

# Augmenting the observers: diagnosability of prefix-closed languages, diagnosers and the fault detection for finite state automata

From observability to diagnosis in discrete event systems

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December 2020

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- To implement a fault detection algorithm an agent which gives, after each observed event, a set of faults that could have happened, or a set of fault states that the system could have reached, must be obtained. Such an agent is called *diagnoser*.
- A standard approach is to build a DES, called *compiled diagnoser*. At each state transition this system provides the set of faults that could have happened (SampathLafortune95), or a set of fault states that the system could have reached (ZadKwongWonham03).

- In general, the compiled diagnoser building is very computation demanding, even if it can be performed offline, and its state space results to be big. However, the computational effort to run a diagnoser is very low.
- The compiled diagnoser provides a fast on-line diagnosis at a price of excessive memory requirements since all the diagnoser state space must be available, and hence, it may be applied only when the state space is bounded. This is the usual approach when the plant is modeled as finite state automata.

- Another approach is to write an algorithm, called *interpreted diagnoser*, which online, after each observed event, computes the set of faults that could have happened, or a set of fault states that the system could have reached.
- In this case, the computational effort to run the diagnoser is bigger than in the case of the compiled diagnoser and it is difficult to derive a diagnosability test, while the memory requirement is much less since there is no need to precompute any state space. This approach is used in particular when the plant is modeled by Petri nets, since their mathematical representation mitigates the effort of the online computation.

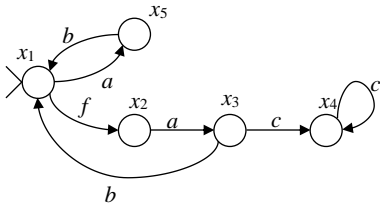
- A mixed approach is to write an algorithm, which online, after each observed event, computes the set of faults that could have happened, or a set of fault states that the system could have reached, on the basis of a system/graph computed offline.
- In this case, a trade-off between offline and online computation is pursued. However, memory requirements are most significant with respect to the interpreted diagnosed case.

- The system to be diagnosed is modeled as a *finite state automaton*  $G$ .
- The model  $G$  includes both the normal and the faulty behavior. The set of events  $E$  is partitioned as  $E = E_o \cup E_u$  in two disjoint subsets, where  $E_o$  is the set of observable events and  $E_u$  is the set of unobservable events.
- Let  $E_f \subseteq E$  denote the set of failure events which are to be diagnosed. Let us assume that  $E_f \subseteq E_u$ , since it is straightforward to diagnose an observable failure event.

Two main assumptions are usually done:

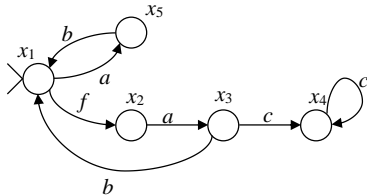
- (A1) The language  $L$  generated by  $G$  is live. This means that there does not exist a state  $x \in X$  from which no event is possible.
- (A2) There does not exist in  $G$  any cycle of unobservable events.



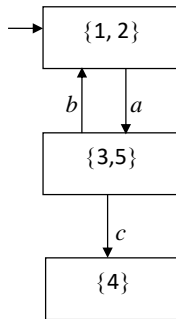


$G$

The set of observable events is  $E_o = \{a, b, c\}$  and the set of unobservable events, that is equal to the set of fault events, is  $E_u = E_f = \{f\}$ .



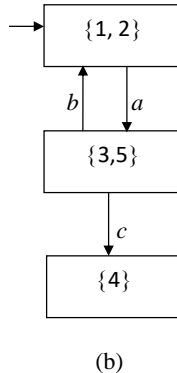
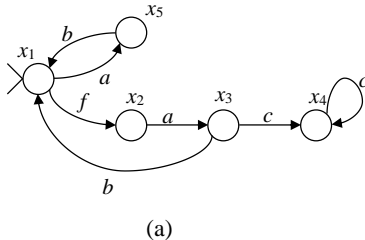
(a)



(b)

(a)  $G$  and (b) its observer

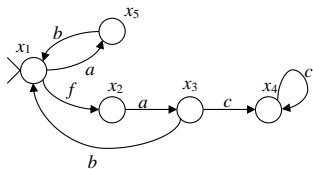
The initial state of the observer is  $x_{0,obs} = \{1, 2\}$ . It means that if no event is observed the system  $G$  can be either in state 1 or in state 2...



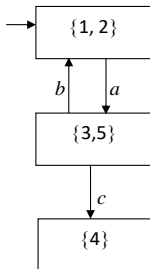
(a)  $G$  and (b) its observer

After observing string  $t = a$ , we do not know if the fault  $f$  is occurred or not, but, after observing  $w = ac$ , we know with certainty that  $f$  must have occurred.

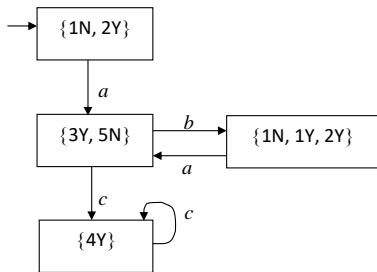
- Diagnosis problem is the problem of associate to each observed string of events a diagnosis state, such as “normal” or “faulty” or “uncertain”.
- The uncertainty can be reduced continuing to make observations.
- We can automate this kind of inferencing about the past constructing an automaton that is similar to the observer, but that contains additional information regarding the occurrence of fault transitions. We call this modified observer a *diagnoser automaton*.



(a)



(b)



(c)

(a) an automaton  $G$ , (b) its observer and (c) its diagnoser

Label  $N$  means that “ $f$  has not occurred yet” while  $Y$  means that “yes,  $f$  has occurred”.

The key modifications to the construction of  $Obs(G)$  for the purpose of building  $Diag(G)$ :

**M1.** When building the unobservable reach of the initial state  $x_0$  of  $G$ :

- (a) Attach the label  $N$  to states that can be reached from  $x_0$  by unobservable strings in  $[E_u \setminus f]^*$ ;
- (b) Attach the label  $Y$  to states that can be reached from  $x_0$  by unobservable strings that contain at least one occurrence of  $f$ ;
- (c) If state  $z$  can be reached both with and without executing  $f$ , then create two entries in the initial state set of  $Diag(G)$ :  $zN$  and  $zY$ .



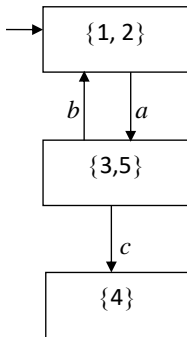
**M2.** When building subsequent reachable states of  $Diag(G)$ :

- (a) Follow the rules for the transition function of  $Obs(G)$ , but with the above modified way to build unobservable reaches with state labels;
- (b) Propagate the label  $Y$ . Namely, any state reachable from state  $zY$  should get the label  $Y$  to indicate that  $f$  has occurred in the process of reaching  $z$  and thus in the process of reaching the new state.

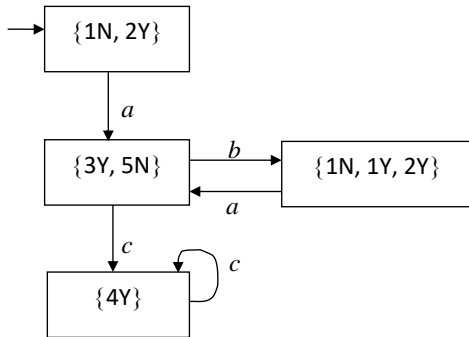
**M3.** No set of marked states is defined for  $Diag(G)$ .

- Diagnoser  $Diag(G)$  is a deterministic automaton, whose set of events is  $E = E_o$  and that generates a language  $\mathcal{L}(Diag(G)) = P[L(G)]$ .
- Each state of  $Diag(G)$  is a subset of  $X \times \{N, Y\}$ .
- Modification  $M1(c)$  implies that if a state can be reached by two paths having the same observable projection and such that one path contains the fault  $f$  and the other one does not in a node of  $Diag(G)$  will exist two pairs  $xN$  and  $xF$ . It means that the cardinality of  $Diag(G)$  is always greater than or equal to the cardinality of  $Obs(G)$ .



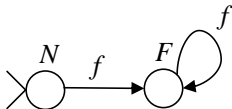


(a)



(b)

An alternative way to build the diagnoser is to consider the following label automation  $A_{lab}$



and to compute  $G \parallel A_{lab}$ . The diagnoser can be obtained as  $Obs(G \parallel A_{lab})$ . Indeed, it is equivalent to the observer of  $G \parallel A_{lab}$ .

We can perform diagnosis by examination of the diagnoser states. In  $Diag(G)$  we can distinguish three different kind of states:

- *negative state*: if in the node of  $Diag(G)$  for all pairs  $(x, I)$ ,  $I = N$ . Thus reaching this node we are sure that fault  $f$  has not occurred yet;
- *positive state*: if in the node of  $Diag(G)$  for all pairs  $(x, I)$ ,  $I = Y$ . Thus reaching this node we are sure that fault  $f$  has occurred;
- *uncertain state*: if in the node of  $Diag(G)$  there exists at least one pair  $(x, I)$  such that  $I = N$  and at least one pair  $(x, I)$ , such that  $I = Y$ . Thus, we cannot say nothing about the occurrence of fault  $f$ .

Consider a DES system  $G$  and event set  $E = E_u \cup E_o$ , where  $E_o$  denotes the observable events and  $E_u$  denotes the unobservable ones, and a fault event  $f \subseteq E_u$ .

Let  $L$  be the live and prefix-closed language generated by  $G$ .

$L/\sigma$  is the post-language of  $L$  after the sequence of transitions  $\sigma$ , i.e.  $L/\sigma = \{v \in T^* \text{ s.t. } \sigma v \in L\}$ .

A sequence  $v \in L/\sigma$  is called *continuation* of  $\sigma$ .

Let  $Pr : T^* \mapsto T_o^*$  be the usual projection, which erases the unobservable transitions in a sequence  $u$ . The inverse projection operator  $Pr_L^{-1}$  is defined as

$$Pr_L^{-1}(r) = \{\sigma \in L \text{ s.t. } Pr(u) = r\}.$$

## Definition (Lafortune95)

A fault event  $f$  is said to be diagnosable if

$\exists h \in \mathbb{N}$  such that  $\forall \sigma = uf$  with  $f \notin u$ , and  $\forall v \in L/\sigma$  with  $|v| \geq h$ ,

it is

$$r \in P_L^{-1}(P(\sigma v)) \Rightarrow f \in r.$$

A fault  $f$  is diagnosable if for every trace  $s$  ending with  $f$ , there exists a sufficiently long continuation  $v$  such that any other trace indistinguishable from  $\sigma v$  (producing the same record of observable events) contains  $f$  (are also faulty).

Assumption (A1) allows us to state that when the property of diagnosability is satisfied, we are sure that if  $f$  occurs, then  $Diag(G)$  will enter a positive state in a bounded number of events after the occurrence of  $f$ .

## Definition (Lafortune95)

Let us consider a system  $G$  and its diagnoser  $Diag(G)$ . We say that a cycle in  $Diag(G)$  is an *indeterminate cycle* if it is composed exclusively of uncertain states for which there exist:

- a corresponding cycle (of observable events) in  $G$  involving only states that carry  $Y$  in their labels in the cycle in  $Diag(G)$  and
- a corresponding cycle (of observable events) in  $G$  involving only states that carry  $N$  in their labels in the cycle in  $Diag(G)$ . ■

The notion of indeterminate cycles is very important because their analysis gives us necessary and sufficient conditions for diagnosability and gives a method to test the property.

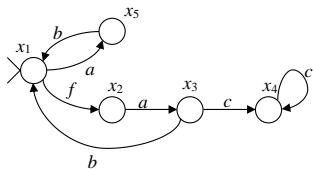
In the general case, the set of fault events is partitioned into  $m$  disjoint subsets that represent the set of fault classes:

$$E_f = E_{f1}, E_{f2}, \dots, E_{fm}.$$

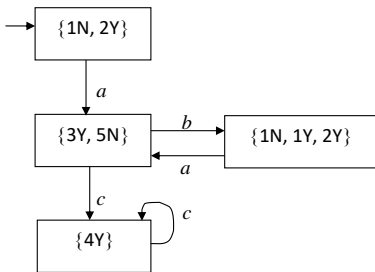
The aim is that of identifying the occurrence, if any, of failure events, given the set of generated words containing only observable events.

## Proposition (Lafortune95)

*A language  $\mathcal{L}$  without multiple failures of the same type is diagnosable if and only if its diagnoser  $\text{Diag}(G)$  has no indeterminate cycles for all failure types  $E_{fi}$ .*

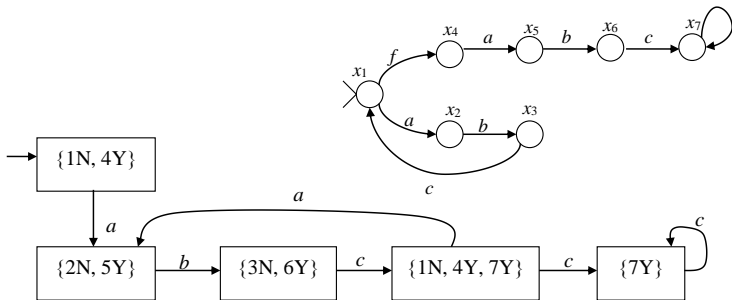


(a)



The diagnoser has a potential indeterminate cycle. Let us verify if conditions of Definition 2 are satisfied. In  $G$  there exists the cycle “ $1 \rightarrow 2 \rightarrow 3 \rightarrow 1$ ” involving only states that carry  $Y$  in their labels and there exists another cycle “ $1 \rightarrow 5 \rightarrow 1$ ” involving only states that carry  $N$  in their labels. Thus, this cycle is indeterminate thus the fault is not diagnosable.



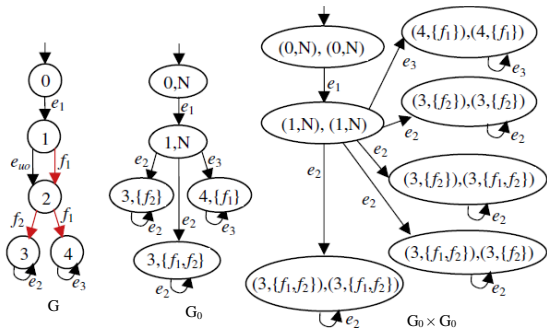


The diagnoser has a potential indeterminate cycle. However the only cycle that can cause the diagnoser to remain in its cycle of uncertain states is the cycle “ $1 \rightarrow 2 \rightarrow 3 \rightarrow 1$ ”, and these states all have the N label in the corresponding diagnoser states. The cycle of uncertain states in the diagnoser is therefore not indeterminate.

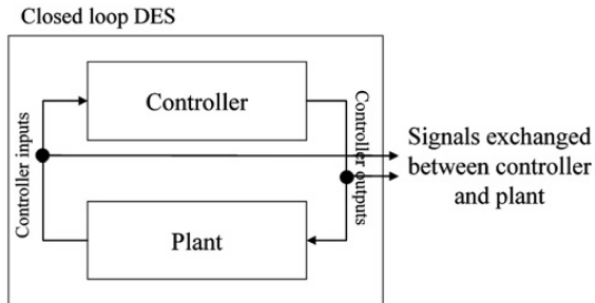
- The construction of the entire diagnoser may be very computation demanding.
- Its size is exponential in the number of states of  $G$ , as well as in the number of faults if a single diagnoser is desired. This second limitation can be addressed by building separate diagnosers for each fault type.
- The first limitation can be addressed by using the “twin machine” technique.
- The idea behind this technique is that a fault  $f$  is diagnosable if and only if there is no pair of arbitrarily long traces having the same observable projection, such that  $f$  occurs in the first trace but not in the second.

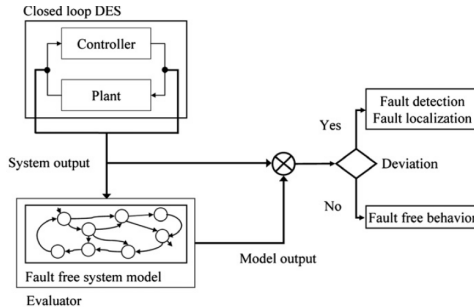




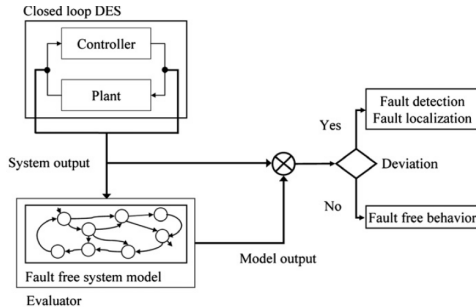


In  $G_0 \times G_0$  there is a self-loop at the state  $((3, f_2), (3, f_1, f_2))$  or at the state  $((3, f_1, f_2), (3, f_2))$ . In each case, the cycle indicates that fault  $f_1$  is not diagnosable in  $G$ , as the presence of each cycle implies the existence of two arbitrarily long traces with the same projection, where  $f_1$  is contained in one trace but not in the other.





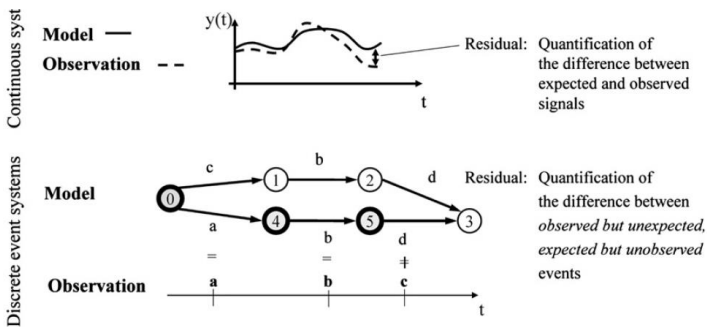
In the context of continuous time systems, diagnosis in consists in the determination of the time of detection, kind, size and location of a fault. Diagnosis in a wide sense includes fault detection, isolation and identification.



In the context of discrete event systems, kind and size has not sense, and the diagnosis task may be considered to be completed after fault detection and localization.



# The concept of residual



A residual is a fault indicator, based on a deviation between measurements and model-based computation.

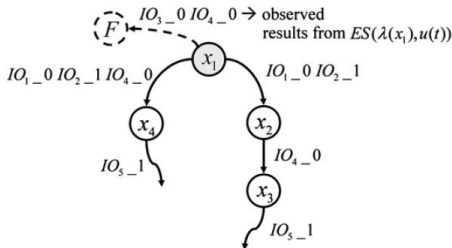
Denote by

- $ES(u(i), u(k))$  the set of rising and falling edges between two I/O vector sets  $u(i)$  and  $u(k)$ , called evolution set;
- $\lambda(\tilde{x})$  the I/O vector set generated by the fault free model of the extended process at state  $\tilde{x}$ ;
- $f(\tilde{x})$  the transition function of the fault free model of the extended process at state  $\tilde{x}$ .

An example of residual is

$$Res1(\tilde{x}, u(t)) = ES(\lambda(\tilde{x}), u(t)) \setminus \bigcup_{\forall x' \in f(\tilde{x})} ES(\lambda(\tilde{x}), \lambda(x'))$$

$\bigcup_{\forall x' \in f(\tilde{x})} ES(\lambda(\tilde{x}), \lambda(x'))$  is the union of the sets of rising and falling edges when the last estimated current state and each of its direct successor states are considered, it is the overall expected behavior of the system. Hence  $Res1(\tilde{x}, u(t))$  represents an unexpected behavior of the system.



Let  $\tilde{x} = x_1$ ,

$Res1(\tilde{x}, u(t)) =$

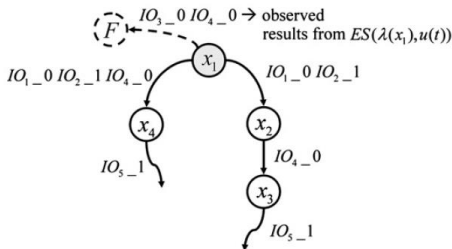
$\{IO_{3\_0}, IO_{4\_0}\} \setminus (\{IO_{1\_0}, IO_{2\_1}, IO_{4\_0}\} \cup \{IO_{1\_0}, IO_{2\_1}\}) = \{IO_{3\_0}\}.$

This result that implies that the system operator should check the sensor or actuator that is connected with  $IO_3$ .

If the fault is not located at the sensor/actuator connected with  $IO_3$ , one may consider a stricter formulation of the expected behavior.

$$Res2(\tilde{x}, u(t)) = ES(\lambda(\tilde{x}), u(t)) \setminus \bigcap_{\forall x' \in f(\tilde{x})} ES(\lambda(\tilde{x}), \lambda(x'))$$

The intersection delivers the I/O edges that must be observed no matter which following state in the model is taken, obviously  $Res1(\tilde{x}, u(t)) \subseteq Res2(\tilde{x}, u(t))$ .



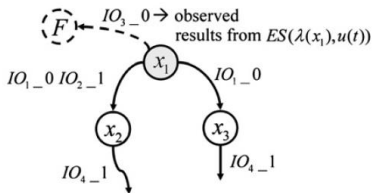
$$Res2(\check{x}, u(t)) = \{IO_{3\_0}, IO_{4\_0}\} \setminus (\{IO_{1\_0}, IO_{2\_1}, IO_{4\_0}\} \cap \{IO_{1\_0}, IO_{2\_1}\}) = \{IO_{3\_0}, IO_{4\_0}\}.$$

This result that implies implies that the occurrence of a change in value of  $IO_4$  is not always expected and thus it is another possible fault localization.

$$Res3(\tilde{x}, u(t)) = \bigcap_{\forall x' \in f(\tilde{x})} ES(\lambda(\tilde{x}), \lambda(x')) \setminus ES(\lambda(\tilde{x}), u(t)).$$

*Res3* is the set difference of the I/O edges that are expected no matter which following state is taken and the I/O edges that have been observed. It characterizes a missed behavior, a less restrictive version is




$$Res4(\tilde{x}, u(t)) = \bigcup_{\forall x' \in f(\tilde{x})} ES(\lambda(\tilde{x}), \lambda(x')) \setminus ES(\lambda(\tilde{x}), u(t)).$$



Let  $\tilde{x} = x_1$ ,

$Res3(\tilde{x}, u(t)) = \{IO_{1\_0}\}$ ,  $Res4(\tilde{x}, u(t)) = \{IO_{1\_0}, IO_{2\_1}\}$ .

First, the component connected with  $IO_1$  should be checked. If a fault is not found at this component, the component connected with  $IO_2$  must be checked.

- Diagnoser and Diagnosability – Chapter 2 (section 2.5.3) in
  -  **C. G. Cassandras and S. Lafortune**  
Introduction to Discrete Event Systems  
Springer, 2008
- Diagnoser and Diagnosability – the seminal works
  -  **M. Sampath, R. Sengupta, S. Lafortune, K. Sinnamohideen, D. Teneketzis**  
Diagnosability of Discrete-Event Systems  
*IEEE Transaction on Automatic Control*, 1995
  -  **S. H. Zad, R. H. Kwong, and W. M. Wonham**  
Fault diagnosis in discrete- event systems: Framework and model reduction  
*IEEE Transaction on Automatic Control*, 2003



- Fault diagnosis (faults built in the model)



M. Sampath, R. Sengupta, S. Lafortune, and K. Sinnamohideen  
Failure diagnosis using discrete event models  
*IEEE Trans. Control System Technology*, 1996

- Fault diagnosis (fault free model)



M. Roth, J.J. Lesage, L. Litz  
The concept of residuals for fault localization in discrete event systems  
*Control Engineering Practice*, 2011

# Augmenting the observers: diagnosability of prefix-closed languages, diagnosers and the fault detection for finite state automata

From observability to diagnosis in discrete event systems

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December 2020



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