

## Unexpected Situations Diagnosis: A Model-based Approach for Human Machine Systems

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Abstract: The paper deals with unexpected behaviors and situations diagnosis for human-machine systems. Operator behavior is modeled using a nondeterministic discrete-event formalism and a specific model adaptation. An extension of pair algebra of partitions to nondeterministic finite state machines is used to develop the diagnosis method proposed in the paper. Possibilities of the proposed method are investigated and discussed. An illustrative example is provided, based on a tramway driving situation.

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### 1. INTRODUCTION

The paper is about safety improvement for rail transport. It concerns mainly human performance and behavior monitoring since accidents are often caused by human errors (Wilson (2005)). The objective of such monitoring is to detect as fast as possible occurrence of unexpected situations and to classify these situations based on expected threat level. The combined operations of detection and classification (identification) contribute to unexpected situations diagnosis. Successful diagnosis is followed then by appropriate control actions, preventive or corrective (the stage of unexpected situations processing, see e.g. Ouedraogo et. al (2011)). This paper focuses solely on unexpected situations diagnosis.

The conventional approach to timely detect and prevent consequences of unexpected situations is based on direct measurements of human emotional and psychological states (Woods et al. (2010)). But existing sensor's technological limitations may hinder the performance of such approaches in practice. It is known that there is a direct causality link between human emotional or psychological states and the corresponding behavior (Woods et.al, (2010)). So, when direct measurements are impossible or difficult, an intuitive solution is to observe variables that are directly linked to the unobservable information we need to assess. In order to do so, qualitative or quantitative models of human-machine systems are required to estimate the human state, the performance or the behavior (Sani and Dawal, 2010).

Several approaches to human-operator performance and behavior modeling exist in literature. The interest to this topic is growing multidisciplinary, attracting significant attention from different scientific communities: Ergonomics, Computer vision and Automatic control. For example, the situational model for the train-driving context was proposed by McLeod and Moray (2005).

The present paper discusses the behavioral diagnosis approach initially presented in Rachedi *et al.* (2012) using

and extending results from Berdjag et al. (2011). The model is a finite state machine (FSM) that combines knowledge of healthy and faulty system's behaviors. Often this model is nondeterministic. Using this model, the solution of the diagnostic problem is reduced to system's state estimation.

The first contribution of this paper is to propose a novel modeling guideline, adapted to diagnosis. The model is designed in such a way that nondeterminism is contained, making the determinization (nondeterminism elimination) step easier. Algebra of Partitions is then used to synthesize distributed Detectors or Diagnosers based on bisimilarity (equivalence) principle. The distributed structure is especially useful to limit exponential growth of models. This is the second contribution of this paper.

The paper is organized as follows. In section two, the modeling problem in general context of human-machine systems is discussed. Section three presents a solution to the diagnostic problem based on nondeterministic FSM modeling. The fourth section illustrates that last part with an example taken from tramway driving situations. Conclusions and perspectives on future works end the paper.

### 2. MODELING APPROACH

#### 2.1 Operator's Behavior Modeling

Many approaches exist to represent human operator expected actions using an *a priori* model. This *a priori* representation is called *formal*, and its strong point is to provide a solid basis for analysis, design and implementation using adequate mathematical formalisms. A good review of formal methods can be found in Shin et al. (2006) based on King (1991). The author considers that formal representation is of two kinds, either property-oriented or model-oriented.

The problem of representing the behavior is twofold: the operator's actions should be represented using state-oriented formalisms while sequences of "actions" should be

represented using transition-based approaches, including the “triggers” coming from the environment and interpreted by the operator to form a “trace” composed of a trigger-action-new trigger sequence. Also, another layer of representation is dedicated to the operator’s states, since an operator will react differently to the same trigger considering different contexts: emotional, workload, environment, etc.

An adequate formalism to choose for the representation is the FSM formalism (model-oriented), because it is compatible with transition-oriented formalisms such as trace-analysis and grammars (Alvarez-Alvarez et al. (2012)). Using this “two-sides-of-the-coin” approach, it is possible to represent most operating situations with a great flexibility.

### 2.2 Train driving guidelines

Train operators are given appropriate guidelines for each expected driving situation and a general plan of actions for unexpected ones. Expected situations are dealt with through more-or-less strict guidelines about two particular points: Actions (what to do and when?) and Information acquisition (what to check and when?).

The guidelines are provided through driver's formation cycle, and are summarized as graphs called MAD (Mouchel (2011) (Figure 1)).

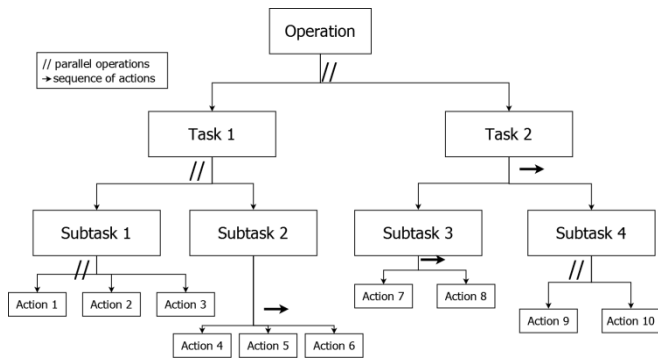


Figure 1: a sample MAD

Nodes represent concrete observational actions and influential actions, and meta-nodes are used to structure related nodes under the same label. Nodes are organized in serial sequences (sequential execution) and parallel ones.

### 2.3 Human operator specifics

Humans deal with most tasks by dividing them into multiple levels of subtasks and deal with "atomic" subtasks with appropriate actions. Figure 2 shows a human interaction with environment through actions, Jagacinski & Flach (2003).

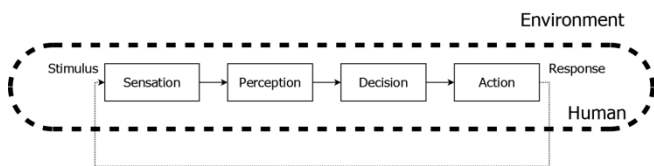


Figure 2: Human Model

Such precise representation is overkill for the discussed problem. Also, in the classical representation, all actions are

similar and fall into the same category. We sustain that expected actions are different from unexpected ones. "Expected" actions are specifically meant to obtain a result to fulfill an atomic subtask. "Unexpected" actions are usually corrective or reactive, and are required to deal with an unexpected consequence of previous actions.

An adaptation of the classical scheme is proposed here; the loop consists of the sequence: Action (Expected actions); Observation (Sensation, Perception and Decision); Reaction (Corrective / Reactive actions).

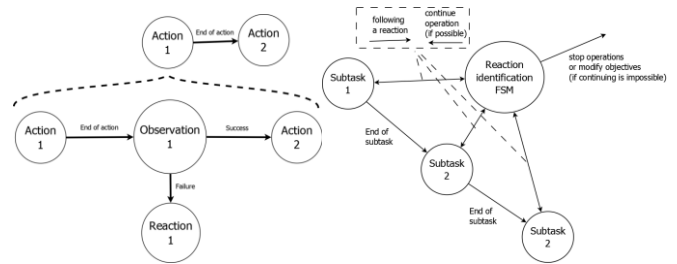


Figure 3: State expansion      Figure 4: Diagnosis model

Figure 3 and 4 describe respectively how action sequence is structured at the "atomic" subtask realization level, and at the global level. In the former nodes represent FSM states (action, observation or reaction) and in the latter, each node corresponds to a subtask-specific FSM. More details will be provided in the third section

### 2.4 Unexpected situation reaction evaluation

Train drivers are well formed professionals that know how to react in standard driving situations. This knowledge is based on guidelines similar to those detailed in previous sections. However, unexpected situations also happen, and in such cases train drivers adapt the standard plan of action to circumstances. Such behavior "deviation" is acceptable.

There are also unacceptable behavior deviations caused by train driver’s state: unconsciousness, drowsiness, loss of focus, etc. Such states should be avoided, by anticipation or by appropriate actions. Indeed, if an automated driver's state monitoring system detects in time symptoms of such states, it is possible to act timely to prevent risky situations. One way to perform such detection is to monitor variations of driver's behavior and to check consistence with prescribed guidelines. This task is not trivial, as false alarms could be caused by legitimate variations due to unexpected situations management. In this paper, a design approach to design such monitoring algorithms is presented.

## 3. TOWARDS A SOLUTION OF THE DIAGNOSIS A NONDETERMINISTIC SETTING

### 3.1 Mathematical Background

Assume that the system under normal operation is described by the asynchronous FSM of the form  $M = (I, S, O, \delta, \lambda)$  where  $I, S$  and  $O$  are the finite sets of the FSM inputs, states and outputs respectively.

The functions of transitions and outputs are written as  $s^+ = \delta(s, i)$  and  $o = \lambda(s)$  where  $s^+ \in S$  is the FSM state after transition from the state  $s \in S$  initiated by an input  $i \in I$ ,  $o \in O$  is an output, corresponding to the state  $s \in S$ . It is assumed that both the functions of transitions and outputs are specified by appropriate tables or directional graph. Abnormal operation due to operator errors may be reflected as the distortions of the transitions and output functions.

A brief sketch of pair algebra of partitions is presented below for nondeterministic FSM. It is an extension of the algebra proposed by Hartmanis and Stearns (1966) for deterministic FSM investigation. The main elements of this algebra are partitions of some sets. Let  $X$  be some finite set (domain); a partition  $\pi$  of  $X$  is a set of subsets (blocks)  $\{B_{\pi 1}, B_{\pi 2}, \dots, B_{\pi v}\}$  such that

$$B_{\pi i} \subseteq X, B_{\pi i} \cap B_{\pi j} = \emptyset, i \neq j, \bigcup_{i=1}^v B_{\pi i} = X.$$

The following notation is used: for  $x, x' \in X$  one denotes  $x \equiv x'(\pi)$  if  $x, x' \in B_{\pi i}$  for some  $i$ . The main aspects of pair algebra of partitions used in this paper are:

- Relation of partial order, denoted by  $\leq$ .
- Binary operations, denoted by  $\times$  and  $+$ .
- Binary relation, denoted by  $\Delta$ .
- Operator  $\mathbf{m}$ .

The first two topics are defined on the set of partitions of arbitrary set  $X$  in a conventional manner, whereas the last two are defined for the set of partitions of the domain being the set of the nondeterministic FSM states  $S_d$ . For more details about pair algebra, check Berdjag et al. (2011).

### 3.2 Nondeterministic FSM State Estimation

Denote by  $\pi_1$  the partition of the set  $S_d$  given by

$$(\forall s_d, s'_d \in S_d)[s_d \equiv s'_d(\pi_1) \Leftrightarrow \lambda_d(s_d) = \lambda_d(s'_d)]. \quad (1)$$

Using only available system outputs, state estimation is possible up to blocks of the partition  $\pi_1$ . Using properties of the operator  $\mathbf{m}$  and knowledge of inputs and outputs, system's state after transition is predicted up to blocks of the partition  $\mathbf{m}(\pi_1)$  (Berdjag et al. (2011)). Likewise, the next transition is predicted up to  $\pi_2 = \pi_1 \times \mathbf{m}(\pi_1)$  and a recurrent formula is deduced

$$\pi_{i+1} = \pi_i \times \mathbf{m}(\pi_i), \quad i = 1, 2, \dots \quad (2)$$

(2) is used to compute the partitions  $\pi_{i+1}$ ,  $\pi_{i+1} \leq \pi_i$ , system's state estimates within the moving time window corresponding to  $i$  transitions. It can be shown that the series converges: there is an integer  $k$  such that  $\pi_{k+1} = \pi_k$ .

These are the basic relations for the design of the system's state estimation procedure. Under this, the index  $k$

characterizes the maximal reasonable size of the moving time window containing sufficient system's inputs and outputs to estimate the system state up to the blocks of the partition  $\pi_k$ .

If  $\pi_k = \mathbf{0}$ , then it is possible to monitor all the faults, taking into account how these faults are reflected on the diagnosis model. However, in the general case, the partition  $\pi_k$  is not nil and an additional analysis is required (Berdjag et al. (2011); Zhirabok et al. (2012)).

### 3.3 Automata Disambiguation

#### A particular modeling paradigm for HMS

Considering a given plan of action, an equivalent FSM can be designed by a relatively simple procedure, based on grammar construction for example. However, such FSM will be nondeterministic, and this will impact greatly the following design procedures.

A classical solution is to use automata determinization (Mohri (1997)) or automata disambiguation (Mohri (2012)), and then to design the diagnoser based on the approach presented in Sampath et al. (1996) or the bisimilarity approach using algebra of partitions presented in Berdjag et al. (2008) or in Berdjag et al. (2011). This approach is intuitive, but the resulting FSMs are not guaranteed to remain informative. By analogy with matrix calculus, where a poorly conditioned matrix will cause computation errors, an abstract FSM will not be very suited for behavior analysis. Also, the complexity and the size of the resulting diagnoser for the first approach are exponential.

Another possibility is to proceed with a different modeling paradigm and use the "Action-Observation-Reaction" pattern to design a particular model well-suited for determinization.

Consider a particular FSM described by  $M(I, S, O, \delta, \lambda)$ .

Let's  $S$  be the set describing possible operator actions. It is safe to assume that each programmed action execution will be monitored by the operator, particularly actions with some execution delay. Let's  $S = S_1 \cup S_2$ , with  $S_1$  and  $S_2$  representing monitored and unmonitored actions.

For each monitored action, an expansion of the state subset  $S_1$  is performed, replacing a particular state  $q_i$  with an action state  $a_i$  and an inactive observation state  $o_i$ . Such states may be considered as transitional states between sequences of actions. Also, for each state  $q_i$ , a reaction state  $r_i$  is added, representing actions to be done if the observation tells that an action  $a_i$  is failed.

#### Global model decomposition

Consider now the global FSM representing the whole possible set of actions during a particular operation or scenario. It is always possible to consider sequences of actions as independent partial FSMs. Actually, each non parallel sequence of action will be modeled as a partial FSM using the previous paradigm. Such partial FSM are interconnected via initial and final states.

**Remark:** FSM formalism does not require strictly initial and final states, as accepters do, however it is possible to demonstrate that a FSM with a tagged initial state and a final subset of  $S$  is equivalent to an accepter automata. For the sake of brevity, we will continue to use the FSM formalism.

If we consider that reaction states are not defined, it is possible to link all observation states  $o_i$  to a single reaction state  $r$ . This state will be an additional final state used to connect the modeled plan of action, with a FSM representing an iterative procedure to determine what action was chosen by the operator using the approach described before. The details are omitted and will be discussed in a distinct companion paper. After an exact or a partial estimation of the reaction, the corresponding partial FSM is activated and so on until the end of the scenario.

Such decomposition is interesting in order to keep the complexity of diagnoser FSM relatively low, even considering the additional  $o_i$  and  $r_i$  states, while limiting false alerts caused by any divergence from the plan of action. Indeed, operator reaction will not be considered as misbehavior, but will indicate the occurrence of an unexpected situation that forced the operator to adapt in order to complete his objectives.

#### *Impact on determinization performance*

If the determinization is applied on the global FSM - obtained directly from the plan of action - the resulting FSM will be huge, and the diagnoser even larger. Again, since the determinization partition will most likely regroup distinct actions into states, the result will lose model informativeness with respect to behavior analysis. However, using the proposed modeling approach, an improvement is obtained.

First of all, decomposing action states into action/observation components, it is possible to reduce FSM nondeterminism before determinization.

Secondly, by construction, observation states will inherit most of the remaining determinism and the new partition of the state set obtained through determinization will subsequently impact transitional observation states subject to nondeterminism. This will keep action states mostly distinct preserving model informativeness.

#### *3.4 FSM Detector (Diagnoser) design*

The approach is based on the algorithm from Berdjag et al (2011). There are other approaches to design discrete-event diagnosers and detectors, see the work of Zoltan et al. (2005) or all the derivatives of Sampath et al. (1996). In author's opinion, the presented approach is best suited to deal with the distributed representation shown Figure 4.

The algorithm provides the minimal FSM such that the bisimilarity (in the sense of FSM equivalence) between the minimal FSM and the full model is guaranteed only if the input (or the input subset) to detect has not occurred. It means that both FSM have equivalent outputs for the same input sequence. However, if the event (input) to detect occurs, the outputs are going to diverge. The detector is based on this

minimal FSM and on comparison logic between its outputs and the outputs of the full model. Based on this logic, the first occurrence of the event of interest is detected.

Note that the existence of the minimal FSM is equivalent to the weak diagnosability condition presented in Sampath et al. (1996).

A short description of algorithm adaptation to suit the application is given below. Such adaptation is required since the former article was about technical fault detection and isolation, and the fault was represented by input symbol. In the actual paper, we need to detect particular behavioral discrepancies, represented by input sequences. In fact, there is no "faulty" input to detect.

The detector is designed with respect to the following steps.

- Given  $I_{ign}$ , an input subset to be ignored and a focus subset  $I_{focus}$ , find the state partition  $\pi_0$  such that the block transitions keep elements of  $I_{focus}$  distinct.
- Find the minimal invariant subpartition  $\pi \subseteq \pi_0$  using the iterative property proposed in Berdjag et al. (2011) or Zhirabok et al. (2012) and build the reduced FSM  $M^*$  based on the state partition  $\pi^*$ .
- Transform  $M^*$  in an appropriate accepter automaton preserving model informativeness.

#### *3.5 Application to driver's behavior change detection*

The accepter automaton will provide three possible responses with respect to a particular input sequence. The sequence will be accepted (respected plan of action), put on hold (if a reaction is detected) or refused (if operator actions are confirmed to be wrong). Following operator unplanned reaction detection, an unexpected situation alert is triggered to the supervisor, and additional analysis of operator actions is performed. Either operator actions are validated, and the operation is carried on, or actions are refused, and the operation objective will change, up to a complete stop. The pattern of detected reactions, if confirmed as repetitive, will indicate also operator habits while working to accomplish a particular task. From a behavioral perspective, such pattern is a personal adaptation (optimization) of the programmed plan of actions. It is the "signature" of a particular operator performing a task.

Following a reaction that will break that pattern, a detection of behavior change can be decided in which case, an important unexpected situation has to be reported and investigated further. In the context of this paper, only the first steps are presented.

## 4. ILLUSTRATIVE EXAMPLE

### *4.1 Case study: Tramway station departure*

An illustrative example is presented to complete reader's understanding of the presented matter. A simple case, based on a sequence of action from tramway driver during station departure operation is investigated. Due to confidentiality

constraints, the sequence is kept generic, but remains meaningful for a first understanding of the approach. A subtask grouping closing tramway doors and initial acceleration is considered, the operator needs to:

- Wait for passengers entering and exiting wagons
- Press doors side selection
- Press close door button
- After all operation completion, accelerate slowly

The scenario ends when tramway speed will be positive. Operator's state and actions cannot be observed using proprioceptive sensors because of the regulation. However, exteroceptive sensors are allowed: oculometers, cameras, microphones and such. Indirect measurements are also used, such as tramway elements status, and also information on position, acceleration and speed of the tramway. Oculometers are used to detect gaze direction. In laboratory conditions, measurements are precise, but in order to design a robust approach, the precision is artificially downgraded. Basically, we want to be sure that the operator is looking through the glass, checking the board or watching the interface. Cameras and movement detection algorithms are used to detect left and right hand movements. We consider the left hand dedicated to acceleration while the right hand is used freely. Dead man system is not modeled, but we will consider that the left hand will never leave its position on the acceleration command.

4.2 Mathematical Model

The required operations are represented Figure 5. Symbol «a» represents right hand movement, while b represents left hand movement. The symbol c is completely external representing a speed increase (from zero).

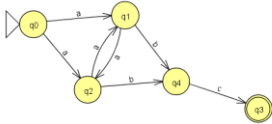


Figure 5:  
Possible operator actions

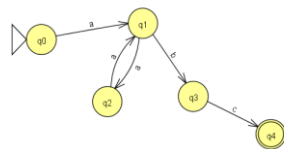


Figure 6:  
Correct FSM

The "correct" procedure is shown Figure 6. A basic determinization will give the result represented Figure 7.

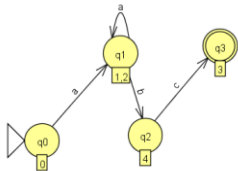


Figure 7: Automata Determinization (from Figure 6)

Despite the simplicity of the example, it appears that determinization aggregated q1 and q2 states, regrouping two distinct actions on the board (q1 being side selection press and q2 being activation of the close button). The following figure provides a behavioral model based on the presented approach.

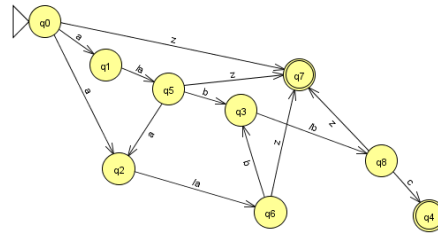


Figure 8: Improved behavioral model

In Figure 8, the state q7 is the reaction state; q5, q6 and q7 are observation states. Symbols "d" and "e" respectively represent the inactivity of the right and the left hands. The symbol "z" represents any other event or trigger, leading to the reaction final state. Figure 9 represents the determinization

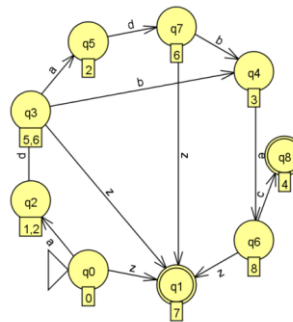


Figure 9: Improved FSM determinization

States 1 and 2 are regrouped, but since another state corresponding to 2 is preserved, that means that the model remains informative.

4.3 Detector Synthesis

The following step is to determine the minimal invariant partition and the corresponding FSM  $M^*$ . Since the behavior change detection is not the primary focus of this article, only the validation of the correct sequence will be covered. The minimal partition  $\pi^*$  is obtained through the iterative procedure discussed before and is given by

$$\pi^* = \{\{4, 7\}, \{1, 2, 3\}, \{0, 5, 6, 8\}\}$$

The accepter corresponding to  $\pi^*$ -defined FSM is shown Figure 10

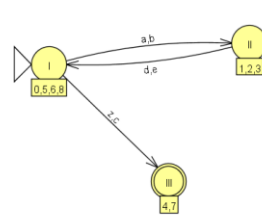


Figure 10:  
Minimal accepter

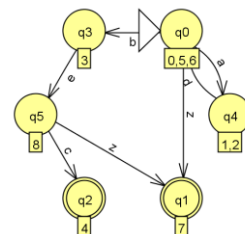


Figure 11:  
Constrained Acceptor

The grammar corresponding to this automaton is regular and context-free (see Eilenberg (1977) for details), and the correct sequence "adadbec" is accepted. However, it is clear that this

result is quite permissive since even the sequence "*adbeadc*" will also be accepted, and this is wrong. Indeed, opening the door while accelerating is suspicious.

The solution is to determine appropriate constraints ensuring selectivity of the accepter. This can be done through the definition of an appropriate grammar, which can prove delicate and time consuming, or by defining an appropriate set  $I_{focus}$ . In this case, setting  $I_{focus} = \{\{a\}, \{b\}, \{c\}\}$  the new partition is given by  $\{\{0, 5, 6\}, \{1, 2\}, \{3\}, \{4\}, \{7\}, \{8\}\}$  and the corresponding accepter is represented Figure 11. This time, sequences such as "*adbeadc*" will not be validated but will be on hold, and considered suspicious.

## 5. CONCLUSION

In this paper, a particular approach to diagnose Human-Machine Systems is presented and discussed. This approach is based on a modeling paradigm based on human operator particularities. It is the first contribution of the paper, because the representation is simpler and more intuitive and this helps to some extent behavior analysis. The second contribution of this paper is the formalization of the design of misbehavior detectors based on algebra of partitions, extending previous results of the authors to input sequence validation on nondeterministic FSM. The detectors help input sequence variation detection, leading to early detection of human errors and indirectly to unexpected situations detection.

This is a work in progress, since the objective is to improve nondeterministic state estimation for recognition of adequate operator reaction. This is very important for Human-Machine system diagnosis, because humans are unpredictable, and existing means of automated diagnosis may generate unacceptable levels of false alarms.

## 6. ACKNOWLEDGMENTS

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