Constraint Processing Techniques for Model-Based Reasoning about Dynamic Systems

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1 Introduction

My research work concerns different areas of Computer Science:

- Model-Based Reasoning (MBR), and more specifically Model-Based Diagnosis (MBD);
- Qualitative Reasoning (QR), including aspects of temporal reasoning (qualitative simulation) and causal reasoning;
- Constraint Processing (CP), as a convenient formalism for modeling and solving complex systems and problems.

The term **Model-Based Reasoning** is generally used to identify a large spectrum of modeling formalisms and reasoning methods, used to infer new knowledge about a given system relying on a specific abstraction (model) of the system. The type of **model** employed depends on the objectives and on the available knowledge. **Qualitative Reasoning**, through the application of suitable abstractions, usually allows us to:

- reason on *classes* of problems;
- reason with *incomplete and/or approximate information* (qualitative model);
- reduce the practical complexity of the reasoning task.

For these reasons, the intelligent agents often use qualitative methods for representing and reasoning about complex systems, in particular when only incomplete or approximate information is available (as it is almost always true in the real world).

In this context, **constraint-based languages and methodologies** (instantiated on a specific domain, such as real values, intervals, finite domains) can be useful for specifying (qualitative or quantitative) models. The Constraint Programming community has also proposed several **heuristic methods** to improve solving combinatorial problems.

Qualitative Reasoning and Constraint Programming are usually considered as quite distinct research areas, but indeed they share several aspects and problems. Existing work trying to show the similarities of the approaches used in these two research areas are still limited [14].

One of our main goal would be to compare and possibly integrate different techniques used in MBR/QR and CP, with a particular emphasis on practical aspects (e.g. realizability and efficiency issues of the proposed algorithms or solutions) and applications.

2 State of the art

In this section, we briefly report some important results and recent work in order to introduce the state of the art of MBD/QR and CP.

2.1 Model Based Diagnosis

In recent years there was an increasing interest in the automated diagnosis of complex systems [5]. The model based approach allows information reuse for different tasks or different versions of the system; for these reasons it is useful and strongly recommended when dealing with complex systems.

For diagnostic applications, it is usually necessary to model not only the normal behavior of the system ("OK" mode), but also its possible faulty behaviors (fault models). In particular, reasoning on dynamic systems (systems with an internal state, which very often cannot be observed) usually requires complex and expensive reasoning. This fact has lead to state-based approaches for diagnosing specific classes of dynamic systems [8, 15], and has encouraged the research of different approaches for handling the complexity of reasoning about temporal aspects, such as qualitative reasoning, causal reasoning and heuristic methods.

2.2 Qualitative Reasoning

The QR literature contains several classes of formalisms for modeling and reasoning with incomplete or approximate information, including approaches based on qualitative intervals [13], orders of magnitudes, sign algebra. Qualitative simulation [6] is often used to deal with the *temporal aspects* in the behavior of a dynamic system in several applications such as design, system analysis and diagnosis. However, the qualitative simulation suffers from the following problems:

- it has a combinatorial complexity;
- it produces ambiguous behavior descriptions.

These issues limit the scalability of the qualitative simulation approach on real world systems, and impose severe restrictions on its applicability to on-line diagnostic systems [1], in which the diagnostic engine must react within a strict time interval in order to avoid damages or risks. To cope with such issues, different classes of approaches have been proposed:

- **problem abstraction and decomposition** techniques, in order to focus the qualitative simulation task on "relevant aspects"; an example of this class of approaches is DecSIM [2], a constraint-based qualitative simulation algorithm which exploits a component-based decomposition for reasoning on independent subsystems.

- extensions of the modeling language in order to support **additional knowledge** in the model (e.g. temporal or causal knowledge);
- **Incomplete Reasoning** approaches, for example the efficient algorithm for diagnosis of dynamic systems based on Temporal Causal Graphs (TCGs) proposed in [9].

2.3 Constraint Programming and heuristic methods

Constraint Programming heuristics are often required in order to solve complex models represented as CSPs. Such methods can be classified in (at least) three different categories:

- Constraint Programming "classic" heuristics, such as (static or dynamic) variable ordering, constraint ordering, value ordering.
- Dynamic Constraint Programming (DCP) and local repair techniques for inference reuse between "similar" problems.
- Inference storage and retrieval (constraint recording and solution reuse), which is a form of learning. The **Truth Maintenance Systems** (TMSs) can be used for these tasks.

3 QR + CP for Diagnosis

The integration of QR and CP techniques has been explored and applied to a specific task, model-based diagnosis (MBD) of dynamic systems.

In particular, our cooperation within the VMBD[1] Brite-Euram project allows us to apply Model-Based Diagnosis and Constraint Programming techniques for the diagnosis of real life automotive subsystems. The considered tasks include system behavior computation and analysis, model-based diagnosis, reconfiguration and recovery after a fault occurrence.

We mainly focused our attention on dynamic continuous physical systems, in which the presence of feedback control loops and compensation effects usually makes fault localization a complex task.

Qualitative Equations and Constraint-based Modeling One of the most challenging issues when dealing with complex (dynamic) systems is the choice of an adequate modeling languages and efficient reasoning algorithms. Qualitative Reasoning techniques in combination with constraint based languages can be used to model technical systems and to cope with the complexity of such tasks in practical applications.

Very often, a technical system is modeled in terms of *differential equations*[2] by engineers. Moreover, in controlled dynamic systems, the system variables

[1] Vehicle Model-Based Diagnosis.

[2] Possibly including appropriate *parameters*, whose values correspond to different (correct or faulty) *behavior modes* of the system.

are often varying according to the system state, its (correct or faulty) behavior mode, and a number of external inputs; therefore a *normal range* of values cannot be easily given. In these cases it is necessary or convenient to reason in terms of relative (instead of absolute) behaviors; for this reason *Qualitative Deviations Equations* (QDEs) have been introduced and appear to be a useful modeling language for qualitative reasoning applications such as diagnosis [8,1] and simulation [3,10].

In such applications, **constraint languages** are useful both for modeling the system and for reasoning on the model. Of course, Qualitative Reasoning about continuous systems also requires domain *abstraction* over a finite set of values. One such abstraction is the sign algebra with domain $S = \{-, 0, +\}$, which has been used in several application domains. Then, operations on qualitative variables (such as addition $\oplus$ and multiplication $\otimes$) are naturally defined as relations (i.e. **constraints**) rather than functions, since in some cases the result is ambiguous (e.g. adding a positive and a negative number: $+ \oplus -$).

Qualitative reasoning across time involves two fundamental types of reasoning, both of them expressed in terms of CSPs:

- *intra-state* reasoning, which in this case means solving the CSP corresponding to a set of equations and assigning a value to each (qualitative) variable;
- *inter-state* reasoning, which involves reasoning on constraints relating values of variables (and their derivatives) in a qualitative state and its successor.

In [12,7], we restrict our attention to the case where our model is a set of qualitative equations, and each one can be written in the form:

$$s = (f_{11} \otimes \ldots f_{1k_1}) \oplus \ldots \oplus (f_{p1} \otimes \ldots \otimes f_{pk_p}) \qquad (1)$$

where s and f_{ij} are qualitative variables over a given finite domain S (e.g. the sign domain), and $\oplus$ and $\otimes$ are qualitative operations defined over S (such as addition and multiplication). We call this language L_{QDE} for brevity.

CSP decomposition. In [7], we focus our attention on CSPs derived from systems of qualitative equations of the form (1), and we propose *cycle cutset* decomposition [4] as an heuristic that proved to be effective on the class of CSPs considered here. In order to apply the cycle cutset heuristic to such class of structured CSPs, it should be noted that each equation of the form (1) (if it does not contain more than one reference to the same variable) gives rise to a tree structured constraint graph (i.e. a cluster of constraints). Then we can represent the structure of our CSP as a bipartite graph $G = (V_1 \cup V_2, E)$, in which nodes in V_1 represent shared variables (i.e. variables appearing in more than one equation), nodes in V_2 represent equations, and edges $(v, u) \in E$ represent the occurrence of a variable $v \in V_1$ into an equation $u \in V_2$.

G is a compact representation of the structure of the original CSP model, and our objective is to develop an efficient algorithm for computing an optimal (i.e. minimum) cycle cutset for the CSP based on this bipartite graph. This problem is called One Side Minimum Feedback Vertex Set on Bipartite Graphs. "One side" means that only vertices in V_1 can be removed from G and contribute to form a feedback vertex set (nodes in V_2 represent equations, and therefore cannot contribute to the feedback vertex set).

In [7], after formally defining the One Side MFVSBG problem, we propose an exact (or anytime) branch and bound algorithm for the One Side MFVSBG, in which bounds are computed based on a spanning forest of the bipartite graph. This algorithm provides a way to evaluate heuristics and approximate algorithms.

Causal Approach. In [11] we presented a causal approach for qualitative simulation-based diagnosis of dynamic systems. In [10] we presented **a constraint-based causal simulation algorithm** and we show how using causal knowledge about the system behavior, it is possible to enhance diagnostic results and the efficiency of qualitative simulation. In particular, we use causal constraints to model state transitions from the "OK" mode to each specific fault mode of the system. This approach, compared with state-based diagnosis, can yield better diagnostic results by pruning spurious solutions. Compared with the "classic" simulation-based approach, a significant performance gain in terms of number of computed states has been obtained.

Our approach has been compared with other approaches for diagnosis of dynamic systems based on temporal causal graphs. For example, [9] presents a causal algorithm for diagnosis, which is efficient but it does not take into account the possibility of ambiguous results contributed through different causal paths.

Online Diagnosis. When focusing on online diagnosis of dynamic systems, we must take into account additional constraints imposed by safety considerations and by the real time environment. This means that the diagnostic system, when a given fault occurs (or is suspected), must produce results and react within a strict time interval in order to avoid damages or risks to other parts of the systems or to users.

For these reasons, we proposed a compilation-based MBD approach for online diagnosis of dynamic systems. This allows us, on one side, to exploit complex reasoning methods (such as qualitative simulation and constraint satisfaction), and on the other side to build an efficient diagnostic engine, which can also be implemented on board of real systems (e.g. cars). We experimented this methodology on automotive subsystems within the VMBD project. In particular, we adopted decision trees as a compact and efficient way for representing diagnostic knowledge [1].

The cooperation with industrial and academic partners has lead to the development of a **constraint-based diagnostic engine**, a C++ software system which integrates several modules: a constraint solver on finite domains, a basic ATMS, a candidate generator, a decision tree generator, and a user interface.

4 Future Work

Possible future work and research directions include:

- The integration of a constraint solver and a focused ATMS system, in order to develop an efficient inference engine, possibly specialized for qualitative simulation applications, whch should be able to reuse inferences made at different time points (i.e. in different states).
- Evaluation and integration of constraint-based heuristics for solving (or adapting) models expressed as CSP.

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