

Diagnosing Hybrid Dynamical Systems

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Abstract: A method of diagnosing the occurrence of arbitrary events in hybrid dynamical systems is presented. The methodology unifies results from the Fault Detection and Isolation (FDI) and Diagnosis (DX) communities. In this approach the diagnosis is not performed on the output trajectory of the system but rather on the fundamental governing dynamics, thus not requiring the computation of residuals. These results are an important step in being able to diagnose, repair and control hybrid dynamical systems which are rapidly becoming ubiquitous in the engineering domain. Computational results are presented for a hybrid dynamical system experiencing events that cause both structural and parametric mode changes.

1. INTRODUCTION

There has been recent, emerging interest in hybrid systems, *i.e.* dynamical systems that have both continuous and discrete dynamics. A significant motivation for this trend has been the increasing complexity of systems that can be analysed and modeled in the hybrid systems framework.

The hybrid system framework unifies two distinct communities that have both been working on Diagnosis; namely the Fault Detection and Isolation (FDI) community and the Diagnosis (DX) community. The FDI community has evolved in the field of automatic control and uses techniques from systems and control theory. In comparison, the DX community has a more recent emergence with foundations in the fields of computer science. As shown in Cordier et al. [2000], the approaches taken in FDI and DX can be linked despite them emerging from two distinct and parallel research communities. The main hurdle in integrating techniques from those two parallel research communities has mainly been due to the fact that the techniques developed within each community tend to apply to systems of different nature. Computer Science (and hence the traditional DX approaches) tends to deal more with logical discrete systems and a large number of techniques have been developed to handle such systems as in Reiter [1987], Cassandras and Lafortune [1999] and Sampath et al. [1996]. On the other hand, the control theory community has studied and developed techniques for dealing with continuous systems CEP [1997]. By defining a hybrid system framework, the aim is to integrate methodologies from both fields in order to address the diagnosis of hybrid dynamical systems. To avoid ambiguities that emerge from

the overlap of the research in the two distinct fields a cross-field translation is presented in Table 1.

Controls (FDI)	Diagnosis (DX)	Hybrid (our framework)
state	-	state
mode	state	mode
-	trajectory	mode trajectory
trajectory	-	state trajectory
-	events	events
-	transitions	transitions

Table 1. FDI and DX cross-field translation.

A common approach to the diagnosis of hybrid systems is residual diagnosis as in McIlraith et al. [2000], Biswas and Narasimhan [2002] and Blanke et al. [2006]. This approach is based on analysis of the function

$$\mathcal{F}(\hat{y} - y)$$

where y and $\hat{y}$ are, respectively, the nominal and observed trajectory of a hybrid system. This approach is characterized by the assertion that deviations of the observed hybrid system trajectory from some nominal trajectory are indicative of a fault having occurred.

Residual generation for fault detection thus requires advance knowledge of the system operation and parameter values. This approach necessitates that the structure and parameters of the underlying dynamics (defined formally in Section 2) are known a priori. *i.e.* the system must be very well characterized. Additionally any explicit parameters in the system dynamics definition must not drift (undergo deviations from their original value) during the operation of the hybrid system. For these reasons and due to the complicated operation of hybrid systems and the potential for a large number of fault modes it is not always certain that it will be possible to uniquely detect and isolate faults using residual generation.

As hybrid systems become increasingly more complex, using the residual generation approach for fault detection

* This research was supported by NICTA in the framework of the SuperCom project. NICTA is funded by the Australian Government as represented by the Department of Broadband, Communications and the Digital Economy and the Australian Research Council through the ICT Centre of Excellence program.

becomes more challenging as the notion of a nominal trajectory is often hard to define in this context. To overcome these challenges the diagnosis methodology we propose focusses on detecting operational mode changes that can be determined by changes in the fundamental governing dynamics of the network. We use methods from estimation and regression to determine the fundamental dynamics before using change-point detection to detect the occurrence of arbitrary events in the hybrid system. This represents a diagnosis on the continuous dynamics but by then applying existing discrete diagnosis methods, this diagnosis can be refined to produce a hybrid systems diagnosis that unifies methods from both the FDI and DX communities.

2. HYBRID DYNAMICAL SYSTEMS

Hybrid dynamical systems (henceforth referred to as hybrid systems) have emerged as a powerful method of analyzing complex systems. Hybrid systems are characterized by having a finite number of discrete operating modes. We deviate slightly from existing definitions of hybrid systems as in Zhao and Hill [2008], however the reasons for this are explained below. From this perspective the governing dynamics for a hybrid system are given by:

$$\begin{aligned}\dot{\mathbf{x}} &= f_\sigma(\mathbf{x}, \mathbf{u}_\sigma, \theta_\sigma) \\ \mathbf{y} &= h_\sigma(\mathbf{x})\end{aligned}\quad (1)$$

where σ defines the operating mode and takes values in $M = \{1, 2, \dots, m\}$. It is assumed that the operating mode is known at time t_0 . $x \in \mathbb{R}^n$ are the internal states, $u_\sigma \in \mathbb{R}^{q_\sigma}$ are the local control inputs and $y \in \mathbb{R}^p$ are the measurable outputs. $\theta_\sigma \in \mathbb{R}^{r_\sigma}$ is a vector of parameters that characterize the dynamics of operating mode σ . The internal dynamics are given by $(f_\sigma(\mathbf{x}, \mathbf{u}_\sigma, \theta_\sigma) : \mathbb{R}^n \times \mathbb{R}^{q_\sigma} \times \mathbb{R}^{r_\sigma} \rightarrow \mathbb{R}^n)$ and the measurable output is given by $(h_\sigma(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^p)$.

The operating mode $(\sigma : \mathbb{R}_+ \rightarrow M)$ for the hybrid system can be characterized by the switching sequence:

$$\Sigma = \{(i_0, t_0), (i_1, t_1), \dots, (i_z, t_z) | i_z \in M, z \in \mathbb{Z}\}$$

where i_0, t_0 are the initial system state and time respectively and $\mathbb{Z}$ is the set of nonnegative integers. When $t \in [t_z, t_{z+1})$, $\sigma = i_z$, we say the i_z -th operational mode is active and the trajectory of the hybrid system $(x(t))$ is defined as the trajectory of the system $(x_i(t))$ with switching signal $i \in M$. We assume that the state of the system is continuous and thus does not exhibit abrupt changes at the instant of changing operating mode.

We can think of the hybrid system being defined by its state, output and control vectors, and parameter vector $S = \langle \mathbf{x}, \mathbf{y}, \mathbf{u}_\sigma, \theta_\sigma \rangle$.

The continuous behaviour of the hybrid system can be described by the evolution of its output, its state and the influence of its control inputs which are governed respectively by the tuple $S_{cont} = \langle f_\sigma, h_\sigma \rangle$ where the elements of the tuple have been defined previously.

The discrete behaviour of the hybrid system can be represented using a deterministic finite automaton. Thus the automaton representing the discrete behaviour of a hybrid system can be given by the tuple $S_{disc} = \langle M, \Omega, \mathcal{T} \rangle$.

- M is the finite set of system modes $(\{1, 2, \dots, m\})$.

- Ω is the set of events $(\omega_1, \omega_2, \dots, \omega_l)$ which determine switching between modes.
- $\mathcal{T}$ is the transition function that maps an event and mode into a new mode, $\mathcal{T} : \Omega \times M \rightarrow M$.

The operating modes in a hybrid system completely describe the operation of the system. These modes can correspond to arbitrary operating conditions, some nominal and some induced through the occurrence of a fault or other event. We use the term events to be very general and include faults and other events of interest that can be characterized by a change in operating mode of the system.

Structural and Parametric Variations in Hybrid Systems

In Eq. (1) we have both f_σ and h_σ characterizing the dynamics of each operational mode determined by σ . The reason for choosing two variable to accommodate this characterization will now be made clear. It is well known that a dynamic system can undergo bifurcations. These bifurcations are caused by a change in the system parameters θ_σ not by any change in the form of the dynamic system itself as would be implied by a change in f_σ . In separating the parametric variations of the operating mode from the structural changes (those changes resulting in a fundamental change in the form of f_σ) it is possible to deal compactly with changes in the operational mode of the hybrid system.

By explicitly allowing parameter variations in a given operation mode we are more able to deal with the subtleties of fault detection as it is now possible to encompass both structural and parametric variations explicitly. It should be noted that current approaches to hybrid systems diagnosis require exact knowledge of parameters ahead of time, thus if a given fault were to induce a bifurcation both the nominal and bifurcation operating modes would need to be simulated, something not required in the approach that we will detail.

3. HYBRID SYSTEM DIAGNOSIS

The goal of diagnosis becomes determining $\bar{\Sigma}$ such that $\bar{\Sigma} = \Sigma$. That is we wish to determine the sequence of operating modes and the events that caused these operational mode changes for all operating time of the system.

In order to diagnose hybrid dynamical systems we will use a two stage approach that combines both FDI and DX techniques. As our observations come from the continuous domain it is necessary to abstract the continuous operation of the hybrid system into observations in the discrete domain. Our approach is to use estimation techniques to identify the underlying dynamics of the hybrid system, thus identifying the current operational mode. In this way we have abstracted the continuous trajectory measurements into discrete observations of the hybrid system mode.

It is then possible to use changepoint detection techniques to determine possible operational mode transitions that may have occurred in the hybrid system. These changepoints are indicative of events occurring. At this point we have a diagnosis of the hybrid system using only the continuous dynamics. Using the deterministic finite automaton finally allows us to determine if the transitions

that emerged from the changepoint detection techniques are valid and if they are what fault has occurred. We now have a diagnosis that incorporates knowledge from both the continuous and discrete dynamics of the hybrid system.

For the analysis that follows we assume that between two observations only one event can occur. This further implies that for any finite $T > t_0$, there exists a positive integer K_T , which may depend on T , such that during the time interval $[t_0, T]$ the operational mode σ changes no more than K_T times. This ensures that it is practically possible to diagnose a system as the sequence of observations will have information about all the faults that occur in the system.

3.1 Estimation

It was detailed in Section 2 that hybrid dynamical systems have m distinct operational modes. These operational modes correspond to different dynamical models, whereby each model has different governing dynamics. Each dynamical model can correspond to a nominal or faulty operating mode and no distinction is made about whether the transition between modes is intentional or due to a fault event occurring.

The estimation approach uses estimation and regression techniques to try and estimate directly the governing dynamics, and hence the current operational mode. This differs markedly from the residual generation techniques cited in Section 1. The fields of estimation and regression have considerable literature, however background material for both fields can be found in Ljung [1999] and Anderson and Moore [2005]. In our approach to estimation we will assume that the form of the dynamics, that is the function f_σ , is known and that we use estimation and regression techniques to determine the parameter vector θ_σ which when coupled with the form of the dynamics in f_σ will provide complete knowledge of the underlying dynamics. This approach is more general than that of residual generation as the form of the dynamics can generally be determined, leaving the often unknown and variable parameters (θ_σ) to be estimated as the hybrid system is observed. That is $\forall i \in M$ we are assuming that f_σ is known and θ_σ is unknown and must be estimated.

The goal of estimation thus becomes the problem of estimating the parameters θ_σ of each model and to then determine the likelihood that a given operating mode f_σ with parameters θ_σ is the best representative of the current operating mode. This is discussed in greater detail below.

Given m possible operating modes or dynamical models we wish to use discrete observations $Y_t = \{y_0, y_1, \dots, y_t\}$ to determine:

$$P(i|Y_t), \quad \forall i \in M \quad (2)$$

for any t where we naturally require:

$$\sum_{i=1}^m P(i|Y_t) = 1 \quad (3)$$

This corresponds to determining the relative probabilities of each of the models, with their current parameter estimate, thereby giving an indication of the model most likely to be responsible for generating the current trajectory. This is related to current work in the field of sparse

estimation (Blackhall and Rotkowitz [2009]) where the relative probability for competing models is an output of the estimator.

This approach may appear similar to the process of residual estimation but there is a subtle and important difference here. In this approach only the structure of a dynamical model is presumed. By using the estimation approach we are not requiring parameters to have a fixed or constant value and even parameter drift can be dealt with in a manner that will not lead to spurious fault generation. Having a record of these probabilities we will now discuss the process by which we can detect possible changepoints in the operating mode of the hybrid system, generating fault observations that will then be passed to the discrete diagnosis algorithms for a final diagnosis.

3.2 Change-point Detection and Fault Generation

Change-point detection is the process whereby changes in the trajectory of a series of measurements can be related to a change in the generation of the trajectory. In our terms change-point detection corresponds to determining the time at which the operational mode generating the trajectory changes. From this change it is then possible to determine the probable events that caused this operational mode change through knowledge of the automaton governing the operation of the discrete component of the hybrid system.

Change point detection can also be regarded as the model selection problem Green [1995] and in this light couples well with the estimation approach detailed in the previous section. Both Chib [1998] and Green [1995] provide some background to change-point detection using estimation approaches. Our approach differs slightly from the methods cited in that we are assuming that it is possible to measure the probability of a given model using observations from the continuous trajectory of the system. That is we assume that our estimation techniques (discussed in the previous section) will give

$$P(i|Y_t), \quad \forall i \in M \quad (4)$$

Given these relative probabilities it is possible to compute the transition probabilities between operating modes as

$$P(i \rightarrow j|t) = P(i|Y_{t-1})P(j|Y_t) \quad (5)$$

$\forall i, j \in M$. If $i = j$ we are computing the probability that the current operational mode remains the same. Using this approach we obtain m^2 transition probabilities. Selecting l transitions where $l \leq m^2$ then represents choosing the l most likely transitions (events) to have occurred. The chosen transitions represent the diagnosis of the hybrid system from observation of the continuous trajectory of the hybrid system. These transitions are the candidate events that may have occurred and must be refined using the discrete diagnosis approaches of the following section to achieve a full hybrid system diagnosis.

3.3 Discrete Diagnosis

Having determined candidate events from observations on the continuous trajectory of the hybrid system we now wish to refine those estimates using discrete diagnosis

methods. We are using model based discrete diagnosis, where we are assuming a model of the discrete operation of the hybrid system (S_{disc} defined in Section 2) is available (*i.e.* given an operational mode, the model describes the possible transitions that will result in a new operational mode).

A discrete event system is characterised as having a discrete state space. To differentiate from the state space of a continuous system, we will call each ‘discrete state’ of a discrete system a ‘mode’ of the system. A discrete event system is event driven and the evolution of its modes depends on the occurrence of asynchronous discrete events over time as in Cassandras and Lafortune [1999].

Discrete event systems are dealt with using different levels of abstraction. These can usually be represented by using languages to capture the “logical behaviour” of the system, *i.e.*, to ensure or determine the particular ordering of events or the reachability of a given set of modes. The term “language” comes from the fact that we can think of a set of events Ω as an “alphabet” and of finite sequences of events as “words”.

To represent languages in a way that highlights structural information about system behaviour, we need to use some form of discrete event modeling formalism. Two common modeling formalisms used in the field are automata and petri nets. Those two formalisms represent languages by using a mode transition structure that is useful for the analysis and synthesis of the systems.

We consider the discrete evolution of a system. The set of all possible behaviours of the system is a language denoted Mod over the set of events Ω that could possibly occur on the system. In our work, we assume that observations are event-based observations as in Sampath et al. [1995]. We denote these observations (a set of possible transitions or events) on the system by a language Obs . It should be clear that the candidate transitions (events) determined by the change-point detection techniques generate events in precisely the manner required by event-based discrete event system diagnosers. The diagnosis of the system can thus be computed as

$$\bar{\Sigma} = Mod \odot Obs. \quad (6)$$

where $\odot$ is the restriction of the model on the actual observations. The diagnosis $\bar{\Sigma}$ essentially determines the likely transitions (events) consistent with the observations. In this way, we are able to refine the original transition (event) estimates in Obs . The strict definition of languages in this context and operations on them are presented in Kan John and Grastien [2008].

4. EXAMPLE

We will use the proposed diagnosis techniques to diagnose the operation of a four mode hybrid system. We use chaotic oscillators with varying parameters to represent both bifurcations and structural changes in the hybrid system.

We use two types of chaotic oscillator, the Rossler and Lorenz attractors. The Rossler attractor (with three internal states) is parametrised by three parameters $\{p_1, p_2, p_3\}$ and is given by:

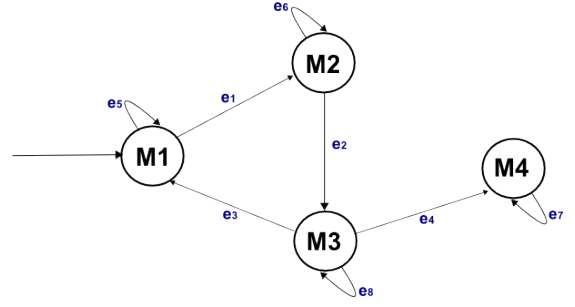


Fig. 1. The automaton for the discrete operation of the hybrid system in this example.

Mode	Structure	Parameters
1	Rosler	[0.2 0.2 5.7]
2	Rosler	[0.15 0.4 8.5]
3	Lorenz	[10 28 1 0 2.667]
4	Lorenz	[10 50 1 0 20]

Table 2. The true dynamical structure and parameters for each of the four operational modes of the hybrid system.

Transition	Time (s)
e_1	100
e_2	250
e_4	350

Table 3. The time and events of the mode changes induced into the simulation that we are attempting to detect using the hybrid systems diagnosis methodology presented in this paper.

$$(\dot{x})_1 = -(x)_2 - (x)_3 \quad (7)$$

$$(\dot{x})_2 = (x)_1 + p_1(x)_2 \quad (8)$$

$$(\dot{x})_3 = p_2 + (x)_3((x)_1 - p_3) \quad (9)$$

The Lorenz attractor (with three internal states) is parametrised by five parameters $\{q_1, \dots, q_5\}$ and is given by:

$$(\dot{x})_1 = q_1((x)_2 - (x)_1) \quad (10)$$

$$(\dot{x})_2 = q_2(x)_1 - q_3(x)_2 - (x)_1(x)_3 + q_4 \quad (11)$$

$$(\dot{x})_3 = (x)_1(x)_2 - q_5(x)_3 \quad (12)$$

Both of these attractors meets the definition of Eq. (1) as they have well defined dynamical structure and parameters that define the operation of the hybrid system. We assume that $y(t) = [(x)_1(t) \ (x)_2(t) \ (x)_3(t)]^T$ is the observable trajectory of the system. The hybrid system has the automaton shown in Fig. 1 and the true dynamics and parameters for each mode are shown in Table 2. We simulate the dynamics of the hybrid system in MATLAB for 400s using the ODE45 integrator. Mode changes are induced into the program with the times and corresponding events given in Table 3.

At this point we now describe the implementation of the diagnosis method outlined in this paper. To estimate the parameters in both the Rossler and Lorenz attractors of Eq. (9) and (12) we use the methodology in Yu and Parltiz [2008]. This methodology proves that using autosynchronization allows the estimated parameters to converge to the true parameters and is thus an ideal estimator for the current diagnosis methodology. As modes one and two are

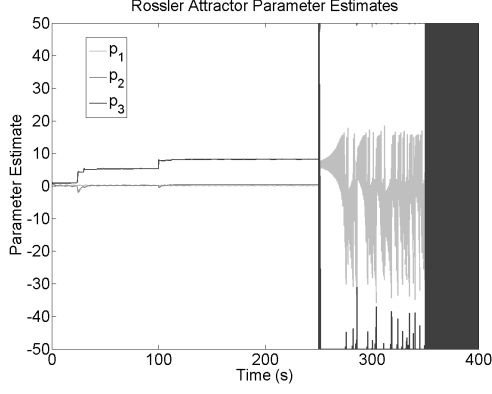


Fig. 2. Rossler attractor parameter estimates.

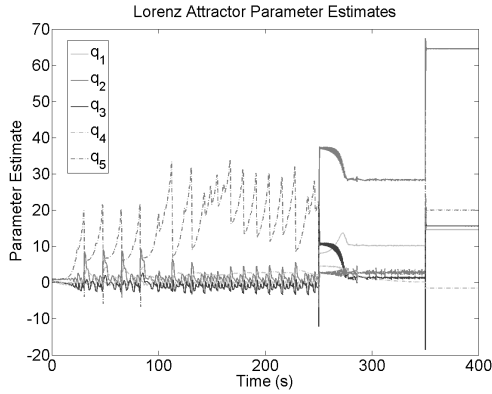


Fig. 3. Lorenz attractor parameter estimates.

both Rossler attractors we need only a single estimator to be able to estimate the parameters for both operational modes. Similarly we need only a single estimator for modes three and four as they are both Lorenz attractors. Using this approach the parameter estimates for both the Rossler (Fig. 2) and Lorenz (Fig. 3) attractors can be seen.

The parameter estimates for the Rossler attractor are convergent in the period $t \in [0, a]$ where $a \approx 250$. This is the period when the true underlying dynamics are a Rossler attractor and thus the estimation algorithm is able to accurately identify the parameters in this regime. After $t = 250s$ when the true underlying dynamics are represented by a Lorenz attractor the parameter estimates oscillate wildly and are forcibly limited to a magnitude of 50 to prevent excessive divergence of the parameter estimates. Similarly the parameter estimates for the Lorenz attractor are convergent in the period $t \in [a, 400]$ where $a \approx 250$ where the reasons are identical to those presented for the Rossler attractor. What is clear from these results is that it is possible to accurately estimate the parameter vector when the structure of the dynamics is assumed, thus providing a good justification for the methodology proposed in this paper.

In order to compute the relative probabilities of each operational mode we define the following cost functions:

$$J_{\text{rossler}} = \frac{1}{3} \sum_{i=1}^3 (p_i - p_{i_{\text{est}}})^2 \quad (13)$$

Mode	Structure	Parameters
1	Rossler	[0 0 5]
2	Rossler	[0 0 8]
3	Lorenz	[9 25 0 0 2]
4	Lorenz	[9 48 0 0 18]

Table 4. The a priori parameter estimates for each operational mode of the hybrid system. Emphasis must be placed on the fact that there are a multitude of ways of generating potential cost functions that do not require a priori information and thus this approach is descriptive rather than prescriptive.

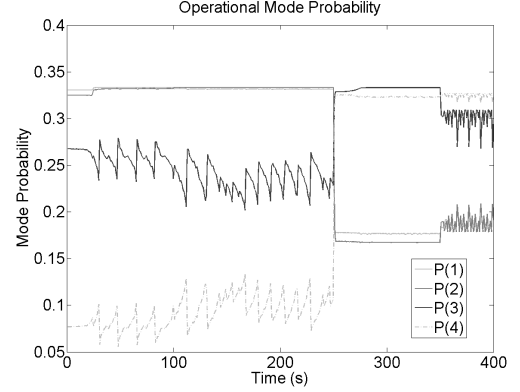


Fig. 4. Operational mode probabilities for each of the four operating modes after each observation.

$$J_{\text{lorenz}} = \frac{1}{5} \sum_{i=1}^5 (q_i - q_{i_{\text{est}}})^2 \quad (14)$$

These cost functions represent the "average" error of the parameter estimates where $p_{i_{\text{est}}}$ and $q_{i_{\text{est}}}$ are a priori estimates of the parameters of each system (given in Table 4 for this example). This can be seen as a similar approach to residual generation except that residuals are being computed on the parameter estimate rather than the output trajectories. This particular implementation however is by no means the only approach and estimators that do not require any information a priori (as in Blackhall and Rotkowitz [2009]) can be used equally well.

We use the notation J_i to indicate the i -th cost function where the cost function and the a priori parameter estimates should be clear from Table 4 and Eq. (9) and (12). From this perspective the probabilities of each mode can be defined as

$$P(i|Y(t)) = \frac{1}{3} \left(1 - \frac{J_i}{\sum_i J_i} \right) \quad (15)$$

where $Y(t) = \{y(0), y(1), \dots, y(t)\}$ is the discrete observation vector where observations are one second apart. The probabilities for each operational mode are shown in Fig. 4. We see that the highest probability accurately reflects the true operational mode, however we are interested in determining if these mode probabilities lead to correct determination of the events that occurred.

At each observation step we determine the transition probabilities using Eq. (5). Given the small number of operational modes in the system we pass all $m^2 = 16$

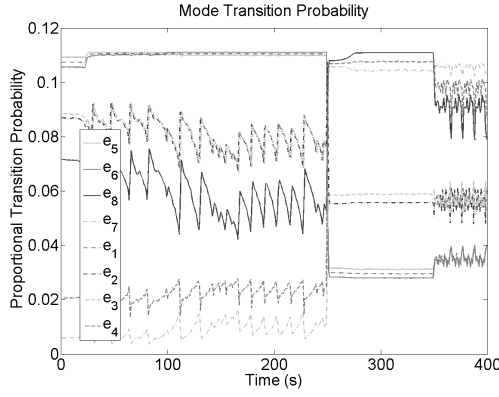


Fig. 5. Transition probabilities between each of the four operating mode after each observation.

Event	Occurrence Time (s)
e_1	151
e_2	251
e_4	351

Table 5. The diagnosed events and the times they occurred using the hybrid systems approach to diagnosis proposed in this paper.

candidate transitions to the discrete diagnosis algorithm to complete the diagnosis. Using the discrete diagnosis algorithm we are able to determine that only eight of the sixteen mode transitions are actually possible at some point during the time of operation of the system and the transition probabilities for these eight transitions are shown for each observation in Fig. 5. The diagnosis of the transitions then follows that the mode transition that is possible (as determined by the discrete diagnoser) with the highest probability (as determined by the estimation and change-point detection methods) is the most likely event that has occurred and is returned as the diagnosis. Using this approach we get the events and the time they occurred in Table 5.

We see that the proposed diagnosis methodology is able to accurately determine the occurrence of events in a hybrid system in an online manner. These results highlight that the overlap of approaches from the FDI and DX communities offers potential for powerful diagnosis methods that can be applied to real world systems.

5. CONCLUSION

We have outlined a diagnosis method that uses methods from both the FDI and DX communities to diagnose hybrid dynamical systems. The overlap of the methodologies provides a natural method of refining the obtained diagnosis and shows that it is possible to approach the diagnosis of hybrid systems without using residual generation. The example we have presented highlights the capability of this method to accurately diagnose hybrid systems and lays the ground work for extending these results to hybrid dynamical networks, that are the interconnection of many hybrid systems.

Future work will focus on using different estimation techniques and applying the result to a variety of simulated and real world systems to understand the applicability of this

approach in providing a robust hybrid systems diagnoser for real world applications.

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