FAULT ISOLATION IN HYBRID SYSTEMS COMBINING MODEL BASED DIAGNOSIS AND SIGNAL PROCESSING

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Abstract. Sensor-rich systems typically employ extensive signal processing techniques for fault detection and isolation tasks. Sensor-poor systems, on the other hand, require system models and analytical redundancy techniques to make diagnostic inferences. The increasing availability of inexpensive, batch-fabricated micro-controllers and MEMS sensors enables deployment of a multitude of sensors and microprocessors for control and diagnosis of embedded systems. We develop a diagnosis method that combines model-based diagnosis with signal processing techniques to address the challenges in diagnosing complex systems with hybrid discrete/continuous behaviors and to reduce the computational requirements by focusing the signal processing algorithms. We demonstrate the approach on problems in reprographic copier paper path diagnosis.

Keywords: Model-based diagnosis, Hybrid systems, Quantitative analysis, Signal processing

1. INTRODUCTION

Embedded systems include supervisory control that switches system modes of operation by discrete control actions necessitating dynamic switching among multiple system models for monitoring, control, and fault isolation tasks. The hybrid nature of systems requires new forms of analysis. Discrete changes are not handled well by continuous algorithms, and abstracting system behavior to discrete models may result in loss of information critical for fault isolation and control. The use of a large number of cheap sensors allow extensive information gathering on the local functioning that can be used to identify system states and isolate faults. However, non-local interactions in complex systems make it difficult to predict system states. Therefore, hybrid system techniques that combine global and local analysis are needed for fault detection and isolation tasks.

Signal processing techniques performing continuous waveform analysis are frequently used to diagnose faults in sensor rich systems where direct correspondence can be established between faults and sensor readings [Hung and Zhao, 1999]. These techniques incorporate classifiers that are designed by extensive analysis of fault data. Computational complexity may make it infeasible to apply all signal processing algorithms on all signals. Therefore, it is important to develop schemes that allow for selective context driven processing of a signal in an efficient manner. Model based diagnosis enables higher-level reasoning using a global view of the system. This can be used to perform selective signal processing on the available signals and results in a more effective and efficient diagnosis scheme.

Current work in model-based diagnosis is primarily based on discrete event, and continuous approaches [Sampath et al., 1996; Lunze, 1999; Mosterman and Biswas, 1999b; Gertler, 1997]. Hybrid system diagnosis is performed by abstracting the system to discrete event form or approximating it as a continuous system with steep slopes. In a hybrid system the behavior evolves continuously until a discrete event causes it to move to a different continuously evolving region in the behavior space. Coming up with continuous representations of hybrid systems can result in very complex non-linear functional relations that are hard to analyze in real time. On the other hand, pure discrete event systems require a lot of simulation and can diagnose only qualitative faults. We propose a diagnosis methodology that uses hybrid models of the system and thereby performs hybrid diagnosis. A prototype system that we have implemented is presented in this paper.

2. AN EXAMPLE SYSTEM

We motivate the need for integrated hybrid model based diagnosis and signal processing by considering a paper moving system (Fig. 1), a sub system of reprographic machines. Such a system consists of a paper tray with sheets of paper, a paper path to a destination point, and rollers along the path to move the sheets forward. Motors drive the rollers through gear assemblies. Rollers may be stationary or mobile in the vertical direction. Typically, mobile rollers are placed above the paper stack, and are dropped onto the stack by energizing solenoids connected to them. Once in contact, the roller moves a sheet forward. When this sheet has moved forward to the next roller, the mobile roller is retracted (by de-energizing the corresponding solenoid) to prevent the next sheet from moving forward till its allocated time.

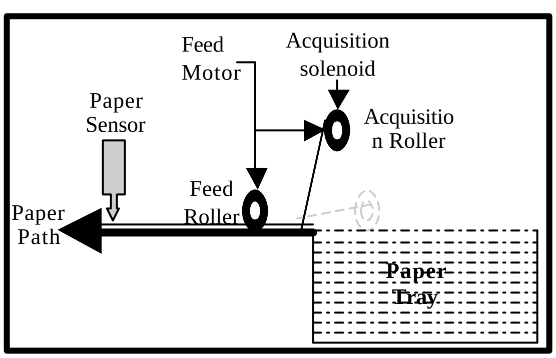

Fig. 1. Sample system

This system behavior contains discrete events like the switching on and off of motors, and the energizing and de-energizing of solenoids. The paper motion and the vibration behavior of the components are examples of continuous variables. A hybrid system model has been developed to simulate the nominal behavior of the system.

The system configuration includes a paper presence sensor at a point along the paper path to detect the arrival of the leading and trailing edge (relative to leading edge) of the sheet. Accelerometers are strategically placed to pick up vibration signals from the motors and solenoids. These are the only sensors used in the test bed. Useful knowledge about the health of the components can be obtained by analyzing the high bandwidth continuous waveform data from the vibration sensors.

If the paper sensor and predictions from models indicate that leading edge of the sheet arrived later than expected, this could be due to a variety of reasons such as motors running slow, solenoid energizing slowly, and motors not ramping up to speed as fast as expected. We can use the model to identify the possible causes of this deviation. We continue to observe the trailing edge of the sheet. If it is on time (after correcting for the delay caused by the late arrival of the leading edge), then we can eliminate the motor running slow hypothesis because the models would predict the trailing edge to be late if the motor is running slow. The level of detail in our models and the current set of sensor readings cannot distinguish between the two remaining fault hypotheses. Therefore, we switch to an analysis of the vibration signals recorded from the accelerometers. The presence or absence of certain signal characteristics tells us whether the energizing process was normal or abnormal. If it turns out to be normal, we can eliminate the solenoid and uniquely identify the fault.

3. FRAMEWORK FOR HYBRID DIAGNOSIS

A primary component of a diagnosis methodology (Fig. 2) is a hybrid observer that uses the hybrid model to track nominal continuous behavior within modes and discrete changes across modes. Discrepancies between predictions and actual measurements are attributed to faults in the system (fault detection). Faults trigger the qualitative fault isolation and quantitative parameter estimation tasks in parallel. The role of the qualitative analysis scheme is to narrow down the set of possible fault hypotheses, and focus the parameter estimation and signal processing tasks. Quick fault isolation and parameter estimation are critical to system analysis and correct tracking of system behavior through mode changes. Faults may change the expected mode sequence of the system, and this further complicates the fault isolation task [McIlraith et al., 2000]. Signal processing techniques can be used to further refine the candidate set.

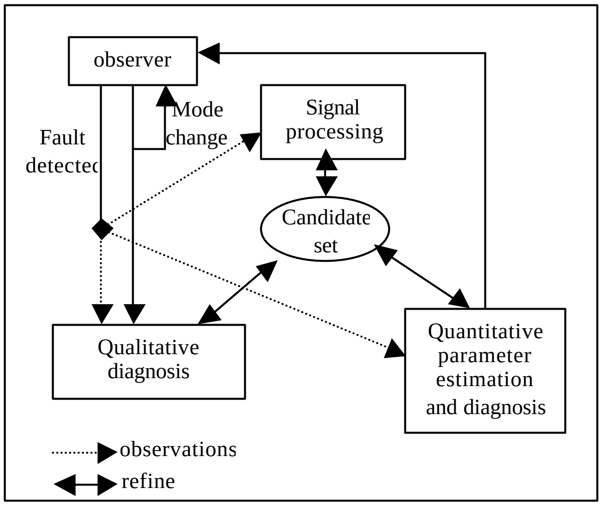

Fig. 2. Overall diagnosis architecture

In this work, we assume all faults of interest can be parameterized, and expressed as component parameters. We make the single fault assumption, and assume all control actions, which cause mode transitions are available to the observer and diagnosis modules. We restrict our attention to the class of problems where there are only a finite number of pre defined mode sequences and faults do not change the mode sequence of the system. This assumption holds for systems where the discrete events that cause mode transition are tightly coupled, and the initial state is known. Under this assumption we do not have to solve the difficult problem of mode identification under fault conditions. In the next three sections we discuss in more detail our modeling paradigm, the fault detection algorithm, and the fault isolation algorithm.

3.1 Modeling for diagnosis

Parsimonious and effective system models have to provide the information necessary to identify faults in the system. Our hybrid models support both qualitative and quantitative analysis.

Hybrid constraint models. The analytic models that define hybrid behavior facilitate the building of nominal and fault observers and allow for fault parameter estimation. Compositional model building techniques are employed to construct appropriate system models by instantiating component models from a generic modeling library. We specify the hybrid models of individual components and the connections between them to synthesize the system model in the HCC (Hybrid concurrent constraint) [Carlson and Gupta, 1995] modeling language. It includes constructs that can be used to specify rules of transition and constraints on the variables, and provides tools for model building. It also includes a simulator to generate system behavior.

Generic component models. Generic component models facilitate the building of a library of component models. This enables multiple instantiations of the component model in a system, and reuse across different models. Component model specifications require the (i) definition of modes, (ii) constraints in each mode, and (iii) transition functions between modes

Modes are linked to operating regions of a component, e.g., a motor component model may have three modes: OFF, SPEEDING_UP or RUNNING_AT_MAX_SPEED. Behavior constraints and the system parameters are defined as ODE's and algebraic constraints. In the RAMPING DOWN mode the torque steadily reduces to 0, which is achieved by setting the derivative of torque to a small negative constant. Hence the constraint is ∂ *(torque) = -K_rampdown*. The transition function, that specifies the rules that trigger mode transitions, can be defined by external control signals that actuate components and autonomous jumps that occur when variables in the system reach certain landmark values. For example, in the RAMPING_DOWN mode, the transitions are triggered either by a MOTOR ON control signal (transitions to RAMPING UP mode) or the torque reaching 0 (transition to the OFF mode). Fig. 3 illustrates the HCC model of the RAMPING DOWN mode of the motor.

```
 // RAMPING_DOWN mode
Ramping_Down = ( ){
   do always torque' = k_ramp_down
       watching (ON || torque = 0),
   when (ON || torque = 0) do {
     if ON then Ramping_Up( ),
     if torque = 0 then unless ON then Off( )
   }
}
```

Fig. 3. HCC model of RAMPING_DOWN mode of Motor

Composing system model from generic component models. The system model can be automatically synthesized by aligning the corresponding input and output connections of the components using connection boxes. Connection boxes play the role of placeholders to transfer values between various components. The total number of modes in the system is a cross product of the number of modes of the individual components. The behavior constraints of the system are derived by composing the constraints from individual components. The transition function is the union of the individual component transition functions. The input /output interaction of the components may cause variable value changes in one component to affect variable value changes in other components, causing a sequence (more than one) of mode transitions at a point in time. Fig. 4 demonstrates the composition of the system model for the example system described in Sec. 2.

```
Connection(Feed_motor_output_torque),
Connection(Solenoid_out_position),
Motor(FM,Power_to_feed_motor,Feed_motor_out_torque,
        0,k_rup_time_fm,k_max_speed_fm,-5.21,5.21,
        FM_ON,FM_OFF),

Solenoid(AS,Power_to_solenoid,Solenoid_out_pos,
          0,k_pullin_time_as1,-1,0.5,AS1_ON,AS1_OFF),

FixedRoller(FR,Feed_motor_out_torque,
            Feed_roll_out_speed,1),

MovingRoller(AR,Feed_motor_out_torque,
             Solenoid_out_pos,Acq_roll_out_speed,
             Acq_roll_out_pos,1,1),
```

Fig. 4. Composing system model in HCC

Qualitative temporal causal graph models. Temporal Causal Graphs (TCG) are directed graphs that capture system dynamics in the form of algebraic and temporal constraints among the variables in the system [Mosterman and Biswas, 1999a]. The nodes in the graph represent the variables in the system and directed edges capture the cause effect relations between them. The label on the edge defines the nature of the relationship, algebraic or temporal, between the associated variables. Algebraic relations defined by proportionality and equalities imply instantaneous effects, and temporal relations defined by integrals, introduce time-delayed effects. Some edges are also labeled with component parameters. This indicates that the parameter participates in the functional relation between the two variables. If an edge between nodes A and B exists with the label parameter P and we see that B has deviated from normal, then it could either have been because A deviated or because P has deviated. For a hybrid system, each mode has a distinct causal graph.

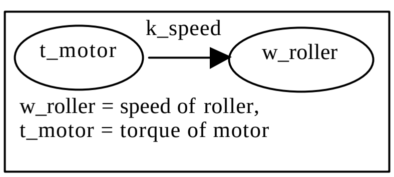

Fig. 5.1. TCG of motor and roller system

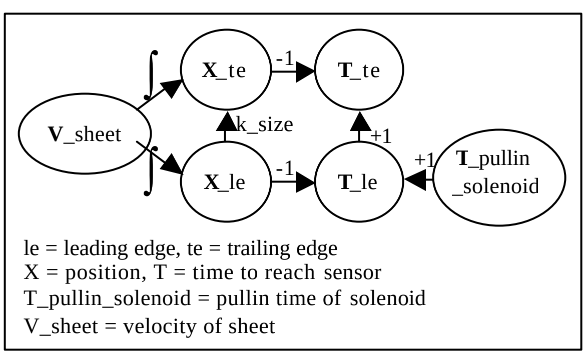

Fig. 5.2. TCG of paper path

The TCG's of the motor and roller, and the paper path are illustrated in Figs. 5.1 and 5.2, respectively. For example in Fig. 5.2, the edge between X_le and T_le indicates that X_le affects T_le and the –1 label on the edge indicates that it is an inverse relationship (i.e., if X_le is behind where it should be then T_le will be high, implying a late arrival at the sensor location). The relation between v_sheet and X_le is integral, i.e., there is a time delay in the effect of a change in v_sheet on X_le. The edge between X_le and X_te is governed by a parameter k_size. The k_size parameter is directly linked to the choice of paper tray that has been selected. A value of + (-) for k_size implies that the paper size selected is larger (smaller) than normal. When the roller comes in contact with the paper, the new TCG of the system is a combination of the two TCG's, obtained by adding an edge from w_roller to v_sheet.

3.2 Fault Detection

The fault detection task identifies if the system behavior has deviated from the nominal behavior, and generates an initial set of fault hypotheses to explain the deviation. The fault detection step uses an observer to attribute discrepancies in predictions and observations to (i) noise, (ii) mode change, or (iii) faults. For faults, an initial candidate fault set is identified and the prediction signatures are generated for each candidate in the fault set.

Observer. The observer compares the predictions from the nominal simulation output with the actual observations from the system. We assume the presence of a simple median filter and use heuristics such as deviations must persist for a few time steps before being labeled a discrepancy [Manders et al., 1999]. We assume that this rather simplistic technique is sufficient to mitigate noise effects and avoid false alarms. More sophisticated and complicated algorithms may also be used for discrepancy detection [Gertler, 1997]. If the discrepancy indicates a mode change then the simulator has to be informed of this change and appropriately restarted in the right mode with the correct initial conditions. For a fault condition, an initial candidate set is derived and the fault isolation task is initiated.

In our work, we assume that the control signals are available to the observer and our models can identify and execute autonomous jumps. Therefore, after accounting for noise, all observed discrepancies are attributed to faults.

Initial Fault hypotheses and generating signatures. TCG models are used to identify an initial set of fault candidates and generate their corresponding signatures. The discrepancy in qualitative form is back propagated through the TCG to identify the possible causes for this discrepancy. A candidate definition includes the faulty component parameter name, it's direction of change and the mode in which the fault is hypothesized to have occurred. The back propagation is performed across past mode transitions since a fault that occurred in an earlier mode may manifest in a later mode. Based on the assumption that faults do not change the mode sequence, the qualitative value of the discrepancy is back propagated through the causal graph going through the mode sequence in reverse to identify an initial candidate set. In back propagation we traverse the graph against the arrows and if an edge with a parameter label is traversed, that parameter is flagged as a candidate.

For example, if we see that T_le is + (leading edge of paper reaches sensor late), we can propagate backwards in the current mode to indicate that (w_roller -) and (T_pullin_solenoid -) can be possible candidates (Fig. 3). We can then propagate back to the previous mode where w_roller could be - because t_motor was - or k_speed was -. Hence, k_speed - is an additional candidate.

For each of the candidates in the candidate set, we can predict future qualitative behavior by forward propagating the effects of that fault (deviated parameter) through the temporal causal graph to get the signature of the fault. Here again we propagate across modes. This is possible only under the assumption that the faults do not change the mode sequences. Otherwise the mode changes under faulty conditions have to be identified using quantitative analysis and forward propagation is performed accordingly. The signatures are in the form of *above*, *same as* or *below* nominal behavior values for magnitude and higher order derivatives for the variables in the system.

For example, if k_speed – is a candidate, we can forward propagate the effects to w_roller – and so on to x_le – in the next mode(Fig. 3). We can further propagate to X_te – and T_te + (trailing edge of paper arrives at sensor late relative to the arrival time of the leading edge). So our prediction would be that the trailing edge should also be late in getting to the sensor. For more details about the back propagation and forward propagation algorithms see [Mosterman and Biswas, 1999b].

3.3 Fault Isolation

There are three ways in which we can refine the candidate set. These steps are often applied in parallel to enable quick fault hypotheses refinement.

Qualitative analysis by progressive monitoring. We compare the qualitative signatures (predictions) of each candidate in the fault set against qualitative sensor readings, eliminating candidates with inconsistent predictions. This comparison is carried out over time and is based on the principle of progressive monitoring, where we try to reconcile observations with the signatures by moving higher order predictions down as time progresses. For more details on progressive monitoring refer to [Mosterman and Biswas, 1999b].

Quantitative simulation using constraint models. If the candidate set is sufficiently small, we can make a quantitative estimate of the deviated parameter values using techniques described in [Manders et al., 2000]. These estimated parameters can be used to predict future system behavior (fault observers) eliminating candidates whose predictions are inconsistent with observations. For example, if we can measure the velocity of the sheet and the speed of the roller, we can easily estimate the parameter k using the relation between these two measured variables.

Unobservable parameters, lack of accuracy and detail in models, and noise in sensor readings make the parameter estimation task difficult. Moreover, if the model is complex and non linear, online estimation by numerical methods is difficult because of stiffness and convergence problems. Therefore, signal processing techniques play an important role in diagnosis.

Signal processing for diagnosis. Depending on the make up of the candidate set we run specific signal processing algorithms (after choosing relevant time windows) and based on the results of the test we can make decisions on whether to drop a candidate or not. For example, we can run a principal component analysis on the vibration signal when the solenoid is being energized to check if the process is normal or abnormal.

Signal processing techniques for fault diagnosis employ test data to learn a classifier, and actual data is then through the classifier to identify a health index. The health index indicates whether a particular actuator is performing a specific operation normally or if it is in a fault mode. In our work, we use simple ranges of values of the health index to identify the mode but a more complicated function of the health index can also be used.

We have developed a set of adaptive signature analysis algorithms for analyzing distributed vibration data and have demonstrated the algorithms on a reprographic copier paper drive plate test bed comprising multiple motors and solenoids [Hung and Zhao, 1999]. Our approach has three main components, (i) signal processing using Wavelet and STFT techniques to extract signal features indicative of component degradation and faults, (ii) compressing high-bandwidth data by Principal Component Analysis, and (iii) fusing multiple sensor data streams using Bayesian decision analysis in a composite feature space. The algorithm has been successfully applied to classifying motor and solenoid faults on the copier test bed. Because the algorithm attains its adaptivity through online training on lifetime test data, we believe it also applies to many other applications that require distributed sensor data analysis.

4. SAMPLE RUN

We present below an example of how the integrated system is employed to derive the true fault associated with the system. LE (TE) indicates the arrival time of the Leading Edge (Trailing Edge) of the sheet at the paper sensor position (Fig. 1). Hence LE 0 (+,-) indicates that the leading edge was on time (early, late). Vib_pullin indicates the result of applying the principal component analysis on the vibration signal form the plate when the solenoid was pulling in. Vib_pullin 0 (1) indicates that pull in was normal (abnormal).

Observation 1: LE +
<u>Faults consistent with Observation 1</u>

- Solenoid pull in time high
- Motor ramping up time high
- Motor nominal speed not reached

Observation 2: TE 0
<u>Faults consistent with observations 1 and 2</u>

- Solenoid pull in time high
- Motor ramping up time high

Observation 3: Vib_pullin 0
<u>Faults consistent with Observations 1,2 and 3</u>

- Motor ramping up time high

5. DISCUSSION AND FUTURE WORK

We have developed a hybrid system diagnosis methodology that combines a model-based approach with signal processing in an efficient way. The hybrid-modeling scheme is compositional and scalable. We have implemented a prototype system for a reprographic device that supports a set of the functionalities presented above.

This work bridges the gap between purely discrete event and continuous system diagnosis. We do not need the extensive simulation (for pre compilation) required by some of the discrete event systems [Lunze, 1999; Sampath et al., 1996]. On the other hand, we reduce some of the computational complexity of continuous systems by eliminating candidates based on qualitative information only. We also provide a framework for integrating model-based diagnosis that performs global analysis and signal processing that performs localized analysis.

Future work would involve building observers that can perform mode identification based only on measurements, under nominal and faulty conditions. Robust online parameter estimation techniques need to be developed. The methodology needs to be tested on other systems.

Acknowledgement. This work was conducted at Xerox Palo Alto Research Center as part of the Smart Matter Diagnostics Project and at Vanderbilt University as part of the Modeling and Analysis of Complex Systems Lab. We thank Markus Fromherz, John Everett, Meera Sampath, and Peter Struss for helpful discussions and feedback on the work, and Vineet Gupta for help with the HCC programming language.

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