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Bridging Technologies for Diagnosis

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Abstract: Diagnosis is the process of identifying or determining the nature and root cause of a failure, problem, or disease from the symptoms arising from selected measurements, checks or tests. The different facets of this problem and the wide spectrum of classes of systems make the diagnosis problem interesting to several communities and call for bridging several technologies. This paper provides a comprehensive picture of the different facets of diagnosis, and exemplifies how different technologies can be synergically integrated to provide better solutions for fault management problems.

Keywords: model based diagnosis, bridge, abstractions, learning models, fault management.

1. INTRODUCTION

The goal of diagnosis is to identify the possible causes explaining a set of observed symptoms. A set of concomitant tasks contribute to this goal and the following three tasks are commonly identified:

- *fault detection*, which aims at discriminating normal system states from abnormal ones, i.e. states which result from the presence of a fault,
- *fault isolation*, also called *fault localization*, whose goal is to point at the faulty components of the system,
- *fault identification*, whose output is the type of fault and possibly the model of the system under this fault.

In front of the diversity of systems and different views of the above problems, several scientific communities address these tasks and contribute with a large spectrum of methods. The Signal Processing, Control and Artificial Intelligence (AI) communities are on the front.

Diagnosis works from the signals that permit efficient fault detection towards the upper levels of supervision that call for qualitative interpretations.

Signal processing provides specific contributions in the form of statistic algorithms for detecting changes in signals, hence detecting faults. This track can be exemplified by the reference books and papers by Basseville (1988); Basseville and Nikiforov (1993); Basseville et al. (2004); Fillatre and Nikiforov (2007); Fouladirad et al. (2008).

Interfaces between continuous signals and their abstract interpretations, in symbolic or event-based form, implement the qualitative interpretations of the signals that are required for supervision. To do that, discrete formalisms borrowed from Artificial Intelligence find a natural link with continuous models from the Control community. These two communities have their own model based diagnosis track :

- the FDI (Fault Detection and Isolation) track, whose foundations are based on engineering disciplines, such as control theory and statistical decision making,
- the DX (Diagnosis) track, whose foundations are derived from the fields of logic, combinatorial optimization, search algorithms and complexity analysis.

In the last decade, there has been a growing number of researchers in both communities, who tried to understand and incorporate approaches from the two parallel research fields to build better, more robust and effective diagnostic systems.

Data-driven diagnosis approaches based on machine learning techniques are also present in both the Control and AI communities and complement synergically with model-based approaches to provide solutions to a variety of diagnostic problems where difficulty arises from the scarce nature of the instrumentation or, conversely, from the massive amounts of data to be interpreted for the emergence of hidden knowledge.

Other bridges can be found when considering that diagnosis is not a goal per se but a component in fault management architectures. It takes part in the solutions produced for tasks such as design, failure-mode-and-effects analysis, sensor placement, on-board recovery, condition monitoring, maintenance, repair and therapy planning, prognosis. The contribution of diagnosis in such architectures means close links with decision tasks such as control and planning and calls for innovative integrations.

In this paper, different facets of diagnosis investigated in the Control or the AI fields are discussed. Some are compared, in particular the concepts and results of the FDI and DX tracks are put in correspondence and the lessons learned from this comparative analysis are pointed. Some are discussed in relation with other technologies that participate to provide solutions for fault management problems. Signal Processing methods are used by these communities at several level but these remain out of the scope of this paper.

This paper is organized as follows. Section 2 first presents a brief overview of the approaches proposed by both the FDI and the DX communities on the other hand. Section 2.3 presents the results of a comparative analysis of concepts and techniques used in both communities and section 3 is concerned with the works that integrate techniques from both sides.

2. DX AND FDI MODEL BASED DIAGNOSIS BRIDGE

The FDI and DX streams both approach the diagnosis problem from a *system* point of view, hence resulting in large overlaps, including the name of the tracks: *Model Based Diagnosis* (MBD).

The diagnosis principles are the same, although each community has developed its own concepts and methods, guided by different modelling paradigms. FDI relies on analytical models, linear algebra, and non linear system theory whereas DX takes its bases in logic formalisms. In the 2000s, catalyzed by the BRIDGE group *Bridging AI and Control Engineering model based diagnosis approaches* [1] within the Network of Excellence MONET II [2] and its French counterpart, the IMALAIA group *Intégration de Méthodes Alliant Automatique and IA* supported by GDR MACS [3], GDR I3 [4], as well as AFIA [5], there were more and more researchers who tried to understand and synergically integrate methods from the two tracks to propose more efficient diagnostic solutions. This collaboration has led to several events :

- a BRIDGE Workshop in 2001 in the framework of DX'01, 12th International workshop on Principles of Diagnosis, Sansicario, Via Lattea, Italy, 5-9 Mars 2001 [6].
- the co-location of the two main events of the FDI and the DX communities, namely the Symposium IFAC Safeprocess 2003 and the International Workshop Principles of Diagnosis DX 2003, in Washington DC (USA) in June 2003 with a BRIDGE Workshop in the form of a join day.

This events were followed by the publication of a special issue of the IEEE SMC Transactions, Part B, on the topic *Diagnosis of Complex Systems: Bridging the methodologies of the FDI and DX Communities* in 2004 by Biswas et al. (2004). The *Bridge track* was launched and is still active today. Lets's mention the two invited sessions *AI methods for Model-based Diagnosis* and *Bridge between Control Theory and AI methods for Model-based Diagnosis* , recently organized in the framework of the 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes Safeprocess'09, Barcelona, Spain, 30 July-3 August 2009 [7].

The next subsections first summarize the foundations of the FDI and DX methods, then proceed to a comparative analysis that allows us to draw some practical assessments in the form of lessons learned.

2.1 Brief overview of FDI approaches

The detection and diagnosis methods of the FDI communauty rely on behavioral models that establish the constraints between system inputs and outputs, i.e. the set of measurable variables Z, as well as the internal states, i.e. the set of unknown variables X. The variables $z \in Z$ et the variables $x \in X$ are functions of time. The typical model may be formulated in the temporal domain, then known as a *state-space model* of the form:

$$\begin{aligned} BM &: dx/dt = f(x(t), u(t), \theta) \\ OM &: y(t) = g(x(t), u(t), \theta). \end{aligned} \tag{1}$$

where $x(t) \in \Re^{n_x}$ is the state vector, $u(t) \in \Re^{n_u}$ is the input vector and $y(t) \in \Re^{n_p}$ is the output vector. BM is the behavioral model and OM is the observation model. The whole model is noted $SM(z, x)$. The equations of $SM(z, x)$ may be associated to components but this information is not represented explicitly. The models can also be formulated in the frequency domain (transfer functions in the linear case).

Models are used in three families of methods:

- the methods based on *parameter estimation* that focus on the value of parameters as representing physical features of the system
- the methods based on *state estimation* that rely on the estimation of unknown variables
- the methods based on the *parity space* that rely on the elimination of unknown variables

The books (Gertler (1998), Blanke et al. (2003), Dubuisson (2001), Patton et al. (1989)) provide excellent surveys, which cite the original papers that the reader is encouraged to consult. The equivalence between observers, parity and paramater estimation has been proved in the linear case (Patton and Chen (1991)).

The concept central to FDI methods is the concept of *residual* and one of the main problems is to *generate residuals.* Let's consider the model $SM(z, x)$ of a system in the form (1) [8]. $SM(z, x)$ is said to be consistent with an observed trajectory z, or simply *consistent with measurements* z, if there exists a trajectory of x such that the equations of $SM(z, x)$ are satisfied.

Definition 1. (Residual generator for $SM(z, x)$). A system that takes as input a sub-set of measured variables $\tilde{Z} \subseteq Z$ and generates as output a scalar r,is a residual generator for the model $SM(z, x)$ if for all z consistent with $SM(z, x)$, we have $\lim_{t\to\infty} r(t) = 0$.

When the system model is consistent with measurements, the residuals tend to zero as t tends to infinity, otherwise some residuals may be different from zero. The residuals are often optimized to be robust to disturbancies (Qiu and Gertler (1993)) and to take into account uncertainties (Adrot et al. (1999)). The evaluation of residuals and

[1] http://monet.aber.ac.uk:8080/monet/monetinfo/monetbridge.htm
[2] http://monet.aber.ac.uk:8080/monet/index.html
[3] http://www.univ-valenciennes.fr/GDR-MACS/
[4] http://www.irit.fr/GDR-I3/
[5] http://www.afia.asso.fr/
[6] http://www.di.unito.it/ dx01
[7] http://safeprocess09.upc.es/
[8] The model may also include algebraic equations.