- El título del artículo
  Another Point of View for Analysis of Intelligent Diagnosis Approaches

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- Un resumen de a lo sumo 200 palabras.
  This paper proposes another point of view for analyzing the approaches to intelligent monitoring and diagnosis, present in the literature we reviewed.
  In first place, the state of the art in diagnosis is reviewed and afterwards, we propose a framework for analyzing the approaches presented so far, based on the KADS standard for development of KBSs.
  In the end, we present the correlation we found for describing intelligent monitoring and diagnosis systems, facing to present a general description of the problem of diagnosis itself.

- Un conjunto de a lo sumo cinco palabras claves.
  Knowledge engineering, intelligent diagnosis

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  - Fundamentos de la Inteligencia Artificial y Representación del Conocimiento
  - Ingeniería del Conocimiento: Ontologías, Adquisición, Representación, Reutilización y Compartición

- Información sobre en qué sección (*Paper Track - Open Discussion Track*) debe considerarse el artículo, algo esencial si el artículo está escrito en inglés. En caso de que el artículo haya sido enviado a otras conferencias deberá ser reflejado también.
  Paper Track
  El articulo es inedito

Another Point of View for Analysis of Intelligent Diagnosis Approaches

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Abstract. This paper proposes another point of view for analyzing the approaches to intelligent monitoring and diagnosis, present in the literature we reviewed.
In first place, the state of the art in diagnosis is reviewed and afterwards, we propose a framework for analyzing the approaches presented so far, based on the KADS standard for development of KBSs.
In the end, we present a "3-correlation" we found for describing the problem of diagnosis, facing to present a general description of it.

1 Introduction

The literature is almost unanimous in recognizing the existence of a major problem in the specification and design of large and complex reactive systems [6]. A reactive system is characterized by being, to a large extent, event-driven, continuously having to react to external and internal stimuli. Examples include cars, communication networks, computer operating systems, the man-machine interface of many kinds of ordinary software, and many other complex industrial processes, such as the operation of blast furnaces, for example [10].
Since there is no operational mathematical model for the dynamics of reactive complex continuous processes, the usual means of control theories cannot be used to design an automatic controller, suited for such complex systems. In addition, processes required to reach a very high level of economic performance tend to be complex.
In the past three decades, however, several approaches have been proposed for dealing with this complexity. One consists of compensating the lack of a mathematical model for the process dynamics by the knowledge used by the human operator who controls those complex processes.
Recent advances in different computer sciences such as artificial intelligence and simulation propose methods, techniques and tools to exploit such informal knowledge, and new kind of controllers have been developed since 1980 [8].
In this paper, we aim to compare different approaches for monitoring and diagnosis of continuous processes, whose behavioral models come from expert knowledge.
In first place, we recall the general definition of diagnosis and we describe the state of the art in intelligent monitoring and diagnosis of industrial systems, namely the heuristic-based, the model-based and the task-based approach.
In a second place, we propose a method for comparing the approaches reviewed so far, as the level of description of them vary and make hard to understand the

differences and coincidences among them. This framework is based on the KADS standard for KBS development.
In the end, we show our conclusions, facing to find a general description for the problem of diagnosis and a correlation for the techniques used for solving it.

2 Diagnosis Problem Solving

Given:

- A system (device, physical system, physiological system, ...)
- A set of observations (measurements, tests, symptoms, examinations ...) corresponding to abnormal (unexpected, anomalous ...) behavior

It is expected to determine what is wrong with the system in order to re-establish the system normal behavior (therapy, repair, reconfiguration, ...) [7].
Diagnosis was a fundamental area for Artificial Intelligence since the 70's, as many Artificial Intelligence methodologies originated from it and then spread to other areas of and because it was a blend of theoretical and experimental research [7].

3 State of the Art in Diagnosis

3.1 Heuristic-Based Approach

The basic assumption of this approach (70's) is that diagnosis is a heuristic process. It implies that experts rely on associational knowledge of the form symptoms → faults (diseases). This kind of knowledge derives from experience and must be elicited from domain experts and represented using suitable knowledge representation languages (Figure 1).

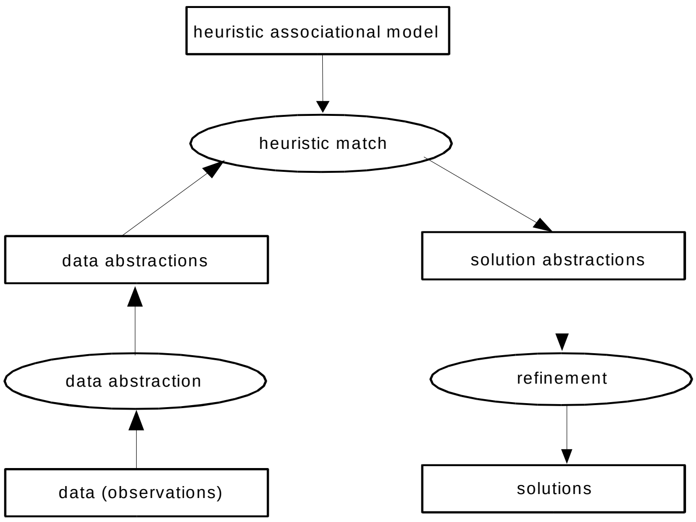

Figure 1. Diagnosis as a heuristic classification [7]

This knowledge often consists of rules of thumb (heuristics) that associate symptoms to possible causes. These systems can reach a high level of performance and may be efficient in their reasoning, but there are some well-known limitations [3,4,5]:

- they exhibit steep performance degradation if the problem lies a bit outside the scope of the system's knowledge,
- knowledge acquisition depends on the existence on human expertise. This means that before a diagnosis system can be built, diagnosis experience should be available,
- they provide limited explanation as to how a solution has been arrived at,
- once a heuristic based system has been built for a specific application, it is difficult to reuse parts in other applications, as the rule sets are strongly device dependent.

Examples in the literature: Mycin (Stanford Univ. 72/79), Delta-Cats1 (General Electric), PIP (MIT, 72-78). [7]

3.2 The Model-Based Approach

The basic paradigm of the model-based approach (late 70's - beginning of the 80's) can be understood as the interaction of observations and predictions (Figure 2) [5].

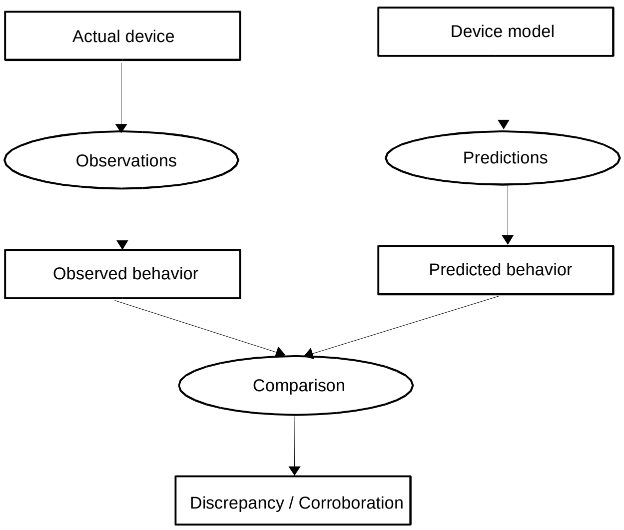

Figure 2. Interaction between observations and predictions

On the one hand, there is the actual device, a technical system whose behavior can be observed. On the other hand, there is the model of the device that is used to make predictions about its behavior. Such a model describes the components of the system, their connections, and the behavior of the components. The device model includes all possible knowledge about it, including correct and fault behavior [3,4,5].

A difference between an observation and a prediction is called a *discrepancy*. A match between an observation and a prediction is called a *corroboration*. Both discrepancies and corroborations are used to identify which parts of the device are incorrect [3, 4, 5].

Model-based means a "deep" model of the device will be used, which can be described in general terms as follows [1]:

Model or System Description SD=<COMP, BM> where

- COMP={c*1*, ..., c*n*}: Structure, i.e. list of components (and interconnections between them).
- BM={bm*1*, ..., bm*p*}: Behaviors, i.e. what each component is supposed to do (each bm is hence a list of behaviors).

Diagnosis Problem DP=<SD, CXT, OBS> where

- CXT= contextual data (parameters and inputs).
- OBS= observations (outputs).

The main feature of this model is to explicitly represent the structure of the device (COMP) and to separately handle the predicted behaviors (BM), faulty or correct, on one hand, and the observed behaviors (OBS) in another hand, the diagnosis process amounting to dynamically comparing them, roughly speaking.

The model is inherently a (more or less) coarse one, i.e. a discrete approximation of the real system, which is suitable to complex systems with simple enough general behaviors (an abstracted model is sufficient and more tractable). Usually, only some relevant outputs are accounted as observations (filtering), others are internal data that can be checked through the model or directly on the device.

- *Pros:* this allows to remove unnecessary details, raising a more compact and robust representation.
- *Cons:* the approximation may lead to an incorrect model, i.e. one might detect non-existent faults that are only due to a lack of detailed information in the model structure or correct behavior description.

Symbolic Models for Static Diagnosis

As already mentioned, the behaviors that are present in the model can be either correct behaviors, or faulty ones, or both.

This distinction and the choices made in the representation according to it, raises the distinction between the two main approaches to model-based diagnosis in Artificial Intelligence, namely the consistency-based and the abductive ones [1].

These include:

- *Consistency-based diagnosis*
  Examples in the bibliography: HT of Davis, DART of Genesereth, GDE of de Kleer and Williams, GDE+ of Struss and Dressler, Sherlock of de Kleer and Williams. [3]
- *Abductive diagnosis*
  Examples in the bibliography: Cover & Differentiate of Eshelman, CHECK of Console and Torasso. [3]

Symbolic Models for Dynamic Diagnosis

Until now, only classical Artificial Intelligent approaches to diagnosis have been presented, which implicitely consider static domains. As far as one is interested in dynamic processes, and needs to take into account states and times, the following problems and requirements appear: [1]

- Fault and correct behaviour models change from one state to another
- *Intermittent faults* = only detected after a certain time, while the system has continued evolving and the faulty component may have moved into some other state meanwhile.
- *Transient faults* = occur during a certain time interval, and then vanish.

- One must distinguish *inter-state* vs *intra-state* faults: the former occur during a dynamic change of a system, the latter correspond to the classical notion of fault, if one makes a kind of "static projection" of the system into one of its states.

There exists many extensions to combine abductive and time-based reasoning. This is particularly important in environments where the observations are dated; and time spans can be added to the causal relations that model the new temporal relations between the occurrence of the causes and that of their effects. The major difficulty consists in exploiting the two types of knowledge; causal and temporal. [2]

We may have three different kinds of symbolic models for dynamic diagnosis: [9]

- *Associative models*, such as the ones used by expert systems and pattern recognition, use representations of the form *effects* $\rightarrow$ *causes*.
  - Expert Systems [1, 2]
    Examples in the industry: IFP (Institut Français du Pétrole) with the Alexip software, for monitoring refining and petrochemical processes [13]; PICON, that was a system for real time reasoning for process control applications and that gave birth to G2 (developped by GENSYM), an expert system generator [14]; Sollac in the SACHEM project, that relies on an approach using the Kool object-oriented language; France Telecom for monitoring the Transpac network using the Chronos software [2], RTWorks and CogSys [15]
  - Pattern Recognition [1, 2]
    Examples in the industry: AUSTRAL project in order to analyze sequence of alarms emitted by substations in a French medium voltage distribution network [29]; GASPAR project in order to analyze alarms issued by the network equipment in a telecommunications network (France Telecom) [2], IxTet in the framework of project Esprit Tiger [16]
- *Predictive models* allow the simulation of different possible system behaviors in any of the different behavior modes available.
  - Qualitative Models [1, 2]
    Examples in the industry: MIMIC, a monitoring system [2], CA-EN system in the frame of the Esprit Tiger project for the monitoring of gas turbines [17]
  - Discrete Models [2, 9, 19]
    Examples in the industry: ESSO refinery in Canada [18]; monitoring of the Transpac network [20, 21, 22, 28]
- *Explanatory models* are of two kinds: Influence graphs, that describe the dependence links among the system variables, and Causal graphs, that describe the causal links among the states or failure situations and their observed effects. The representations used are of the form *causes* $\rightarrow$ *effects.*
  - Influence Graphs [2]
    Examples in the industry: Esprit Alliance project [23], CA-EN software in Tiger project [17]
  - Causal Graphs [9]
    Examples in the industry: Matra Marconi Space for its satellite monitoring software [24, 25, 26], DIAPO system for diagnosing the cool and pump sets in EDF nuclear power plants [27].

3.3 The Task-Oriented Approach

The task-based approach (beginning of the 90's) aims at modeling problem solving behavior in terms of the knowledge that is used for the problem solving. Thus, regardless how a diagnostic system is implemented (rule based, frame based, connection based), it is possible to focus on the goal of the system and on the knowledge that is applied to achieve the goal. This modeling is reached by identifying tasks at various levels of abstraction above the implementation level.

Examples in the bibliography: Generic Tasks of Chandrasekaran, KADS of Wielinga et al., Problem Solving Methods of McDermott, Components of Expertise of Steels, Method-to-Task Approach (used to characterize the work of PROTEGE of Musen, PROTEGE II of Puerta et al., and the work of Klinker)

These approaches aim at modeling problem solving by identifying tasks at various levels of abstraction above the implementation level. The key concepts involved are:

- *Task:* a task is associated with a goal to be achieved
- *Primitive inference:* a procedure that directly achieves a goal
- *Problem solving method:* a competence characterization that describes a way to perform a task. It decomposes a task (with a goal) into a set of subtasks and primitive inferences (with sub-goals)
- *Control knowledge of a method:* the control regime that determines the execution of the subtasks and primitive inferences of a method
- *Domain knowledge or domain models:* the knowledge about the application domain that is consulted to achieve goals.
- *Knowledge requirements of problem solving methods:* suitability conditions that specify when methods are applicable to perform a task.
- *Role of knowledge in reasoning process:* the role that domain concepts play in the process of achieving the goal.

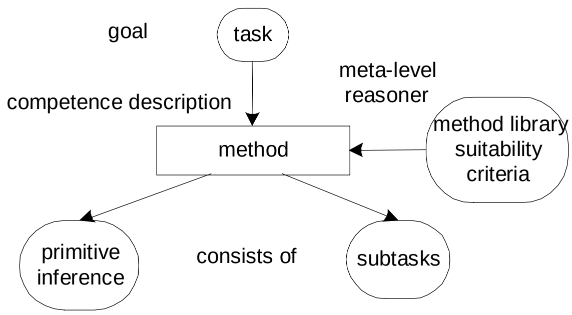

Figure 3. Task-oriented approach to diagnosis

A task is characterized by a goal that it has to achieved. A task can potentially be performed by a method, selected from a method library, that decomposes a task into subtasks and/or primitive inferences. A method is associated with a competence description that describes what it can achieve. Selection of a method can be performed by a meta-level reasoning engine that queries suitability criteria of methods. A method consists of subtasks, each associated with a sub-goal, and/or primitive inferences, that directly achieve goals (Figure 3) [3].

4. Our Framework for Analysis

Having reviewed the state of the art of intelligent diagnosis present in the literature, the main remark to note is that the levels of description of each approach vary (some of the approaches show aspects for modeling, but others face the resolution of the problem). This way it is hard to have a real comparison of the goals and scope of each of them.

Due to the fact that CommonKADS is a standard for development of KBSs, it might be used for describing any knowledge-based system. Therefore, we have decided to describe the approaches in Section 3, according to it.

The CommonKADS abstraction cycle is based on a *conceptual model*, CM, and makes a distinction among this model and the Functional Model (FM) and the Design Model (DM) (see Figure 4).

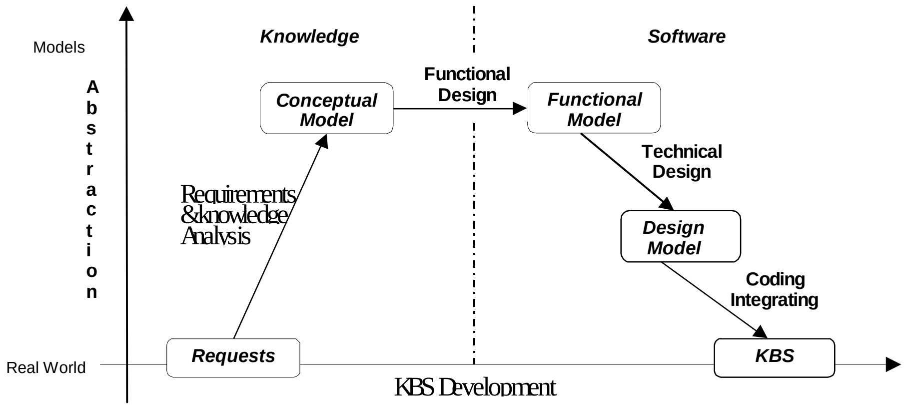

Figure 4. Abstraction cycle in CommonKADS

This general framework makes a specific differentiation among the Conceptual Model, the Functional Model and the Design Model, each of them representing different views of the system to be conceived.

The main characteristics of each model are described as follows:

- The Conceptual Model is supposed to contain all the knowledge, and may be validated by the "client". It lies at knowledge level.
- The Functional Model is supposed to contain all the functions, and may be validated by the development team. It lies at symbol level.
- The Design Model includes all the techniques used to perform the functions described at the functional level. It also lies at symbol level.

These three models gives us three levels of description that will allow us to perform a critical analysis on the approaches for diagnosis present in the literature up to now and described in Section 3.

- *Conceptual Level* (associated with the Conceptual Model): At which we describe the nature of the knowledge source and the nature of the reasoning process.
- *Functional Level* (associated with the Functional Model): At which we describe the nature of the models or, in other way, how causality is represented.

- *Technical Level* (associated with the Design Model): At which we describe the nature of the underlying theory for representing and exploiting the knowledge (technical calculus or computation).

5. Our Proposal

We propose to reconsider the State of the Art in Intelligent Diagnosis according to those 3 levels of description, explained in Section 4.

	Conceptual Level	Functional Level	Technical Level
Static Model Based Approach			
Heuristic Approach	Heuristic System Model	Associative models	Expert Systems First Order Predicate Calculus
Consistency-based diagnosis	"Predict & compare"	Logical Models	First Order Predicate Calculus Non-monotonic reasoning
Abductive diagnosis	"Observe & Explain"	Logical Models	First Order Predicate Calculus
Dynamic Model Based Approach			
Recognition based approach	Heuristic System Model	Temporal models	Temporal Constraint Propagation Infinite State Machine (DEVS)
Simulation based approach	"Tracking & Interpretation"	Qualitative models	Constraints Propagation Qualitative Calculus
	"Predict & compare"	Discrete Models	Finite State Machine (Petri nets)
Task-Oriented Approach			
PSM for diagnosis	"Symptom detection Hypothesis generation Hypothesis discrimination"	any	KBSs
KADS / CommonKADS	Task templates	any	KBSs

Regarding the Functional Level, we remark:

- In Associative Models, there is no explicit notion of causality. There's only the notion of associative empairement between what would be "causes" and "consequences".
- In Logical Models, "causes" imply "consequences"
- In Temporal Models, temporal correlation is viewed as causality.
- In Qualitative Models, causality is compiled as algebraic expressions ..

- In Discrete Models, ordering is viewed as causality.

6 Conclusions

If we take into account the Technical Level described on Section 5, we have the following:

a) Logic techniques

a_1) Monotonic

a_2) Non-monotonic

b) Pattern Matching Techniques

b_1) Temporal Constraint Propagation

b_2) Automata

b_{21}) DEVS

b_{22}) Petri Nets

c) Qualitative Calculus

On the other hand, if we review the Functional Level, we also find 3 kind of models:

a) Causality Models

a_1) Associative Models

a_2) Logic Models

b) Temporal Correlation Models

b_1) Temporal Models

b_2) Discrete Models

c) Algebraic Models

c_1) Qualitative Models

It may be noticed that there are 3 levels of correlation, both at the Technical and Functional levels.

Causality Models ↔ Logic Techniques

Temporal Correlation Models ↔ Pattern Matching Techniques

Algebraic Models ↔ Qualitative Calculus

At this moment, we are working on the Conceptual Level to try and find the "3-level" correlation we already found at the other two levels.

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