Derivative Estimation for Diagnosis

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In engineering systems, diagnosis is the process of detecting anomalous system behavior and then isolating the cause for this behavior. This report is concerned with the detection and isolation of abrupt faults through analysis of the transients that occur after the fault. We have developed a comprehensive framework for monitoring and diagnosis of dynamical systems that attempts to overcome the difficulties associated with quantitative techniques. A key step in our monitoring and diagnosis framework is the transformation of measurements into symbols that encode the trends in the measurements. That is, the symbols are the signs of the first and second time derivatives of the measurements. This report outlines how these symbols are used in diagnosis, considers several methods for estimating the symbols from measured data, and shows the behavior of the method we have chosen to use on measurements taken with our cooling system diagnosis testbed.

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1 Introduction

Diagnosis is an important potential application for the emerging class of distributed measurement systems. In engineering systems, diagnosis is the process of detecting anomalous system behavior and then isolating the cause for this behavior. This cause may be a faulty control setting or a faulty component in the system. The model-based approach to 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 changes in model parameters – possible faults – when inconsistencies arise. We distinguish three types of faults: intermittent faults, incipient faults (gradually evolving) and abrupt faults. Our work concentrates on the detection and isolation of abrupt faults through analysis of the transients that occur after the fault.

Transients require more complex dynamic models and are harder to analyze. First, the system model may contain modeling deficiencies (significant higher order phenomena) and system parameters may not be estimated accurately enough. This lack makes it difficult to interpret system behavior. Second, measured signals are typically noisy and sensors may have responses that are a function of environmental conditions, may have characteristics which drift over time, or may become faulty. Third, quantitative techniques such as parameter estimation may not work well for complex systems because of difficulties inverting functions by either analytic or numeric methods.

We have developed a comprehensive framework for monitoring and diagnosis of dynamical systems that attempts to overcome the difficulties associated with such quantitative techniques [12]. This advantage comes from the judicious use of qualitative reasoning (as opposed to quantitative computation) when testing whether various failure hypothesis explain the behavior of the failing system. Another advantage of our framework is that it separates the measurement and signal processing tasks from the reasoning tasks in a way that we believe will facilitate the framework's deployment in a distributed measurement and diagnosis system.

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 either quantitative or 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 of energy storage elements accumulates, the prediction may be in terms of higher order derivatives.

Therefore, one of the primary functions of the monitoring component is extracting the signs of the time derivatives (or perhaps even second derivatives) of measured quantities.

We have performed a number of different simulations using lumped parameter models to evaluate the approach [10, 11, 12]. In addition, we have contstructed a testbed for verifying the framework. The testbed includes an automobile engine cooling system into which various failures (e.g., leaks) can be introduced, sensors for measuring physical variables within the cooling system, a PC-based data acquision system, and prototype diagnosis software. Details of the testbed appear in [9], which also discusses some of the critical signal analysis issues that must be dealt with to make the methodology work with real world signals.

This extended abstract focuses in more detail on one of the signal analysis issues: on-line estimatation of the sign of first and second derivatives of measured signals. The next section describes the technique we have used on measurents from our testbed for estimating signs of derivatives and briefly refer to other techniques in the literature. We show typical behavior of our technique applied to measurements obtained from our testbed when the dynamic effects of failure are present.

2 Determining signs of derivatives of measured signals

The derivative operation on measured data is inherently a high-pass filter, accentuating noise in the measurements. The key objective, then, in determining the sign of a derivative is minimizing the influence of noise in the determination.

2.1 Least squares polynomial fit

One way to estimate the value of the derivative of a measured signal is to find the least-squares linear approximation to a set of consecutive measurements. The slope of the resulting line is an estimate of the derivative of the signal within the window. The second derivative can be estimated similarly by finding a least-squares quadratic approximation. This technique is intuitively correct and simple to implement. As long as the number of data used in each fit remains constant, the technique is efficient because the resulting matrix needs to be factored only once, and the factorization can be re-used for each sucessive derivative estimation.

2.2 FIR filter with optimum noise attenuation

Another technique for estimating the value of the derivative is to use an FIR filter that is an unbiased estimate of the derivative and that has minimum estimate variance (i.e., maximum noise attenuation) from among all such filters.

The filter coefficients $\mathbf{f} = (f_{-n}, \ldots, f_n)^T$ depend only on the sample rate τ and the number of taps $2n+1$. They are found by solving a least-squares problem [13]. First, assume that the signal is a piecewise-polynomial with the same degree d as the order of derivative desired (e.g., $d = 2$ for second derivative). Assume that the noise has zero mean and finite variance σ^2. Then the filter is an unbiased estimate of the signal's derivative at the center of the filter's time window if and only if for all $j \in \{0, \ldots, d\}$,

$$\sum_{i=-n}^{n} f_i (i\tau)^j = \delta_{jd} d!, \tag{1}$$

where δ is the Kronekker delta. The variance of each derivative estimate output from the FIR filter is

$$\sigma_{\mathbf{f}}^2 = \sigma^2 \sum_{i=-n}^{n} f_i^2. \tag{2}$$

Minimizing this quantity with respect to the linear constraints of Equation 1 is a linear least squares problem that is easy to solve with off-the-shelf numerical software.

The filter coefficients can also be derived by application of the Gauss-Markov Theorem, [6] p. 141. Another implication of this theorem is that the outputs of the FIR filter will be the same as those of the polynomial fit technique described in the previous section. Advantages of FIR filter derivative estimation include a fast recursive implementation [13]. Moreover, the explicit formula for the variance of the derivative, can be used for setting thresholds between derivative values to be considered *positive*, *zero*, and *negative*.

2.3 Other techniques

Other filters for estimating derivative values include stochastic model-based differentiation [2], error minimization at low frequencies [7], and adaptive differentiators [14].

All of the techniques above involve computing an estimate of the derivative and then thresholding it to determine whether to classify it as *positive*, *negative*, or *zero*. An alternative might be to use the geometric V-mask technique ([1] p. 43) borrowed from statistical process control ([3] pp. 519–527). Here, the derivative of a measurement would be classified as *positive* at the current time if the measurement had recently achieved a significantly lower value than the current one.

3 Results on measurements

The testbed described in [9] was used to collect the measurements shown in this section. The instrumented automobile engine was started and allowed to come up to a normal operating temperature. A valve was opened that allowed much of the coolant to run rapidly out of the cooling system. The measurements were obtained at a sampling rate of 50 Hz. They are shown in Figure 1. The upper graph shows three Celsius temperatures measured at various locations around the cooling loop as a function of time in seconds into the experiment. The lower graph shows two uncalibrated coolant pressure measurements as a function of time. The failure occured just before t=20sec. The failure is visually aparent in the two pressure measurements.

Optimum noise attenuation FIR filters with 50 taps were used to estimate the first and second derivatives of the temperature measurement T2. The filter coefficients are shown in Figure 2. The frequency response of the first derivative filter appears in Figure 3. The amplitude response shows that the filter suppresses high-frequency noise somewhat. The variance of the noise in T2 was estimated as the sample variance of T2 within a portion of the signal where T2 was almost constant. This variance was used as σ^2 in Equation 2 to estimate the variances of the the first and second derivative filter outputs. Thresholds for classifying the deriviatives as *positive* or *negative* were chosen as four times the filter output variances.

Figure 5 shows the estimated derivative of the temperature T2 (thin solid line), the thresholds used to classify the sign of the derivative (thin dashed lines), and the result of the classification as +1, 0, or -1 (thick grey lines). Figure 6 shows the estimated second derivative of T2, the thresholds, and classification in the same way.

4 Conclusions

Diagnosis of dynamical systems is an important potential application for the emerging class of distributed measurement systems. Diagnosis of abrupt faults through analysis of transient behavior measurements made during and after the onset of a fault is complicated because an adequate system model may no longer available after the fault. Our diagnosis framework attempts to make up for this lack through the use of qualitative reasoning on wide discretizations of the measurements and their derivatives.

A key step in our diagnosis algorithm is determining the signs of the derivatives (and sometimes second derivatives) of measurements of the transient behavior of the system being diagnosed. We have demonstrated in this extended abstract that this determination can be performed efficiently and accurately in the presence of measurement noise using optimal noise attenuation FIR filters. The determination is probably efficient enough that it can be deployed within a measurement node of a distributed monitoring and diagnosis system.

The next step in our work is to collect a large set of data measured during different failures induced in our testbed, to verify that the diagnosis algorithm, including the derivative sign classifier, is reliable.

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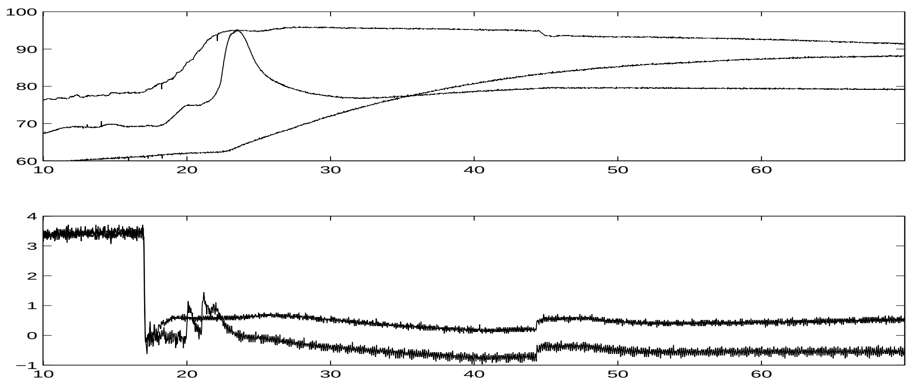
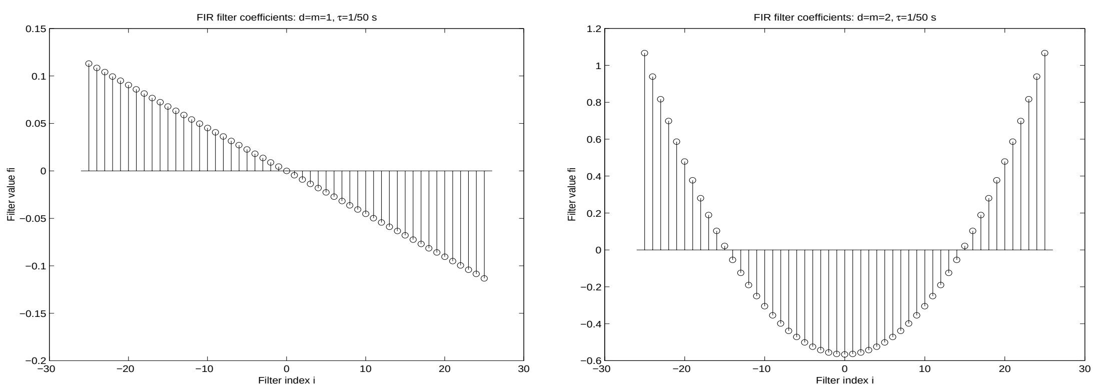


Figure 1: Abrupt loss of coolant. Time in seconds vs. temperature in deg C (top) and uncalibrated pressure (bottom). Various curves in each plot are temperatures or pressures obtained at different locations in the cooling system.



(a) (b)

Figure 2: Coefficients of optimal noise attenuation derivative estimate filters (a) first derivative filter used in Figure 5, (b) second derivative filter used in Figure 6.

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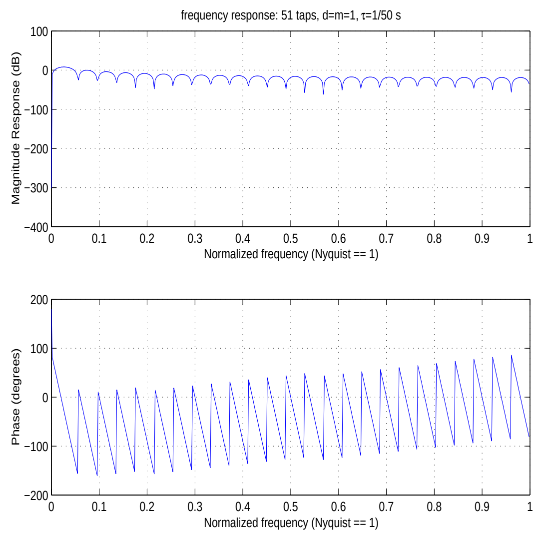

Figure 3: Frequency response of filter in Figure 2(a).

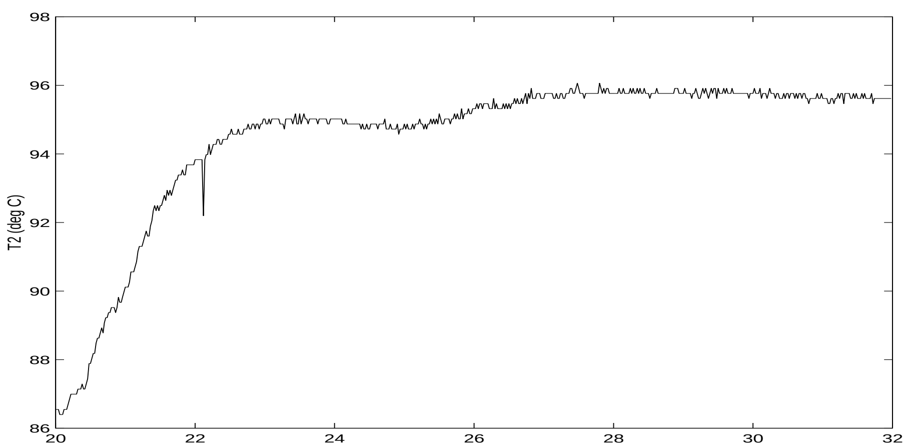

Figure 4: Temperature T2 for several seconds after the coolant loss.

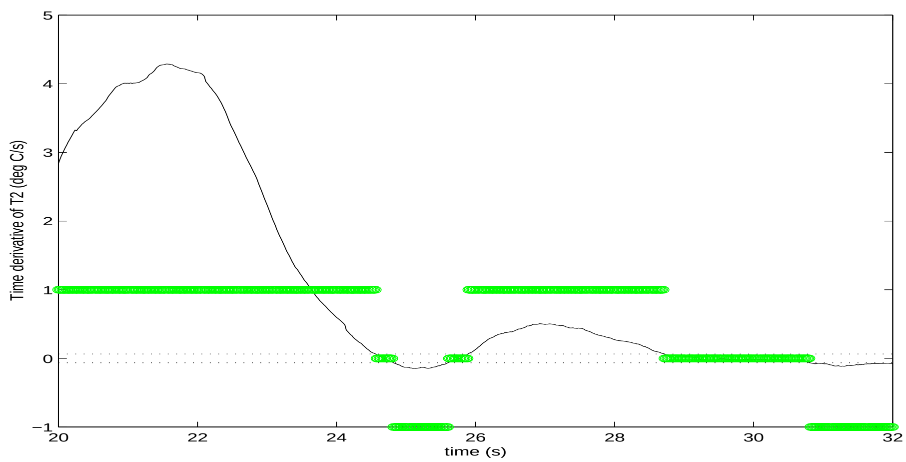

Figure 5: Estimate (thin solid line), thresholds (thin dashed lines), and sign classification (thick lines) of $\frac{dT2}{dt}$.

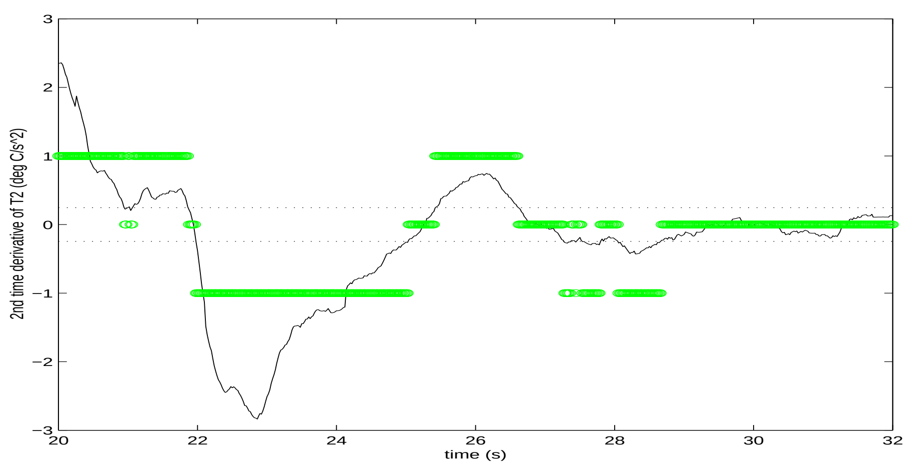

Figure 6: Estimate (thin solid line), thresholds (thin dashed lines), and sign classification (thick lines) of $\frac{d^2T2}{dt^2}$.