DIAGNOSIS USING QUALITATIVE METHODS

A Survey of Qualitative Modeling Methods in Fault Diagnosis

draft version

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5.8. Diagnosis using qualitative methods

Research in qualitative reasoning became more important both in Artificial Intelligence (AI) and Fault Diagnosis (FD). This interest was inspired by the observation that humans are much more capable of operating appropriately with incomplete knowledge than any of the currently available automatic devices. It was perceived that this capability is somehow related to our ability to dealing with knowledge in qualitative terms.

Various qualitative reasoning paradigms have been developed, including expert systems, neural networks, qualitative physics, discrete-event systems, fuzzy systems, and others. What they all have in common is that each of them tries to deal with uncertanity in one way or another, they all try to reach decisions without being provided with complete information. If everything is known, qualitative reasoning does not offer any advantage over quantitative reasoning.In fact, that then it should be avoided due to its worse performance.

Qualitative reasoning includes two steps: qualitative modeling, followed by qualitative simulation. Model-building starts with a description of a physical situation and it builds an appropriate simplified model.
Qualitative modeling can be done in two different ways considering the description technique. The **Shallow Reasoner** method is based on the behavior of the system. It tries to cover the observed behavior and formulate a model which produces the same.
The **Deep Reasoner** tries to capture the knowledge about a system in terms of its structure rather than its behavior. It operates on a **qualitative state-space model**, in which it uses variables with qualitative values and qualitative operators, therefore it avoids the problem of numerically integrating sets of differential equations.

The qualitative simulation uses the qualitative model to predict the possible behaviors of the modeled system. In Fault Diagnosis the qualitative simulation is used in several ways to produce the residuals. The obvious method is to generate output behavior from the same inputs that the modeled system got, and to compare the observed and simulated outputs. This is the basic principle of **Simulation-based Qualitative Fault Diagnosis**.

In this chapter examples of both modeling techniques are shown. The **Consistency-based Diagnosis** uses logical description of the system, observations, and in some cases fault model to determine if the observed system is in a faulty state or not. **Inductive Reasoning** is a shallow reasoner. It builds a model of a system from previous observations and uses it to predict the current behavior.

In the first part (chapter 5.8.1) a survey is presented. This survey descibes the current research in the field of Qualitative Fault Diagnosis. It can be used as a basic repository for people looking for more details in this research area.

The second part (from chapter 5.8.2) contains the main ideas of each basically different qualitative diagnosis method, along with the short summaries of applications, research people and references.

5.8.1 A Survey Of Qualitative Modelling Sites On The Internet

This survey is intended to give a brief overview of research sites interested in qualitative system modelling and/or qualitative fault diagnosis. This collection is based on an exhaustive search for online research sites. It does not contain sites that has not appeared on the Internet in any way. The search was done by the Digital's Altavista search engine. The closing date of the search was 1 July 1996.

Qualitative Reasoning Community

http://ai-www.aist-nara.ac.jp/doc/qphysics/

The purpose of this Web site is to provide archival information such as conference and workshop information, bibliography, or discussion through the mailing list. It contains about 12 references to research groups, some references to forums, workshops and a few bibliography entry.

Exeter Qualitative Reasoning Resources

http://www.ex.ac.uk/ESE/KBS/

This another repository also has several research group references (chategorized by location) and some conference links.

Informations and Information Sources about Qualitative Simulation

http://www.ipb.uni-bonn.de:80/~laszlo/qsim/qsim.html

This site contains several links to institutions and people working in qualitative simulations.

MONET: Model Based and Qualitative Reasoning Systems Network

http://www.aber.ac.uk/~dcswww/MONET/

MONET (formerly known as QRNET) is the title of a European group of researchers who have submitted a proposal to the EC for funding to establish themselves as a Network of Excellence.
These researchers are involved in qualitative reasoning, qualitative physics, qualitative modelling, functional modelling, multiple modelling and applications of these techniques.
The aim of a Network of Excellence is to bring together the main European research teams from industry, academia and research centres sharing a common long-term technological goal, and which aim to coordinate research and technological development, including demonstration, technology transfer, and training activities related to the network's domain.

Exeter Knowledge-Based Systems Research Group

http://www.ex.ac.uk/ESE/KBS/

The research areas include Automated Failure Modes and Effect Analysis for design support, fault diagnosis of dinamic systems, fault diagnosis of processes where predictive modelling is precluded and condition monitoring as support for condition-based maintenance. Main techniques used in these fields include model-based reasoning, qualitative simulation, bond graphs, neural networks in pattern recognition and candidate generation, distributed systems for condition monitoring, and statistical data analysis.

TEKES: Adaptive and Intelligent Systems Applications

http://pena.kareltek.fi/opp/projects.html

The Technology Development Centre of Finland (TEKES) has set up a national technology programme entitled Adaptive and Intelligent Systems Applications. It has several projects. The following are related to the qualitative system modeling: Modelling of Dynamic Systems, Adaptive and Intelligent Systems in Fault Diagnosis, Knowledge-based Fault Alarm Handling in GSM Network.

DV, University Of Duisburg

http://www.fb9dv.uni-duisburg.de/

Research areas at this site include modelling and simulation of industrial processes for monitoring and fault diagnosis (Prof. Geisselhardt); and simulation, testgeneration and fault diagnosis based on structural models (Prof. Hunger).

Robust Fault Detection and Fault Tolerant Systems

http://hcm.uni-duisburg.de/home.htm

The title of their research is Development of Novel Approaches to Robust Fault Diagnosis in Uncertain Dynamic systems using Comparative Model-Based, Fuzzy Logic and Neural Network Techniques.
The objectives can be classified into the following scientific categories:

- Introducing fuzzy logic and neural networks into model-based fault diagnosis to enhance fault supervision techniques in automatic systems.
- Providing a detailed and publishable comparison of existing residual generation methods, based on parity space, observer (state estimation) and identification (parameter estimation) approaches, knowledge-based modelling, and neural models with the goal of combining model-based residual generation with fuzzy logic and neural decision-making.
- Investigating the possibility of using qualitative (symbolic) residual generation together with quantitative (numerical) techniques for fault diagnosis, as a way of improving the reliability and performance of fault diagnosis for uncertain processes.
- Finally, to give a detailed assessment of the most appropriate procedures and of practical issues associated with the combination of robust residual generation methods with fuzzy logic and neural network techniques considering the requirements of typical automatic systems.

DCS Group, TIMA-CMP Laboratory, Grenoble, France

http://tima-cmp.imag.fr/tima/dcs/dcs.html

Research activities of the Diagnosis of Complex Systems Group deal with new approaches of test and diagnosis of VLSI circuits and electronic systems in general, and partly related to macromodeling, behavioral modeling languages. behavioral model generation, artificial intelligence approaches and non classic logic for the test and diagnosis of analog systems.

HUT Control Engineering Lab

http://www.hut.fi/TKK/Yksikot/Osastot/T/Saatotekniikka/

Several research areas are realted to qualitative modelling like Quantitative and qualitative modelling, simulation and control of industrial production, energy and water treatment processes (Virkkunen, Jouko; Golemanov, Ljudmil), Quantitative and qualitative modelling, simulation and control of industrial production, energy and water treatment processes (Virkkunen, Jouko; Golemanov, Ljudmil), and Artificial intelligence in dynamic systems modeling (Hyötyniemi, Heikki).

Model-based Systems and Qualitative Reasoning Group Munich (P. Struss)

http://wwwradig.informatik.tu-muenchen.de/forschung/qreason/General/

The two main areas at this site are Model-based systems and Qualitative Reasoning. Some of the topics related to fault diagnosis are automated diagnosis and diagnostic tools for technical systems, and model-based behavior prediction for ecological systems. Research in qualitative reasoning involves qualitative modeling, temporal and behavior abstraction, multiple modeling, spatial reasoning, and functional modeling.

Active Electronics Communications and Computing

http://www.sunderland.ac.uk/~ts0jti/projects.htm

One of the research projects is Intelligent Methods Of Power Systems Monitoring By Artificial Neural Network And Optimisation Using Evolutionary Computing Techniques (Patrick Wrong - SEAT research student). The objective of this research project is to apply artificial intelligent methods to power systems monitoring. Artificial neural networks (ANN) was chosen to be the monitoring mechanism. The evolutionary computing techniques (Genetic algorithm), will be applied to optimise ANNs.

Berkeley Expert Systems Technology Laboratory (Prof Alice Agogino)

http://pawn.berkeley.edu:80/~best/

Current research areas include Application of Real Time AI/Expert Systems to Diagnostics, Monitoring and Supervisory Control of Mechanical Systems.

Under direction of Prof. A. Agogino, in the Real Time Influence Diagrams for Monitoring and Controlling Mechanical Systems project influence diagrams are used as an architecture for integrating dynamic sensor readings, statistical data, and subjective expertise for solving both the inference and control problems in computer-integrated applications requiring real time performance. IDES (Influence Diagram based Expert System) provides both an influence diagram representational scheme and an efficient computational architecture for performing probabilistic inference and expected value decision making.

In the Monitoring and Diagnosing Manufacturing Processes Using a Neural-Fuzzy Hybrid Architecture (directed by Kai Goebel) a hybrid architecture featuring fuzzy logic and neural networks is described to cope with the shortcomings of the traditional methods of monitoring and diagnosing an unattended milling machine.

A Hybrid Approach to Real Time Fault Diagnosis of Systems via the Integration of Analytical and Knowledge-based Systems (Satnam Alag) aims at developing a monitoring system which uses sensor observation data about discrete events to construct dynamically a probabilistic model of the world. This model is a Bayesian network (influence diagram) which can reason under uncertainty about both the causes and consequences of the events being monitored. This work also address specific monitoring problems, such sensor validation, Data Association and sensor fusion.

The Qualitative Modeling and Simulation Laboratory (Dr. François E. Cellier)
http://www.ece.arizona.edu:8001/~cellier/psml.html

The Qualitative Modeling and Simulation Laboratory concerns itself with the qualitative and mixed quantitative and qualitative modeling and simulation of ill-defined systems, including biomedical systems and economic systems. Fuzzy Inductive Reasoning and Neural Networks are our main analysis and design tools.

Fuzzy and Qualitative Simulation, Comp. Eng. Sec., DEI, Politecnico di Milano
http://www.elet.polimi.it/section/compeng/air/f_simulation/

The aims of this research group is to extend quantitative simulation approaches to simulate models described qualitatively or approximately. They first developed a system (QQSIM - Qualitative and Quantitative Simulator, A. Bonarini, V. Maniezzo) extending a traditional approach to qualitative simulation with some quantitative information and models. Then, they have implemented QUA.SI. (A. Bonarini, G. Bontempi), a system able to simulate algebraic-differential models and fuzzy rules-based models, for both of which initial conditions and internal parameters can be described by fuzzy numbers. QUA.SI. produces an hyperspace where the behavior of the modeled system lays.

Laboratoire d'Intelligence Artificielle (LIA), École Polytechnique, Lausanne
http://diwww.epfl.ch/w3lia/en/activities.html

Research at the Artificial Intelligence Laboratory is specifically oriented towards the different types of reasoning in Artificial Intelligence, which includes Model-Based Reasoning and Qualitative Reasoning, an expert system technology that permits using models rather than rules. In general, the former are easier to come up with and to maintain, which solves the big software engineering problems encountered in expert systems. One of the research projects is Qualitative Spatial Reasoning.

Control Laboratory, EE Department, University of Twente
http://www.rt.el.utwente.nl/

Integrated modelling, design and simulation of physical systems project: the central theme of this research is a multi-disciplinary, integrated approach to modelling physical system behaviour in different engineering domains. It follows an energy-based approach making extensive use of the (multi-)bond graph notation. Results include 20-SIM: a Computer-Aided Modelling, Analysis and Simulation tool, and MAX: a Modelling and Analysis eXpert system.

Qualitative Reasoning Research at Utexas (Prof. Benjamin Kuipers)
http://www.cs.utexas.edu/users/qr/

The Qualitative Reasoning (QR) research group does research in several areas: Qualitative Reasoning about the Physical World (QSIM), Spatial Reasoning and Intelligent Robotics (TOUR and SSH), and Access-Limited Logic for Knowledge Representation (Algernon).

In the first area they have developed a substantial foundation of tools for model-based reasoning with incomplete knowledge: QSIM and its extensions for qualitative simulation; Q2, Q3 and their successors for quantitative reasoning on a qualitative framework; and the CC and QPC model compilers for building QSIM QDE models starting from different ontological assumptions.
The QSIM representation for qualitative differential equations (QDEs) and qualitative behaviors was originally motivated by protocol analysis studies of expert explanations. A QDE represents a set of ODEs consistent with natural states of human incomplete knowledge of a physical mechanism. Qualitative simulation can be guaranteed to produce a set of qualitative behavior descriptions covering all possible behaviors of all ODEs covered by the QDE.

CONFIG Modeling and Simulation Tool

http://tommy.jsc.nasa.gov/~malin/configinfo.html

CONFIG is a prototype software tool that supports integrated modeling, simulation, and analysis of several types of dynamic reconfigurable systems and their failures and operations. Modeling and design evaluation are supported by object-oriented model parts libraries, abstraction and animated graphics. CONFIG supports conceptual design evaluation from early in the product life cycle, by supporting isolated or integrated modeling, simulation, and analysis of the behavior, structure, failures, and operation of system designs. Integration is supported among a number of modeling approaches (component view, behavior view, configuration or flow path view, and procedure view), and among a number of analysis techniques including discrete event simulation and various types of graph analysis.

CONFIG supports abstracted qualitative and symbolic modeling, for early conceptual design. CONFIG system models are structures of connected component (device) models, with operating and failure modes and embedded time-related behavior models. The behavior of each device during a simulation depends on its current operating or failure mode and on changes in its input received from operations actions or from other devices via local connections or global flow path changes. CONFIG operations models are designed to support operation analysis with procedure models, in nominal and anomalous situations. These models are also designed to support analysis of proposed design changes (reconfigured systems and revised procedures) that are developed during operations in response to failures. Operations models are activity structure models that interact with system models. These capabilities enable several types of evaluation of system operability, including analysis of impacts over time of faults, failures, and procedural or environmental difficulties.

Support is provided for analysis in diverse domains, including mechanical and electromechanical systems, distributed computer systems, and chemical processing and transport systems. CONFIG has been used to model and analyze effects of failures in a reconfigurable computer network with alternate communications protocols, and in subsystems of the Space Shuttle Remote Manipulator System. The current Thermal Bus System demonstration model includes a system of connected models of devices for removing heat (e.g., heat exchangers, valves, sensors, accumulator), and a model of a pump safing procedure.

AI Lab, Computer Science Dept., Vanderbilt Univ. (Gautam Biswas)
http://www.vuse.vanderbilt.edu/~biswas/ResearchPages/diagnosis.html

Much of their work in the area of diagnosis has concetrated on the diagnosis of complex, continuous valued systems which has resulted in the DOC system (Diagnoser of Continuous Valued Sytstems). In diagnosing natural systems such as physiology where models of expected behavior are difficult to elicit, they have adopted Association-based Causal Reasoning. Association-based models are represented as a directed graph between effects and causes. Unlike Model-based Reasoning, functional dependencies between observations can be difficult to elicit and quite time consuming across the number of cause-effect relationships present in an extensive domain. Their work has focused on inductively determining such dependencies which can be used to improve the efficacy of diagnosis.

Intelligent Systems Lab., Dept. Of CEE, Heriot-Watt Univ. (Prof. Roy Leitch)
http://www.cee.hw.ac.uk/~isldemo/

The Model Based Diagnosis work started in 1986 with participation in the Esprit Project (QUIC) in which a model based diagnostic system, based on (static) qualitative models, was developed for the diagnosis of operating faults on a steam condenser. Since then the focus of the work has been of the use of qualitative simulations of dynamic systems for the early detection of incipient faults. One of the first such systems, Dynamo, was developed based on fuzzy qualitative simulation and a novel iterative search technique for generating possible fault candidates. The Laboratory has made substantial contributions to the Esprit funded project ARTIST that developed a generic architecture and supporting specification methodology for a range of model based diagnostic applications. The work on methodology has continued under an EPSRC (ACME) grant, MIND: Models in Diagnosis. It is refining the methodological work based on a classification of diagnostic tasks, definition of a primitive model properties and fault characteristics, and the relationship between these problem characteristics and the features of existing solution techniques. the use of multiple models to improve the computational and cognitive efficiency of diagnostic systems is also under development. The models are supported by a generic modelling language, the Component Based Language (CBL), that allows qualitative and quantitative models to be expressed in the same format and to be coupled to a wide range of qualitative and numerical simulation algorithms.
A further collaborative project, Timely, has recently been started to extend the model based diagnosis techniques to reasoning under time constraints and to include repair action within the architecture of the overall system.

5.8.2. Consistency-based diagnosis (Oskar Dressler, Peter Struss)

keywords: *model-based, first order logic, assumption-based truth maintenance*
method:
sheme:
reference: *[D1]*
examples: *GDE (de Kleer and Williams 1987),*
GDE+ (Struss and Dressler 1989, Dressler and Farquhar 1990),
SHERLOCK (de Kleer and Williams 1989)
DP (Struss 1992)
MAGELLAN (Böttcher and Dressler 1993)

This method is a model-based fault diagnosis technique. A model of the correct device is used to predict its expected behavior which can be compared with the actual behavior. The possibly detected discrepancies indicate malfunctioning.

The basic consistency-based method

The basic consistency-based method localises the faults by exploiting the models of correct behavior only. (However, it is extended to include models of faulty behavior, thus enabling the identification of particular faults.) The correct system behavior is modelled componentwise, so deviations can be traced back to individual components.
The method uses first order logic for describing the behavior of components and aggregates of components. Object constants and predicates allow to name the individual components and specify the interactions between them. The components interface with their environment using **ports** wich can be designated by functions. Unary predicates are used to assign values to parameters and variables. Explicitly identifying ports via equalities allows specifying the device structure.
The components can be in two modes: *ok(C)* and *NOT ok(C)*.
The diagnosis problem is the following: we assume that all components are working correctly and this contradicts a set of observations:

$$M \cup OBS \cup D(0, COMPS) \; \alpha \;\; \times$$

where $D(FAULTY, Ok\} \equiv \{ok(x) | x \in OK\} \cup \{\neg ok(x) | x \in FAULTY\}$

(D is the simple mode assignment)

FAULTY: set of faulty components, *COMPS*: set of components, *OBS*: set of observations,

x: contradiction, *SD*: system description

In other words: Based on the system description (SD), current observations (OBS) and components (COMPS) the following expression is satisfiable:

$$SD \cup OBS \cup D(FAULTY, \cdot)$$

The **minimal diagnosis** assumes, that only one component is faulty (the device has been working correctly before).

The diagnostic engine used in this method is based on the General Diagnostic Engine (GDE) by de Kleer and Williams (1987). It computes minimal diagnoses and features:

- handles multiple faults.

- Computes candidates for diagnosis from minimal conflicts, i.e. minimal sets of component mode assumptions derived from detected incosistencies,
- exploits an assumption-based truth maintenance system (ATMS) to identify conflicting assumption sets, and
- uses it as a basis for determining optimal probing points.

The diagnostic cycle is shown on the following figure.

During the **Behavior Prediction**, the system description and observations are used to derive conclusions about variable values. Whenever the sufficient variables are available around a component, the other (missing) variables of the same component are calculated (constraint satisfaction) based on the correct behavior of the component.
The **Conflict Detection** checks the contradictions between variable values. Whenever a variable gets contradictory values in the same context, the supporting assumption must be considered as *nogood*, i.e. an inconsistent environment. The ATMS maintains a set of minimal *nogood*s, therefore the identification of minimal conflicts is trivial for the diagnostic engine. This is the most difficult key step of the operation.
The minimal conflicts contain the essence of the detected discrepancies between model and artifact behavior. The **Candidate Generation and Candidate Ranking** must thus hipothetise a fault for at least one of them. GDE computes hitting sets from minimal conflicts by simultaneously maintaining the set of minimal hitting sets encountered so far. Unfortunately, in worst case both the set of minimal conflicts and the set of minimal diagnoses grow exponentially in the number of device components.
In the **Discriminitation** step the diagnostic agent chooses between several diagnoses based mostly on the likelihood of component failures (which can be based on the manufacturer's specification, and extended by previous observations, failures, etc.).

The main advantage of consistency-based diagnosis systems is that all deviations from normal behavior can be diagnosed without specifying the possible malfunctions. However, human experts use more knowledge during diagnosis about the possible faults. This can be neccesary when lacking observations. Under limited observability of a system, the only way to localize potentially faulty components may be to rule out that faults are presented in the others. This exoneration of components, of course, relies on the assumption that all possible faults are known and refuted.
Therefore, the basic method was extended by incorporating descriptions of faulty behavior as well.

The extended consistency-based diagnosis

In this case, the simple *ok(C)* mode was replaced by a set of **different, mutually exclusive behavior modes,** *modes(C)*, for each component. Accordingly, *SD* can contain models of several component faults which are associated with the respective modes.
The diagnosis in this extended method is to assign exactly one mode to each component finding out what is wrong and which component works properly.
The previously used simple mode assignment is replaced with the comple mode assignment defined as

$$D = \bigcap_{C_i \in COMPS} m_{j_i}(C_i) \ , \quad \text{where} \quad m_{j_i} \in modes(C_i)$$

The concept of a diagnosis remain unchanged, namely a mode assignment that does not contradict the observations.
The incorporation of fault models makes the diagnostic system stronger in that it allows for **fault identification**, i.e. detecting which fault is present. However, the larger mode set grows the complexity of the model and therefore, the cost of the diagnosis. This larger cost could be cut by the **focusing** principle: "Do (or consider) only what appears necessary for the case at hand". Applied to diagnosis, this means not to establish and check fault hipotheses that are not necessary to solve the current problem. However, the focusing problem is not a simple one in automated diagnosis. It could be a bigger problem to identify the proper focus for diagnosis, thus, the focusing principle is complemented by a second one, called the **preference principle**: "Determine and shift the focus according to the order of prefences". The preferences are various focuses sorted in most promising (more likely, more dangerous) - less preferable order.
The example systems using this method are the SHERLOCK, GDE+, DP and MAGELLAN

Diagnosis and Hypotetical Reasoning

The previous section illustrate the importance of control principles that focus the diagnosis activities. The predictive engine must be focused on a substructure of the whole model (but not excluding any part of it from the investigation forever), diagnoses generation must be confined to the most promising diagnoses, etc. The system must be capable of reconsidering and regenerating observations, models, and diagnoses that were neglected before, due to some control decision. It is important to establishing working hipotheses as well as noticing when they turn out to be wrong and to recover from this situation. Hence, the basic framework of consistency-based diagnosis have to be extended in order to

- explicitly represent the various diagnostic assumptions, and to
- explicitly represent the knowledge required for reasoning about the presence of these assumptions as important constituents of any real diagnostic process.

For this purpose, the previously given definition of diagnosis have to be extended in the following way:

$$SD \cup OBS \cup D \cup WHYP'$$

where *WHYP'* is the **working hypotheses**, a subset of the diagnostic hypotheses.

Using the basic consistency-based diagnosys (considering only *ok* and $\neg ok$ modes) this leads to the idea of DP (Diagnosis and Process).

Diagnosis with Multiple Models

Most of the research in the field of diagnosis is focused on problems of the diagnosis procedure, presuming there exists a good model of the device. However, the modeling procedure (by its nature) uses abstractions, simplifications and approximations, resulting that the model could be inadequate in particular cases. It may fail to describe the system's actual state, it may reveal existing contradictions, or may suggest an inconsistency that is only virtual. However, using more precise and detailed models to protect against such errors, tends to make the diagnostic task unnecessary complex.

This dilemma can be solved using **multiple models** of a system and let the diagnostic system use the appropriate model for the particular case. The system description (*SD*) is then considered as a repository for various, alternative models, and the diagnosis process uses a subset *SD'* of it for prediction. It is also required from the diagnosis engine to be able to switch from one model to another carrying over as much information as possible. The first reason for that is it may not be obvious from the very beginning what model is required for the particular case. The second is that different stages in the process require different models (e.g. cheap models for generating initial diagnostic candidates and more detailed ones for discriminating among them).

Using multiple models brings up several important questions to be answered:

- How can a set of multiple models be structured appropriately?
- How can results obtained from using one model carry over to a diagnostic using different model?
- How can the system deal with wrong or contradictory information derived from an inappropriate model?
- How can the system obtain criteria for deciding which model or which part of it to use?

The various relationships among the models can be reduced to two types of fundamental logical relations that sufficient in consistency-based diagnosis.

A model *M'* is a **view** of another model, *M*, if $M \Rightarrow M'$.

A model *M'* is a simplification of *M*, if $\exists \{whyp_i \subseteq WHYP(M) \; \bigwedge_i whyp_i \Rightarrow M'\}$.

In both cases the intentionally simpler and "cheaper" model *M'* can be used as a substitue for the original one, *M*. If the former is refuted, then so is the latter. However, in case of a simplification, one can only be sure if the modeling assumptions hold. The impact on consistency-based diagnosis is captured by the following theorem:

Let $SD' \subset SD$, $WHYP' \subseteq WHYP$, $whyp_0 \in WHYP$, *D* a mode assignment and *M*, *M'* be two models. If *D* is a diagnosis for the system

$$(SD' \cup \{M\}, COMPS, OBS)$$

under *WHYP'* and *M'* is a simplification if *M*: $M \wedge whyp_0 \Rightarrow M'$, then *D* is a diagnosis for the system

$$(SD' \cup \{M'\}, COMPS, OBS)$$

under *WHYP'*, or the modeling assumption $whyp_0$ ha to be retracted:

$$SD' \cup \{M\} \cup OBS \cup WHYP' \cup D \models \neg whyp_0 .$$

Equipped with this logical formalism, multiple models including abstract, simplified, and approximate models can be exploited in consistency-based diagnosis. However, there remains the problem to recognize or establish the various model relations when analyzing or constructing variations of models. After all, the models of the physical systems that are of interest here are usually not given as sets of first order formulas.

Usually, the ordinary representation is given in terms of differential equations involving a number of characteristic physical variables and parameters that often take values in the domain of real numbers, integers, or intervals of such.

Therefore, the behavior of some constituent of the system to be diagnosed is described by (vectors) of possible values of some variables and parameters $v_i \in VARS$ taken from domains $DOM(v_i)$.
A representation is a pair of variables and domain:

$$(\underline{v}, DOM(\underline{v})) = ((v_1, v_2, \ldots, v_k), DOM(v_1) \times DOM(v_2) \times \ldots \times DOM(v_k)).$$

Under the multiple modeling aspect, different representations for the same constituent are allowed, varying $\underline{v}$ and/or $DOM(\underline{v})$. If a constituent is in a particular condition, its respective behavior can be characterized by constraining the set of possible values for $\underline{v}$ which can be expected in a physically realizable situation. Hence, the model is specified by some relation $R \subseteq DOM(\underline{v})$. A change in a model may be caused by the use of different variables, different domains for the same variables, or different relations while the variables and the domain remain the same.

Further Research

The **time-varying behavior of systems** can impose restrictions on the time available for the diagnostic reasoning. The consistency-based method currently is lacking general principles to handle this problem. A **real-time architecture** for diagnostic systems is needed, which is guided by the goal to have a useful dagnosis available at all times. Some present theories of this method can be used to solve this problem, like the method of multiple models, reasoning under simplifying assumptions, etc.

Real diagnostic processes include reasoning **and acting** as well as the aim of **re-establishing the desired functionality**. This method does not include any task of fixing the fault, however, there is a strong relation between fault diagnosis and fault repair. For instance, it does not make sense to spend efforts on discriminating between two faults that require the same repair action. Repair actions can support the diagnosis, (e.g. by replacing a suspect component).

The concept of this method is strongly based on the assumption that the faults do not change the original structure. However, **structural faults** can easily occur, for instance, by a bridge fault, or by overheating of a component by an adjacent one. The structural changes in modeled connections can be easily handled by treating the modeling connections like components that may fail. Dealing with other changes requires the extension of the models with structural descriptions and a theory of diagnosis that includes structural faults.

5.8.3. Inductive Reasoning (François E. Cellier)

keywords:	*behavior patterns, prediction, fuzzy systems, redundant reasoning, finite state machine*
method:	
sheme:	
reference:	*[C5]*
examples:	*SAPS (Uyttenhove, 1979)*
	SAPS-II (Cellier, Yandell, 1987)

Inductive reasoning attempts to induce future behavioral patterns of a system or time series from observation of the behavioral patterns of their past. No assumption is made about the underlying model structure. Inductive reasoning represents a pure behavioral modeling and simulation of systems.
Fuzzy Inductive Reasoning incorporates the advantages of fuzzy systems dealing with uncertanity. The C**ausal Inductive Reasoning** goes on this way farther introducing a voting scheme. It uses multiple independent analists to make predictions under uncertain conditions.

The Modeling Principle in Inductive Reasoning

Inductive reasoning models the behavior of time-dependent phenomena by a pure pattern-matching approach. In order to limit the complexity of available patterns, it simplifies the observed patterns using a discretization process, called **recoding**. Real-valued signals are recoded into a - usually rather small - set of discrete classes. Evidently, this causes infomation loss. Selecting the number of discrete classes relates to the struggle between generality and specificity. The more levels are chosen, the larger will be the expressiveness of the model. However, this goes hand in hand with an increased difficulty of making predictions. The smaller the number of levels chosen, the better will be the predictiveness of the model, but the less useful will these predictions be.
In SAPS-II the recoded behavior is stored in a **raw data matrix**. Each column of this matrix represents one observed variable, and each row represents one time point of the observation. The values of the matrix are in the set of legal levels that the variable can assume.

The next step following the recoding is the **inductive modeling**, in which a qualitative model is induced in the form of a finite state machine relating qualitative inputs to qualitative outputs.
We could represent this relation by a **state transition matrix**. The values of the matrix are transition probabilities between given levels of two observed and recoded variables: $ST_{i,j} = p\{w = 'j' \,|\, v = 'i'\}$. However, this is only a static model of the system.

Our modeling effort is to find these finite automata relations between the recoded variables that make the resulting state transition matrices as deterministic as possible. This finite automata relations, which include the dinamic behavior of the system, could look like:

$$y_1(t) = \tilde{f}(y_3(t-2\delta t), u_2(t-\delta t), y_1(t-\delta t), u_1(t)),$$

where $\tilde{f}$ represents a qualitative relationship. (It does not stand for any known or unknown explicit formula, but only represents a generic causality.)
The matrix form of this equation can be represented as follows:

$$\begin{array}{c c} t \setminus x & \begin{array}{ccccc} u_1 & u_2 & y_1 & y_2 & y_3 \end{array} \\ \begin{array}{c} t-2\delta t \\ t-\delta t \\ t \end{array} & \begin{pmatrix} 0 & 0 & 0 & 0 & -1 \\ 0 & -2 & -3 & 0 & 0 \\ -4 & 0 & +1 & 0 & 0 \end{pmatrix} \end{array}$$

In inductive reasoning this matrix is called a **mask.** It contains the same number of columns as the episodical (i.e. recorded) behavior to which it should be applied, and it has a certain number of rows, called the **depth** of the mask. The negative elements of the matrix represent the inputs of the given equation, and the (usually one) positive element represents the output. In this example the inputs are numbered from *-1* to *-4* (the sequence of enumeration is immaterial).
This mask can be used to flatten a dynamic relationship out into a static relationship. We can shift the mask over the episodical behavior, pick out the selected inputs and outputs, and write them together in one row.
After the mask applied to the raw data, the formerly dynamic episodical behavior has become static, i.e. the relationships are now contained within single rows.

Choosing the proper δt can be done following this rule: The mask should cover the largest time constant that we wish to capture in our model, and the depth should not be larger than 3 or 4, otherwise the inductive reasoner will not work well, since the computing effort grows exponentially with the size of the mask.

An inductive reasoning model is simply a set of masks that relate the input variables and previous values of the output variables to the current values of the outputs.
Finding the optimal mask means the compromission between generality and specificity. With growing mask complexity, more and more possible input states exist, and we shall confronted with the situation when every state has ever been observed has been observed once. The precision of the model in case of observed input states will be very good, but the global predictiveness may be still very poor, since the currently observed input state has probably never seen before.
On the other hand, reducing the mask complexity makes the model less specific, it will no longer represent the true dynamics of the observed system, leading to non-deterministic input/output behavior.

Simulation using Finite State Machine

Once the optimal mask has been found and the corresponding finite state machine (FSM) generated, forecasting future behavior is almost trivial. In the step of **deductive simulation** all that needs to be dobe is compare newly observed input patterns witch those stored in the FSM, and read out the corresponding output patterns. If the FSM is not totally deterministic, i.e., there are several output patterns for the same input state, then we have several choices: (I) we can report all possible outcomes together with their previous relative observation frequencies, (ii) we can limit the reporting to the most likely outcome, or (iii) we can draw a random number and predict one of the previous observations with the correct (measured) probability of occurrence.
We can use the relative frequency of occurrence of an output pattern for any given input pattern as a measure of correctness of the prediction made.

Two accounts of successful applications of this methodology to a linear system and a Boeing 747 airplane in high altitude horizontal cruise flight were reported in [C1] and [V1].

Fuzzy Inductive Reasoning

Introducing **fuzzy measures** into the recoding means replacing the simple class values with qualitative triples, consisting of the previously introduced class value augmented by a fuzzy membership function value and a side value. The role of class value remains the same as before. The fuzzy membership value denotes the level of confidence expressed in the class value chosen, and the side value tells us whether the qualitative value is to the left or to the right of the peak value of the associated membership function. This latest measure is a speciality of this method, it is responsible for preserving the complete knowledge in the qualitative triple that had been contained in the original quantitative value. The fuzzy recoding is also called fuzzification.

The determination of the optimal mask and the process of forecasting remain basically the same. However, instead of measuring the likelihood of a certain outcome through the frequency of its occurrence, the fuzzy membership function values are now used to compute a measure of confidence. Therefore, the confidence information not thrown away in the process of recoding sharpens the discrimination power of the methodology, and thereby significantly reduces the ambiguity of predictions made by it.

Using fuzzy techniques also makes possible to make **quantitative predictions** of output variables by means of inverting the process of fuzzy recoding (defuzzification).
It has been demonstrated that the predictions obtained in this manner are good enough for mixed quantitative and qualitative simulations ([C2], [C3], [N1]) and for the systematic design of fuzzy controllers ([M1]).

Causal Inductive Reasoning

To improve the inductive reasoner (i.e. to reduce its information loss) a **voting scheme** could be introduced. Instead of having only one selected mask, three suboptimal mask is selected and the final decision is made by a simple voting procedure.
A distance measure between predictions is introduced, and the two nearest prediction is choosen after each independent predictor has made its forecast. The final prediction is the mean value of the two choosen predictions.

In **Causal Inductive Reasoning** the recoding is also changed. The real-valued variables are recoded into qualitative quadruples, in which the first three piece of information is the same that were used in fuzzy inductive reasoning. The forth value is a qualitative derivate value that indicates whether the recoded variable is currently increasing, decreasing, or staying at about the same level.
This is basically the extension of the above mentioned voting scheme allowing more and more far “voters” (with lower and lower quality) to contribute to the final decision.

At the time of writing this report this method was under development. Some of its issues needed more consideration. However, the basic idea of this method is clear and it is shown that using Causal Inductive Reasoning could efficiently help to increase the precision of the predictions.

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