressure signals and slower transients in the temperature signals can clearly be seen.

We compute the symbolic signatures 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. Note that the monitoring component computes the signal slope at every step, but the diagnosis algorithm uses this only after a magnitude deviation occurs. Abrupt change detection using the GLR algorithm is applied to the pressure signals only. We use the fact that we know 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 results from step 3 to step 8 (the fault occurs at step 5). the format for the signatures is an '+/−/0' pair for magnitude deviation and slope, and a '$\star$' to indicate if an abrupt change was detected during a step.

We cannot show the complete simulation results in this paper, but the prediction for the punctured hose

| Step | T1 | T3 | P1 | P2 |
|---|---|---|---|---|
| 4 | (0,+) | (0,–) | (0,+) | (0,0) |
| 5 | (0,+) | (0,0) | (0,+) | (0,+) |
| 6 | (+,+) | (0,–) | (–,–,⋆) | (–,–,⋆) |
| 7 | (+,+) | (+,+) | (–,–) | (–,+) |
| 8 | (+,+) | (+,+) | (–,–) | (–,0) |

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

| Meas | magn. | 1st | 2nd | 3rd |
|---|---|---|---|---|
| T1 | 0 | 0 | 0 | + |
| T2 | 0 | + | – | + |
| P1 | 0 | – | + | – |
| P2 | – | + | – | + |

**Table 3. First prediction step after fault introduction for the hypothesized punctured hose fault.**

fault is shown in Table 3. It is the output of the prediction algorithm one step after the fault is introduced in the model. The parameter that is altered for this fault is the resistance value for the lower radiator hose.

The prediction step is computed up to the 3rd order effects. with a lower order prediction, no change in behavior in T1 is predicted for this fault. As discussed in section two, the sign of higher order derivatives is propagated to lower order derivatives. From this we can see that the algorithm predicts that the temperature will rise on both T1 and T2. We can also see that the model predicts that P1 and P2 will drop, and in fact the model predicts and abrupt change for P2 (magnitude deviation without a previously predicted slope change). The model does not predict an abrupt change for P1 which believe we can attribute to a known modeling deficiency (there is a secondary coolant flow path within the engine block that is not modeled yet, which would contribute dynamics in this fault).

## 5 Conclusions

The development of a suitable testbed is vital to demonstrate utility of research results in the field of monitoring and diagnosis on real systems. The comparisons of signatures 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 with sophisticated signal to symbol transformation methods is promising.

## Acknowledgments

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## References

[1] M. Basseville and I. Nikiforov. *Detection of abrupt changes: theory and applications.* Prentice-Hall, 1993.

[2] M. J. Chantler, S. Daus, T. Vikatos, and G. M. Coghill. The use of quantitative dynamic models and dependency recording for diagnosis. In *Seventh International Conference on Principles of Diagnosis,* pages 59–68, Val Morin, Canada, Oct. 1996.

[3] P. Frank. Fault diagnosis: A survey and some new results. *Automatica: IFAC Journal,* 26(3):459–474, 1990.

[4] R. Isermann. A review on detection and diagnosis illustrate that process faults can be detected when based on the estimation of unmeasurable process parameters and state variables. *Automatica: IFAC Journal,* 20(4):387–404, 1989.

[5] E. J. Manders, V. V. Ram, J. Barnett, G. Biswas, and P. J. Mosterman. The engine testbed: An experimental system for model-based monitoring, prediction and fault isolation. Technical Report #CS-98-03, Department of Computer Science, Vanderbilt University, 1 March 1998.

[6] P. J. Mosterman. *Hybrid Dynamic Systems: A hybrid bond graph modeling paradigm and its application in diagnosis.* PhD dissertation, Vanderbilt University, 1997.

[7] P. J. Mosterman and G. Biswas. An integrated architecture for model-based diagnosis. In *Seventh International Conference on Principles of Diagnosis,* pages 167–174, Val Morin, Canada, Oct. 1996.

[8] P. J. Mosterman and G. Biswas. Monitoring, prediction, and fault isolation in dynamic physical systems. In *AAAI-97,* pages 100–105, Rhode Island, Aug. 1997. AAAI Press, 445 Burgess Drive, Menlo Park, CA, 94025.

[9] P. J. Mosterman and G. Biswas. Diagnosis of continuous valued systems in transient operating regions. *IEEE Transactions on Systems, Man, and Cybernetics,* 1998. in review.

[10] P. J. Mosterman, G. Biswas, and E. J. Manders. A comprehensive framework for model based diagnosis. In *Ninth International Conference on Principles of Diagnosis,* pages 86–94, Cape Cod, Massachusetts, USA, May 1998.