An Event-based Approach to Distributed Diagnosis of Continuous Systems

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ABSTRACT

Distributed fault diagnosis solutions are becoming necessary due to the complexity of modern engineering systems, and the advent of smart sensors and computing elements. This paper presents a novel event-based approach for distributed diagnosis of abrupt parametric faults in continuous systems, based on a qualitative abstraction of measurement deviations from the nominal behavior. We systematically derive dynamic fault signatures expressed as event-based fault models. We develop a distributed diagnoser design algorithm that uses these models for designing local event-based diagnosers. The local diagnosers each generate globally correct diagnosis results locally, without a centralized coordinator, by communicating a minimal number of measurements between themselves. The proposed approach is applied to a multi-tank system, and results demonstrate a marked improvement in scalability compared to a centralized approach.

1 INTRODUCTION

The complexity of modern engineering systems warrants the adoption of fault diagnosis capabilities to ensure system safety, reliability, and availability. Faults must be quickly isolated so that mitigation or recovery actions may be taken. As systems become more complex, it is correspondingly more difficult to develop and deploy centralized diagnosis solutions. Further, such centralized schemes have single points of failure, do not scale as the size of systems increases, and have large computational and memory requirements. This, along with the increased pervasiveness of distributed, networked components, fuels the need for distributed diagnosis frameworks.

In previous work, we have developed a centralized framework for qualitative event-based diagnosis for parametric faults in continuous systems (Daigle et al., 2009). Deviations of measured behavior from predicted nominal behavior, termed fault signatures, are captured qualitatively using magnitude and slope symbols, forming the basis of the qualitative fault isolation scheme (Mosterman and Biswas, 1999). The orders in which these deviations manifest, termed relative measurement orderings, are also used for fault isolation, thus forming event-based descriptions of fault-induced behavior. This diagnostic information may be computed from the system model and used to build event-based diagnosers similar to those used for discrete-event systems (DES) (Sampath et al., 1996). However, this centralized approach scales poorly, because as the number of faults and measurements increases, the possible number of event traces increases as well.

To address the problems of centralized diagnosis, we apply the distributed diagnoser design methodology presented in (Roychoudhury et al., 2009) to the formal event-based framework developed in (Daigle et al., 2009). The distributed diagnoser design approach of (Roychoudhury et al., 2009) is based on global diagnosability analysis, where the local diagnosers are designed to provide globally correct diagnosis results, without a centralized coordinator, and by communicating a minimal number of measurements among themselves. The approach does not incorporate measurement orderings, but the addition of measurement orderings improves diagnosability, allowing the local diagnosers to be more efficient.

This paper presents, using a multi-tank system as a case study, how a global event-based diagnoser may be decomposed into several independent local event-based diagnosers, each of which leverages measurement orderings for diagnosis. We develop an algorithm for designing distributed diagnosers based on the ideas of (Roychoudhury et al., 2009), but which uses measurement orderings to guide the diagnoser design process. Distributed diagnoser design results demonstrate the reduction in diagnoser size that may be obtained using this approach, resulting in, for each subsystem, a small, compact local diagnoser capable of providing globally correct diagnoses of local faults. Results demonstrate the improved scalability of the distributed approach over a centralized approach.

The paper is organized as follows. Section 2 formulates the system model. Section 3 reviews quali-
tative fault isolation and event-based fault modeling, and defines diagnosability in the event-based framework. Section 4 describes the distributed diagnoser design problem. Section 5 discusses the global and local diagnoser construction, and Section 6 demonstrates the approach in simulation, and provides scalability results. Section 7 concludes the paper.

2 MODEL FORMULATION

We consider the problem of single fault diagnosis in continuous systems. We assume the system, $S$, is described by

$$\dot{x}(t) = f(x(t), \theta(t), u(t)) + v(t),$$

$$y(t) = h(x(t), \theta(t), u(t)) + n(t),$$

where $x(t) \in \mathbb{R}^{n_x}$ is the state vector, $\theta(t) \in \mathbb{R}^{n_\theta}$ is the parameter vector, $u(t) \in \mathbb{R}^{n_u}$ is the input vector, $v(t) \in \mathbb{R}^{n_v}$ is the process noise vector, assumed to be zero-mean Gaussian, $f$ is the state equation, $y(t) \in \mathbb{R}^{n_y}$ is the output vector, $n(t) \in \mathbb{R}^{n_n}$ is the measurement noise vector, assumed to be zero-mean Gaussian, and $h$ is the output equation. The dimension of a vector $a$ is denoted by $n_a$.

We denote a measurement as $m$, which is a time-varying signal of $y(t)$ obtained from an associated sensor. A measurement set is denoted as $M$.

We consider single, abrupt, parametric faults, where faults are modeled as unexpected step changes in system parameter values. We name faults by the associated parameter and the direction of change, i.e., $\theta^+$ denotes a fault defined as an increase in the value of parameter $\theta$, and $\theta^-$ denotes a fault defined as a decrease in the parameter value. We denote a fault as $f$ and a set of faults as $F$.

Throughout the paper, we will use a multi-tank system as a running example. The tanks are connected serially as shown in Fig. 1, and we will consider a variable number of tanks. For tank $i$, $u_i$ denotes the input flow, $C_i$ denotes the capacitance, and $R_i$ denotes the drain pipe resistance. For tanks $i$ and $j$, $R_{ij}$ denotes the resistance of the connecting pipe. For an $n$-tank system, the pressure of tank $i = 1$ is described by

$$\dot{p}_i = \frac{1}{C_i} \left( u_i - \frac{1}{R_i} (p_i - p_{i-1}) \right),$$

of tanks $i = 2, \ldots, n - 1$ by

$$\dot{p}_i = \frac{1}{C_i} \left( u_i + R_{i-1,i} (p_i - p_{i-1}) \right),$$

and of tank $i = n$ by

$$\dot{p}_i = \frac{1}{C_i} \left( u_i - \frac{1}{R_i} (p_i - \frac{1}{R_{i-1,i}} (p_{i-1} - p_i)) \right).$$

The complete fault set consists of $\{C_i^-, C_i^+, R_{i}^-, R_{i}^+ : i = 1, \ldots, n\}$ union $\{R_{i,i+1}^-, R_{i,i+1}^+ : i = 1, \ldots, n - 1\}$. The complete measurement set is defined as $\{q_i : i = 1, \ldots, n\}$, where $q_i$ describes the output flow of tank $i$, i.e.,

$$q_i = \frac{1}{R_i} (p_i).$$

3 QUALITATIVE EVENT-BASED DIAGNOSIS FRAMEWORK

We develop an event-based, qualitative diagnosis framework. Faults are viewed as unobservable events, manifesting as persistent abrupt changes in system parameter values. These faults cause transients in the system behavior, causing deviations in observed measurement values from nominal measurement values. In this section, we first review the theoretical framework for qualitative fault isolation, followed by a formal framework for event-based fault modeling.

3.1 Qualitative Fault Isolation

Measurement deviations from nominal values caused by faults are abstracted using qualitative $+, -, 0$ values to form fault signatures (Mosterman and Biswas, 1999). Fault signatures represent these deviations as the immediate change in magnitude and the first nonzero derivative change.

Definition 1 (Fault Signature). A fault signature for a fault $f$ and measurement $m$ is the qualitative magnitude and slope change in $m$ caused by the occurrence of $f$, and is denoted by $\sigma_{f,m} \in \Sigma_{f,m}$.

In general, ambiguities may exist in the fault signatures, so $\sigma_{f,m}$ may not be unique. A fault signature is written as $s_1s_2$, where $s_1$ is the qualitative magnitude change and $s_2$ is the qualitative slope change, e.g., $+-$. We also capture the temporal order of measurement deviations, termed relative measurement orderings (Daigle et al., 2007b), based on the intuition that fault effects will manifest in some parts of the system before others. Measurement orderings are based on analysis of the transfer functions from faults to measurements (Daigle et al., 2007b).

Definition 2 (Relative Measurement Ordering). If fault $f$ manifests in measurement $m_i$ before measurement $m_j$, then we define a relative measurement ordering between $m_i$ and $m_j$ for fault $f$, denoted by $m_i \prec_f m_j$. We denote the set of all measurement orderings for $f$ as $\Omega_{f,M}$.

The fault signatures and measurement orderings can be computed automatically from a system model. One method is to use a temporal causal graph (TCG) representation that is derived from the system model, along with a forward propagation algorithm to predict qualitative effects of faults on measurements and their possible sequences of deviations (Daigle, 2008).

The fault signatures and measurement orderings for a three-tank system with $F = \{C_1^-, C_2^-, C_3^-, R_1^-, R_2^+\}$,
Table 1: Fault Signatures and Relative Measurement Orderings for the Three-tank System

<table>
<thead>
<tr>
<th>Fault</th>
<th>$q_1$</th>
<th>$q_2$</th>
<th>$q_3$</th>
<th>Measurement Orderings</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_1$</td>
<td>$+$</td>
<td>$-$</td>
<td>$+$</td>
<td>$q_1 &lt; q_2, q_2 &lt; q_3$</td>
</tr>
<tr>
<td>$C_2$</td>
<td>$0+$</td>
<td>$+$</td>
<td>$0+$</td>
<td>$q_2 &lt; q_1, q_2 &lt; q_3$</td>
</tr>
<tr>
<td>$C_3$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$q_2 &lt; q_1, q_2 &lt; q_3$</td>
</tr>
<tr>
<td>$R_1^+$</td>
<td>$-$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$q_1 &lt; q_2, q_1 &lt; q_3, q_2 &lt; q_3$</td>
</tr>
<tr>
<td>$R_2^+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$q_2 &lt; q_1, q_2 &lt; q_3$</td>
</tr>
<tr>
<td>$R_3^+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$q_2 &lt; q_1, q_2 &lt; q_3$</td>
</tr>
<tr>
<td>$R_{12}^+$</td>
<td>$0+$</td>
<td>$-$</td>
<td>$0+$</td>
<td>$q_2 &lt; q_1, q_3 &lt; q_1, q_3 &lt; q_2$</td>
</tr>
<tr>
<td>$R_{23}^+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$0+$</td>
<td>$q_2 &lt; q_1$</td>
</tr>
</tbody>
</table>

Figure 2: Fault models for some faults of the three-tank system, where $M = \{q_1, q_2, q_3\}$.

3.2 Event-based Fault Modeling

Fault signatures combined with relative measurement orderings provide event-based information for diagnosis. For a given fault, the combination of all fault signatures and measurement orderings yields all the possible ways a fault can manifest in the measurements. We denote each of these possibilities as a fault trace.

Definition 3 (Fault Trace). A fault trace for a fault $f$ over measurement set $M$, denoted by $\lambda_{f,M}$, is a string of length $\leq |M|$ that includes, for every $m \in M$ that will deviate due to $f$, a fault signature $\sigma_{f,m}$, such that the sequence of fault signatures satisfies $\Omega_{f,M}$.

Note that the definition implies that fault traces are of maximal length, i.e., a fault trace includes deviations for all measurements affected by the fault. We group the set of all fault traces into a fault language. The fault model, defined by a finite automaton, concretely represents the fault language of a fault.

Definition 4 (Fault Language). The fault language of a fault $f$ over measurement set $M$, denoted by $L_{f,M}$, is the set of all fault traces for $f$ over measurements $M$.

Definition 5 (Fault Model). The fault model for a fault $f$ over measurement set $M$, denoted by $\mathcal{L}_{f,M}$, is a finite automaton that accepts exactly the language $L_{f,M}$, and is given by $\mathcal{L}_{f,M} = (S, s_0, \Sigma, \delta, A)$ where $S$ is a set of states, $s_0 \in S$ is an initial state, $\Sigma$ is a set of events, $\delta : S \times \Sigma \rightarrow S$ is a transition function, and $A \subseteq S$ is a set of accepting states.

The finite automata representation allows for the composition of the fault signatures and relative measurement orderings into fault models. The possible fault signatures and measurement orderings can be composed automatically to form the fault models based on the synchronization operation (Daigle et al., 2009).

Selected fault models for a three-tank system are shown in Fig. 2. For example, as seen in $\mathcal{L}_{C_2^-,M}$, the fault $C_2^-$ may manifest as the fault traces $q_2^+ q_1^0 q_3^0 q_1^+$ and $q_2^+ q_3^0 q_1^0$, as implied by the fault signatures and measurement orderings.

3.3 Diagnosability

With the formal fault isolation framework defined, we may now establish the notions of distinguishability and diagnosability in this framework. Using these definitions, we can then formally define the distributed diagnoser design problem. Distinguishability between faults is characterized as follows.

Definition 6 (Distinguishability). With measurements $M$, a fault $f_i$ is distinguishable from a fault $f_j$, denoted by $f_i \sim_M f_j$, if $f_i$ always eventually produces effects on the measurements that $f_j$ cannot.

Under our framework, one fault will be distinguishable from another fault if it cannot produce a fault trace that is a prefix (denoted by $\subseteq$) of a trace that can be produced by the other fault. If this is not the case, then when that trace manifests, the first fault cannot be distinguished from the second.

We define a system in our framework as follows.

Definition 7 (System). A system $S$ is tuple $(F, M, L_{F,M})$, where $F = \{f_1, f_2, \ldots, f_n\}$ is a set of faults, $M$ is a set of measurements, and $L_{F,M} = \{L_{f_1,M}, L_{f_2,M}, \ldots, L_{f_n,M}\}$ is the set of fault languages.

If a system is diagnosable, then we can make guarantees about the unique isolation of every fault in the system.

Definition 8 (Diagnosability). A system $S = (F, M, L_{F,M})$ is diagnosable if ($\forall f_i, f_j \in F$) $f_i \neq f_j \Rightarrow f_i \sim_M f_j$.

If $S$ is diagnosable, then every pair of faults is distinguishable using the measurements in $M$. So, each fault trace we observe can be linked to exactly one fault, meaning that we can uniquely isolate all faults of interest. If $S$ is not diagnosable, then ambiguities

\footnote{A fault trace $\lambda_j$ is a prefix of fault trace $\lambda_k$ if there is some (possibly empty) sequence of events $\lambda_\ell$ that can extend $\lambda_j$ such that $\lambda_j \lambda_\ell = \lambda_k$.}
will remain after fault isolation, i.e., after all possible measurement deviations have been observed.

4 DISTRIBUTED DIAGNOSES DESIGN

Given a system that is diagnosable\(^2\), our objective is to decompose the overall diagnosis task into smaller sub-tasks performed by local diagnosers with the following properties: (i) all single faults of interest in the system can be diagnosed, and (ii) the local diagnosis results are globally correct. These two properties eliminate the need for a centralized coordinator.

The system \(S\) is split into \(n\) subsystems, where each fault is assigned to exactly one subsystem, and each subsystem gets a subset of the complete measurement set. The subsystem definitions are provided by the user as input.

**Assumption 1.** \(S = (F, M, L_{F,M})\) is split into \(S_1, S_2, \ldots, S_n\), where \(S_i = (F_i, M_i, L_{F_i,M_i})\), such that (i) \(F = F_1 \cup F_2 \cup \ldots \cup F_n\), (ii) \(\forall i \neq j \in [1, n]\), \(F_i \cap F_j = \emptyset\), and (iii) \(\forall i \in [1, n]\), \(\forall j \in [1, n]\), \(F_i \in F_j \Rightarrow f_i \approx M_j, f_j\). We say two faults \(f_i \in F_i\), and \(f_j \in F_j\) are locally distinguishable if \(f_i \neq M_j, f_j\). Local diagnosability is not sufficient for local diagnosers to achieve globally correct diagnoses. The subsystems must satisfy a notion of global diagnosability. We define the distributed diagnoser design problem as determining, for each \(S_i\), the minimal number of measurements to pull in from other subsystems to achieve global diagnosability. Formally, the problem can be defined as follows.

**Problem** (Partitioned System Diagnoser Design). Given \(n\) subsystems, where \(S_i = (F_i, M_i, L_{F_i,M_i})\), construct, for each subsystem, a measurement set \(M_i^+ \subseteq M\) such that (i) \(M_i^+ - M_i\) is minimal, and (ii) \(S' = (F_i, M_i^+, L_{F_i,M_i}^+)\) is globally diagnosable.

This problem is a variation of the measurement selection problem, which is an instance of the set covering problem, known to be NP-complete (Narasimhan et al., 1998). Our goal, while designing the local diagnosers, is to minimize the sharing of measurements across subsystems in order to limit the size of the local diagnosers and their communication requirements. We simplify the measurement search using measurement orderings as a guide, based on the intuition that measurements that deviate before others are more helpful. Further, these measurements provide the fastest diagnosis. To do this, for each fault that is not globally distinguishable, we determine the measurements that deviate first by looking at the measurement orderings, and this set of measurements over all the globally indistinguishable faults forms the current working measurement set, i.e., measurements with which we try to resolve global diagnosability. This heuristic simplifies the search process, but the algorithm is still exponential in the general case, where \(O(2^{\left| M \right|})\) measurement sets must be considered for a single subsystem. The heuristic reduces the number of measurements to consider at each iteration, so only \(O(2^{\left| M_i^+ \right|})\) combinations end up being considered, where typically, \(\left| M_i^+ \right| \ll \left| M \right|\). The introduction of the heuristic trades off optimality of the diagnoser design for algorithm efficiency. Additional heuristics may also be used, e.g., the subsystem distance heuristic presented in (Roychoudhury et al., 2009).

The distributed diagnoser design procedure is given as Algorithm 1. For a diagnosable system \(S\), for each \(S_i\), we first determine, using diagnosability analysis, the set of faults \(\overline{F_i} \subseteq F_i\) which are not globally distinguishable using \(M_i\). At each iteration, for each fault that is not globally distinguishable using the current

\(^2\)If the system \(S\) is not diagnosable, we can define aggregate faults, where an aggregate fault is a set of faults that are indistinguishable from each other. The diagnosis methodology can be applied to the modified fault set that includes the aggregate faults (Roychoudhury et al., 2009).
Algorithm 1 Distributed Diagnoser Design

Input: \( \mathcal{S} = \{\mathcal{S}_i = (F_i, M_i, L_{F_i, M_i}) : i = 1, \ldots, n\} \)

for all \( \mathcal{S}_i \in \mathcal{S} \) do

\[
F_i^+ = \{ f_i : f_i \sim_{M_i} f_j \text{ for } f_i \in F_i, f_j \in F, \text{ and } f_i \neq f_j \}
\]

\( M_i^+ \leftarrow M_i \)

while \( F_i^+ \neq \emptyset \) do

\[
M_i^+ \leftarrow \{ m : \forall m', (m' \prec m) \notin \Omega_{f_i^+, M_i - M_i^+} \}
\]

end for

identify minimal \( M_i^+ \subseteq \bigcup_{f_i^+ \in F_i^+} M_i^f \) such that \( M_i^+ \cup M_i^* \) isolates maximal \( F_i^+ \subseteq F_i^* \)

\( M_i^+ \leftarrow M_i^+ \cup M_i^* \)

\( F_i^+ \leftarrow F_i^+ - F_i^* \)

end while

construct \( \mathcal{D}_{F_i, M_i^+} \)

end for

measurement set, \( M_i^+ \), we compute the set of measurements out of \( M - M_i^+ \) that may deviate first for the fault, as \( M_i^f \). We then find the minimal set of measurements to add to \( M_i^+ \) from the set of measurements found in this way over all \( f_i^+ \) that resolves the most globally indistinguishable faults, and add these to \( M_i^+ \). The process repeats until \( \mathcal{S}_i \) is globally diagnosable, resulting in the local diagnoser \( \mathcal{D}_{F_i, M_i^+} \), whose construction is described in the next section.

It is easy to see that Algorithm 1 always succeeds in making \( \mathcal{S}_i \) globally diagnosable, because (i) \( \mathcal{S} \) is diagnosable, so global diagnosability for \( \mathcal{S}_i \) can be achieved (at worst by setting \( M_i^+ = M \)), and (ii) the algorithm continually adds measurements to \( M_i^+ \) until \( \mathcal{S}_i \) is globally diagnosable (and in the worst case all measurements are considered).

We apply this algorithm to the \( n \)-tank system, where for \( i = 1, \ldots, n - 1 \), \( \mathcal{S}_i \) is defined by \( F_i = \{ C_i^{-}, R_i^- R_{i,i+1}^+ \} \) and \( M_i = \{ q_i \} \), and for \( i = n \), \( \mathcal{S}_i \) is defined by \( F_i = \{ C_n^-, R_n^- \} \) and \( M_i = \{ q_n \} \). For tank 1, \( R_{12}^- \) is not globally distinguishable. From the measurement orderings, \( q_2 \) will deviate before \( q_3 \), so \( M_1^+ = \{ q_2 \} \). This measurement alone is sufficient to add to \( M_1^+ \) to obtain global diagnosability, so no further iteration is necessary. For tank 2, \( R_{23}^- \) is not globally distinguishable, and both \( q_1 \) or \( q_3 \) belong to \( M_2^+ \). Measurement \( q_3 \) alone is sufficient to achieve global diagnosability. For tank 3, the subsystem is already globally diagnosable. The new measurement sets are therefore \( M_1^+ = \{ q_1, q_2 \} \), \( M_2^+ = \{ q_2, q_3 \} \), and \( M_3^+ = \{ q_3 \} \).

5 DIAGNOSER IMPLEMENTATION

In this section we describe the construction of the event-based diagnosers. The goal of the event-based diagnoser is, given a sequence of measurement deviation events, to determine which faults are consistent with the observed sequence. We define formally a diagnosis and a diagnoser in our framework (Daigle et al., 2009).

Definition 11 (Diagnosis). A diagnosis \( d \subseteq F \) is a set of faults, each of which is consistent with the observations.

Definition 12 (Diagnoser). A diagnoser for a fault set \( F \) and measurement set \( M \) is a tuple \( \mathcal{D}_{F,M} = (S, s_0, \Sigma, \delta, A, D, Y) \) where \( S \) is a set of states, \( s_0 \in S \) is an initial state, \( \Sigma \) is a set of events, \( \delta : S \times \Sigma \rightarrow S \) is a transition function, \( A \subseteq S \) is a set of accepting states, \( D \subseteq 2^F \) is a set of diagnoses, and \( Y : S \rightarrow D \) is a diagnosis map.

A diagnoser is a finite automaton extended by a set of diagnoses and a diagnosis map. It takes events as inputs, which, as with fault models, correspond to measurement deviations. From the current state, a measurement deviation event causes a transition to a new state. The diagnosis for that new state represents the set of faults that are consistent with the sequence of events seen up to the current point in time.

Accepting states correspond to a fault isolation result. We say that a diagnoser isolates a fault if it accepts all possible valid traces for the fault and the accepting states map to diagnoses containing the fault.

Definition 13 (Isolation). A diagnoser \( \mathcal{D}_{F,M} \) isolates fault \( f \in F \) if \( \mathcal{D}_{F,M} \) accepts all \( \lambda_{f,M} \in L_{f,M} \) and for each \( s \in A \) that accepts some \( \lambda_{f,M}, \{ f \} = Y(s) \).

Unique isolation corresponds to system diagnosability. We say that a diagnoser uniquely isolates a fault if each accepting state maps to the single fault.

Definition 14 (Unique Isolation). A diagnoser \( \mathcal{D}_{F,M} \) uniquely isolates fault \( f \in F \) if \( \mathcal{D}_{F,M} \) accepts all \( \lambda_{f,M} \in L_{f,M} \) and for each \( s \in A \) that accepts some \( \lambda_{f,M}, \{ f \} = Y(s) \).

We would like to systematically construct a diagnoser for a system \( S \) that isolates all \( f \in F \), and show that if \( S \) is diagnosable, then this diagnoser uniquely isolates all \( f \in F \). This procedure has been developed in previous work (Daigle et al., 2009). Here, we briefly review the main points.

First, we construct a diagnoser, for each fault \( f \), that isolates \( f \), i.e., \( \mathcal{D}_{(f),M} \). These are shown in Fig. 3 for some of the faults of the three-tank system. They are constructed directly from the fault models \( L_{f,M} \), cf. Fig. 2. Because the fault model \( L_{f,M} \) accepts the fault language \( L_{f,M} \), it is easy to show that this diagnoser isolates \( f \).
Figure 4: Three-tank system centralized diagnoser for $F = \{C_1^-, C_2^-, C_3^-, R_1^+, R_2^+, R_1^{12}, R_2^{23}\}$ and $M = \{q_1, q_2, q_3\}$

Figure 5: Local diagnosers for the three-tank system for $F_1 = \{C_1^-, R_1^+, R_1^{12}\}$, $M_1 = \{q_1, q_2\}$, $F_2 = \{C_2^-, R_2^+, R_2^{23}\}$, $M_2 = \{q_2, q_3\}$, $F_3 = \{C_3^-, R_3^+\}$ and $M_3 = \{q_3\}$.

A composition operator is then defined that composes two diagnosers, such that if each diagnoser isolates its own set of faults, the composed diagnoser will isolate the combined set of faults. We may then compose the individual diagnosers into a global diagnoser $D_{F,M}$ that isolates the complete set $F$. We have shown that the system defined by $F$ and $M$ is diagnosable if and only if the diagnoser constructed in this way uniquely isolates all faults in $F$ (Daigle et al., 2009).

The resulting global diagnoser for the three-tank system described in the earlier sections is given in Fig. 4. It is clear from this figure that the system is diagnosable, as each accepting state has a unique diagnosis. In this case, a unique diagnosis is even known after only a single measurement deviation. The resulting diagnoser may be pruned to reduce diagnoser size by removing states and transitions occurring after a unique diagnosis is known (Daigle, 2008).

5.1 Local Diagnoser Implementation

The design of local diagnosers follows the same procedure as the global diagnoser, i.e., given $F_i$ and $M_i$ for subsystem $S_i$, we construct $D_{F_i,M_i}$. The local diagnosers for the distributed diagnoser design example from the previous section are given in Fig. 5. Note that each local diagnoser except the third needs only two measurements, whereas the global diagnoser needs all three. As $n$ increases, each local diagnoser still needs at most two measurements, whereas the global diagnoser needs all $n$ measurements, significantly increasing its size.

In terms of scalability, the distributed diagnosis scheme clearly improves on the centralized diagnosis approach. In the worst case, the size of a diagnoser increases factorially with the number of measurements (Daigle et al., 2009). Therefore, the fewer the measurements associated with a diagnoser to achieve local and global diagnosability, the smaller a diagnoser will be. By creating local diagnosers such that each diagnoser uses only a limited number of measurements, each local diagnoser can be significantly smaller than the centralized diagnoser, and the combined size of all local diagnosers can be smaller also.

The distributed diagnosis approach works as follows. Each local diagnoser starts in its initial state. A measurement deviation event is received by all subsystems that include that measurement in their measurement set. If there is a matching event from the current state, a local diagnoser will follow that path to the next state, and remain active. If not, the local diagnoser will block, and its diagnosis result will be $\emptyset$. The process continues until a local diagnoser reaches an accepting state. At this point, a globally correct diagnosis is known, if each subsystem was designed to be globally diagnosable. If so, no other local diagnoser may reach an accepting state. Therefore, a globally correct diagnosis result is achieved without the use of a centralized coordinator. If the subsystems are not globally diagnosable, then two or more local diagnosers may both reach an accepting state and a coordinator is needed. We may prove this result as follows.

**Theorem 1.** Given a distributed diagnoser design where each subsystem $S_i$ is globally diagnosable, then if some $f \in F$ occurs, exactly one $D_i$ will uniquely isolate it, and all remaining diagnosers will give $\emptyset$.

**Proof.** When $f$ occurs it will produce some trace $\lambda$, seen as $\lambda_{f,M_1}, \ldots, \lambda_{f,M_n}$, to each $D_i$. Since $F$ is par-
tioned (Assumption 1), \( f \) belongs to exactly one \( F_i \) of \( D_i \). Since \( S_i \) is globally diagnosable, no other \( f_j \in F_i \) can produce a trace that is a prefix of \( \lambda_{f,M_i} \), and since \( D_i \) is constructed correctly, it must capture \( \lambda_{f,M_i} \) and will uniquely isolate \( f \). Any other \( D_j \) will observe the trace \( \lambda_{f,M_j} \), and, since \( S_i \) is globally diagnosable, no fault \( f_j \in F_j \) could produce a trace that is a prefix of that trace, so \( D_j \) will block, yielding \( \emptyset \).

A globally correct diagnosis result may be declared earlier if a local diagnoser has not yet reached an accepting state, but has a unique diagnosis, only if all other local diagnosers have blocked. A globally correct diagnosis result may otherwise only be declared when all measurements for a subsystem have deviated (i.e., an accepting state is reached). These conditions correspond directly to those outlined in (Roychoudhury et al., 2009) in the absence of the event-based framework.

6 RESULTS

As an example to demonstrate online diagnosis in this framework, consider a six-tank system, with \( R_{23}^+ \) occurring at time 10.0. The plots of \( q_2 \) and \( q_3 \) are shown in Fig. 6. At time 10.3 a 0– is detected in \( q_3 \), using the symbol generation mechanism described in (Daigle et al., 2010). Both the local diagnosers for \( S_2 \) and \( S_3 \) use this measurement and compute this symbol. Partial diagnosers (with some faults omitted) for these subsystems are shown in Fig. 7. The \( S_2 \) diagnoser moves to a state with \( R_{23}^+ \) as the sole candidate, and the \( S_3 \) diagnoser moves to a state with \( R_{34}^+ \) as the sole candidate. At time 10.4, a 0+ is detected in \( q_2 \). The \( S_2 \) diagnoser moves to an accepting state with \( R_{23}^+ \) as the sole candidate. The \( S_3 \) diagnoser does not use this measurement so takes no action. Because the \( S_2 \) diagnoser reached an accepting state, a global diagnosis has been achieved.

For the scalability analysis, we consider \( n \)-tank systems where for \( i = 1, \ldots, n-1 \), \( F_i = \{ C_i^-, C_i^+, R_i^+, R_i^-, R_{i+1}^+, R_{i+1}^- \} \) and for \( i = n \), \( F_i = \{ C_i^-, C_i^+, R_i^+, R_i^- \} \). The diagnoser design algorithm determines that for \( i = 1, \ldots, n-1 \), \( M_i^+ = \{ q_i, q_{i+1} \} \) and for \( i = n \), \( M_i^+ = \{ q_{n-1}, q_i \} \), i.e., each subsystem pulls in a measurement from an adjacent subsystem. The local diagnoser for \( i = 1, \ldots, n-1 \) is always 13 states with 14 transitions for the non-pruned version, and 11 states and 10 transitions for the pruned version. For local diagnoser \( n \), both the non-pruned and pruned versions have 7 states and 6 transitions.

The scalability results of the approach as compared to a centralized approach are shown in Table 2. For both non-pruned and pruned diagnosers, we report the number of states, \( |S_i| \), and number of transitions, \( |\delta| \). For the local diagnosers, we sum the number of states over each diagnoser, \( \Sigma |S_i| \), and the number of transitions, \( \Sigma |\delta_i| \). The sum of the local diagnoser sizes increase linearly, whereas the size of the centralized diagnoser increases exponentially, demonstrating a clear improvement in scalability. In the case of the pruned diagnosers, the centralized diagnoser size increases linearly as well, although its size is still larger than for the local diagnosers. The linear increase of the pruned

![Figure 6: Six-tank predicted and observed flow outputs.](image)

![Figure 7: Some partial local diagnosers for the six-tank system](image)

\( D_{F,M} \) is not a general result, but arises here because of the structure imposed by the measurement orderings.

7 CONCLUSIONS

We developed a formal framework for event-based qualitative diagnosis of continuous systems. Global and local diagnosers are automatically derived from fault signatures and relative measurement orderings, which, in turn, may be derived automatically from a system model. This results in a distributed diagnosis framework that eliminates the single point of failure associated with centralized diagnosis frameworks or distributed frameworks that require the use of a centralized coordinator, while the local diagnosers still
obtain globally correct diagnoses. The approach may be naturally applied to systems with clear subsystem boundaries. The distributed approach also scales well with an increase in the number of subsystems, particularly in comparison to a centralized diagnoser.

The event-based framework presented here relates to discrete-event diagnosis methods, e.g., (Sampath et al., 1996; Zad et al., 2001), and also distributed discrete-event diagnosis methods such as (Debouk et al., 2000). Our approach may be viewed as an implementation of Protocol 3 in (Debouk et al., 2000), in which we solve the design problem to achieve the conditions for a coordinator-free approach. In (Ribot et al., 2008), local diagnosers are extended with communicated events and additional sensors. We assume a diagnosable system in which sensor selection has been performed initially. The use of measurement orderings is similar to (Meseguer et al., 2008; Puig et al., 2005), where signatures are derived from analytical redundancy relations, but do not utilize the rich symbol framework for fault signatures used here. In (Bayoudh et al., 2006), a similar approach is applied to hybrid systems, where the events are defined as changes in ARR values due to mode changes.

In future work, we will be extending the approach to multiple faults based on previous work in (Daigle et al., 2007a), and to hybrid systems, based on results presented in (Daigle et al., 2010). We will also investigate alternative distributed design algorithms and design heuristics.

REFERENCES


