Towards a scheduling application using fuzzy temporal constraints

Marco Falda
Ph. D. student at the "Dottorato in Ingegneria Informatica ed Elettronica Industriali",
Dept. of Information Engineering - University of Padova
V. Gradenigo 6/B - 35131 Padova - Italy
Phone: 049-8277740, email: marco.falda@dei.unipd.it

Extended Abstract[1]

The main objective of this research is the development of a temporal reasoning system able to manage qualitative and quantitative information also affected by vagueness and uncertainty; this is, in fact, the usual way in which temporal information about the external reality reaches us.

A well-known method for modelling temporal reasoning problems is CSP. A limit of this method is its intractability, and there are two directions that can be considered in order to reduce the computational complexity: the first is the development of heuristic techniques that prune the search space, the second is the definition of tractable sub-algebras to work with.

Classic CSPs are based on crisp constraints (i. e. constraints that are either completely satisfied or violated), for this reason over-constrained problems do not have solution while under-constrained problems have multiple solutions. Furthermore CSPs can not express uncertain or vague information.

The above limits can be overcome using the FCSP theory (Dubois et al., 1996) that replaces the crisp constraints with fuzzy relations, that is constraints extended with possibility distributions; these distribution allow the auto-relaxation of the constraints in the over-constrained problems and add an order among multiple solutions of the under-constrained problems.

Dealing with a real scheduling problem, two types of constraints may be present: qualitative and quantitative. As far as the qualitative constraints are concerned, the classic framework is the Allen's algebra (Allen, 1983); here the temporal entities are intervals and there are 13 atomic disjunctive relations. As far as the quantitative constraints are concerned, the main classical model is that proposed by (Dechter et al., 1991).

Real problems are usually affected by vagueness and uncertainty, because a problem can be known partially and/or in a imprecise manner. So it is important include in a scheduling system fuzzy information.

[1] This research is developed in collaboration with S. Badaloni (Univ. of Padova - Italy) and M. Giacomin (Univ. of Brescia - Italy)

Qualitative constraints have already been extended to the fuzzy case in IA^{fuz} algebra (Badaloni and Giacomin, 2000a); quantitative constraints are similar to those in FCN (Godo and Vila, 1995) and have trapezoidal possibility distributions that represent the uncertainty or preference degrees.

Another approach by (Khatib et al., 2001) is based on a simple merge of TCSPs and soft constraints, where soft constraints are represented by a general framework built on semirings (Rossi et al., 1997). They focuse their attention on STPPs (STPs with preferences) and associate to each constraint a semi-convex preference function. We adopted the representation by means of trapezes because they can model more easily than semi-convex functions various temporal constraints affected by uncertainty and they are enough expressive (Dubois & Prade, 1989).

Furthermore, our research focuses on the integration of qualitative and quantitative temporal constraints in a fuzzy framework; the procedure is a generalization of the Meiri's framework (Meiri, 1996): we define a qualitative fuzzy algebra and also the transformation functions that map the qualitative relations into quantitative relations and vice versa.

In (Badaloni and Giacomin, 2000b) the optimum solution is obtained by means of a Branch&Bound algorithm. This procedure instantiates the variables in static order and prunes the search space by applying the Path-Consistency algorithm whenever a new constraint is tried. It is quite fast because the data structures for the constraints are simple as well as the operations on the constraints; furthermore the fuzzy qualitative Allen relations are suitable for clever heuristic techniques in the path-consistency algorithm that improves the speed.

We generalize the IA^{fuz} algebra algorithms embedding the constraints in abstract data types maintaining, when applicable, all the heuristic techniques.

Three ways that can improve the computational efficiency and the flexibility of our previous Branch&Bound algorithm are presented here:

1. moving from the recursive nature of the Branch&Bound algorithm to an iterative strategy;
2. applying heuristic techniques to order both the variables and the values of the variables;

3. adopting a backjumping technique that tries to identify the conflicting constraints.

The first step renders the algorithm similar to a greedy local search procedure that explores the solution space choosing always the more promising instantiation. In a local search algorithm several strategies can be adopted, for example in (Selman et al., 1992) three directions are considered: the choice of the initial instantiation, the kind of the local changes and the criterion for rate the current solution.

We think that the best initial instantiation is that which picks the atomic relations with the maximum degree of preference; in this manner if a solution is found it is necessarily the optimum solution.

Furthermore, local changes can follow two opposite methods: first-improvement ("hill-climbing") or best-improvement ("steepest-descent"). The former accepts every change that enhances the solution, the latter instead is a greedy algorithm that chooses always the best possibility. We follow the second criterion with some differences. In fact the second and the third of the previous listed steps are both "steepest-descent" approaches, but the second orders the variables to reach as soon as possible the best solution, the third tries to minimize the dead-ends, maintaining the same goal. It is analogous to the principle of choosing the variable that minimize clauses not satisfied used in GSAT algorithm (Selman et al., 1992).

A known problem of the local search is that the local minima can entrap the algorithm in a solution that is not optimal; the local minima are the cause of the incompleteness of the local search algorithms. Many approaches have been proposed to reach the global optimum, for example simulated annealing, tabu search or genetic algorithms (Kirkpatrick et al., 1983), (Glover, 1989), (Holland, 1992); in the field of NP decision problems a promising way is GSAT (Selman et al., 1992). An inprovement of the techniques proposed by Selman (Selman et al., 1992) can be achieved by applying ordering heuristics both to the variables and to the values of the variables, since this aid to keep track of the remaining instantiations.

By using a local strategy, backjumping becomes easier because it is a simple choice on the next variable to instantiate, whereas backtracking algorithms have to jump to the right node of the searching tree and to skip the deeper ones (point 3).

Challenging applications of the new system are diagnostic reasoning and scheduling.

In diagnostic applications there is the need to match some hypotheses with a database of initial and partially known facts with the new data inferred; moreover there could be multiple reasoning contexts. From these considerations and also from tractability issues involving manageable subalgebras comes the idea of using labelled constraint satisfaction networks (Barber, 2000). In these networks labels associated to every atomic relation give to the network itself additional properties bringing the temporal context information. Our idea is to associate to these labels other useful information depending on the domain of application.

In AI the most common approach to solving a scheduling problem is to represent it as a constraint satisfaction problem. The variables model the decisions while the contraints limit which combinations of decisions are valid (Smith et al., 2000).

With a system able to treat fuzzy constraints it is possible to model the problems in a more flexible manner. For example we have considered a typical temporal problem example proposed by (Meiri, 1996) in which two people have to organize their travel to the office. Our new scenario deals with the possibility that an accident delays a route or that one of the two people assigns a higher priority to a certain meeting. By modifying the corresponding constraints also the scheduled times change accordingly. Another application of fuzzy constraints is in scheduling problems where data are vague and uncertain or in human-computer interfaces where the vagueness of the natural languages has to be represented.

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