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The Path-repair algorithm

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Abstract

In this paper, we introduce a new solving algorithm for Constraint Satisfaction Problems: the path-repair algorithm. The two main points of that algorithm are: it makes use of a repair algorithm (local search) as a basis and it works on a partial instantiation in order to be able to use filtering techniques. Different versions are presented and first experiments with both systematic and non systematic versions show promising results.

1 Introduction

Many industrial and engineering problems can be modeled as constraint satisfaction problems (CSPs). A CSP is defined as a set of variables each with an associated domain of possible values and a set of constraints over the variables.

Most of constraint solving algorithms are built upon backtracking mechanisms. Those algorithms usually explore the search space systematically, and thus guarantee to find a solution if one exists. Backtracking-based search algorithms are usually improved by some filtering techniques which aim at pruning the search space in order to decrease the overall duration of the search.

Another series of constraint solving algorithms are local search algorithms. They perform a probabilistic exploration of the search space and therefore cannot guarantee to find a solution. The interest of local algorithms (e.g. Tabu search [12], GSAT [25]) is that, following local gradients in the search space, they may be far more efficient (wrt response time) than systematic ones to find a solution.

Several works have studied cooperation between local and systematic search [6,8,20,22,23,30]. Those hybrid approaches have led to good results on large scale problems. Three categories of hybrid approaches can be found in the literature:

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(1) performing a local search before or after a systematic search;
(2) performing a systematic search improved with a local search at some
points of the search (typically for optimisation problems, to try to improve
the quality of a solution);
(3) performing an overall local search, and using systematic search\(^1\) either
to select a candidate neighbor or to prune the search space.

The hybrid approach presented in this paper falls in the third category. It will
use filtering methods to both prune the search space and help in choosing the
neighbor in a local search. This leads to a new search technique over CSPs
which is called \textit{path-repair}. Different variations of this search technique are
discussed, some of them are shown to be complete. Very promising first results
are presented.

The paper is organized as follows. Section 2 gives some notations. Section 3
presents the \textit{path-repair} algorithm. Section 4 discusses related works and fi-
nally section 5 summarizes the first results obtained in the field of open shop
scheduling problems.

\section{Preliminaries}

A CSP is a couple \(<V, C>\) where \(V\) is a set of variables and \(C = \{c_1, \ldots, c_m\}\)
a set of constraints. Domains of the variables are handled as unary constraints.

For a given constraints set \(S = \{c_1, \ldots, c_k\}\), \(\hat{S}\) will be the logical conjunction
of the constraints in \(S\): \(\hat{S} = (c_1 \land \ldots \land c_k)\). By convention: \(\hat{\varnothing} = \text{true}\).

Classical CSP solving simultaneously involves a filtering algorithm (to \textit{a priori}
prune the search tree) and an enumeration mechanism (to overcome filtering
algorithm incompleteness). For example, for binary CSP over finite domains,
arc-consistency can be used as filtering technique. After a filtering step, three
situations may arise:

(1) the domain of a variable becomes empty: there is no feasible solution;
(2) all the domains are reduced to a single value: those values assigned to
their respective variables provide a feasible solution for the considered
problem;
(3) there exists at least one domain which contains at least 2 values: search
has not yet been successful. In a classical approach, it would be time for
enumeration through a backtrack-based mechanism.

\(^1\) Note that filtering techniques can be considered as a limited form of systematic
search.
In a more general way, for any filtering algorithm $\Phi$ applied on the set $C$ of constraints of a given CSP (let $C' = \Phi(C)$), there exists a function $\text{obviousInference}$ which, when applied on $C'$, answers:

- $\text{noSolution}$ iff it is immediate to infer that no solution can be find for $C$ (as in situation 1 above).
- $\text{allSolution}$ iff the current constraints system\(^3\) can immediately provide a solution that verifies all the constraints in $C'$ (as in situation 2 above).
- $\text{flounder}$ in all other situations (as in situation 3 above).

The function $\text{obviousInference}$ has typically a low computational cost. Its aim is to make explicit the use of some properties that depends on the used filtering algorithm. The example of arc-consistency filtering with an empty domain or with only singleton domains has already been given, but a function $\text{obviousInference}$ can be made explicit in many other filtering or pruning algorithms. For example, in integer linear programming, the aim is to find an optimal integer solution. This can be done by using the simplex algorithm over the reals. If there is no real solution or if the real optimum has only integer values, then a $\text{obviousInference}$ function would respectively return $\text{noSolution}$ or $\text{allSolution}$.

Enumerating discrete binary CSPs is assigning a value\(^4\) $a$ to a variable $v_k$ i.e. adding a new constraint $v_k = a$ in the system. For other kinds of problems, enumerating may be different: for example, for numeric CSP, enumerating is adding a splitting constraint (eg. $v_k < a$). When dealing with scheduling problems, enumerating is often adding a precedence constraint between two tasks of the problem.

In the next section, the $\text{path-repair}$ algorithm is presented through an abstraction of the solved problems: they may be discrete binary CSP, numeric CSP as well as scheduling problems. This will be possible thanks to:

1. the parameter $\Phi$ which represents the filtering algorithm used;
2. the function $\text{obviousInference}$, tightly related to the used filtering algorithm, that is able to examine a set of constraint in order to continue or not the computation;
3. the concept of $\text{enumerating}$ constraint. An hypothesis holds over the way such constraints are generated: there exists an integer\(^5\) $N_e$ such that

\[^2\text{A filtering algorithm } \Phi \text{ applied on a set } C \text{ of constraints returns a new set } C' = \Phi(C) \text{ such that } C \subseteq C' \text{ (redundant constraints may have been added).}\]
\[^3\text{We consider that domain reductions are added as redundant constraints in the constraint system.}\]
\[^4\text{a is an element of the domain of variable } v_k.\]
\[^5\text{For discrete CSPs where enumerating constraint are value assignments } N_e \text{ is clearly the number of involved variables. For numeric CSPs } N_e \text{ strongly depends on the}\]
whatever the set $E$ of at least $N$ different enumerating constraints, the call $\text{obviousInference}(\Phi(C \cup E))$ will not answer \textit{flounder}. This condition is necessary to ensure termination (in the case of the systematic version of the algorithm), and is fulfilled by any reasonable search strategy.

3 The path-repair algorithm

The idea of the \textit{path-repair} algorithm is very simple. First observe that:

- current local search algorithms mainly work upon a total instantiation of the variables;
- backtracking-based search algorithms work upon a partial instantiation of the variables.

The ability of backtracking-based search algorithms to be combined with filtering techniques only comes from the fact that they work upon a partial instantiation of the variables. Thus, \textit{a local search algorithm working upon a partial instantiation of the variables would have the same ability.}

Indeed, the \textit{path-repair} algorithm is such an algorithm. The considered partial instantiation is defined by a set of enumerating constraints (as defined above) upon the variables of the problem. Such a constraint set defines a \textit{path} in the search tree.

3.1 Principles of path-repair

The principle of the \textit{path-repair} algorithm as shown in figure 1 is the following: let $P$ be a path in the search tree. At each node of that path, an enumerating constraint has been added. Let $C_P$ be the set of added enumerating constraints while moving along $P$.

The \textit{path-repair} algorithm starts with an initial path (it may range from the empty path, to a path that defines a complete assignment). The main loop first checks the \textit{conditions of failure}\footnote{These conditions depend on the instance of the algorithm; examples are given in the following sections.}. A filtering algorithm is then applied on $C \cup C_P$ giving a new set of constraints $C' = \Phi(C \cup C_P)$. The function $\text{obviousInference}$ is then called over $C'$. Three cases may occur:

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desired precision on the result.
procedure Path-repair(C)
P := initial path
loop
  if conditions of failure verified then
    return failure
  else
    C' := \Phi(C \cup C_P)
    if obviousInference(C') = noSolution then
      let k be a nogood explaining the failure
      P := neighbor(P, k, \Gamma)
    else if obviousInference(C') = allSolution then
      return C'
    else
      P := extend(P, \Gamma)
  end loop

Fig. 1. The path-repair algorithm

- \texttt{obviousInference}(C') = \texttt{allSolution}: a solution has been found. The algorithm terminates and returns C'.
- \texttt{obviousInference}(C') = \texttt{flounder}: the path-repair algorithm tries to extend the current path P by adding an enumerating constraint. That behavior is similar to that of backtracking-based search algorithms. For that purpose, a function \texttt{extend}(P, \Gamma) is assumed to exist that chooses an enumerating constraint to be added and adds it to P. The meaning of parameter \Gamma will be made clear later.
- \texttt{obviousInference}(C') = \texttt{noSolution}: C \cup C_P is inconsistent. We will say that P is a dead-end, or P is inconsistent: P cannot be extended. The path-repair algorithm will thus try to repair the current path by choosing a new path through the function \texttt{neighbor}(P, k, \Gamma). Parameters k and \Gamma will be explained later.

The path-repair algorithm appears here as a search method that handles partial instantiations and uses filtering techniques to prune the search space. The key components of this algorithm are the neighboring computation functions (\texttt{neighbor}) and the extension functions (\texttt{extend}).

3.2 Properties of the neighborhood of path-repair

In a local search algorithm such as GSAT (on boolean CSPs), an inconsistent instantiation is replaced by a new one built from the first one by negating the value of one of its variables. That variable is chosen by a heuristic (for example: the one whose negation will allow the greatest number of clauses
to become satisfied). More generally, a local search algorithm uses complete instantiations (called states) and replaces an inconsistent state with another state chosen among its neighbors.

The path-repair algorithm works in the same way except that it uses partial instantiations (paths): as soon as a path becomes inconsistent, one of its neighbors needs to be chosen. A path (partial instantiation) synthetizes all the included complete instantiations. Switching paths is like setting aside many irrelevant complete instantiations in one movement.

Like any local search algorithm, path-repair may use a heuristic way to select an interesting neighbor. The algorithm can even choose a neighbor in order to implement a systematic search algorithm. Completeness comes from the fact that a path summarizes numerous complete instantiations.

The following sections discuss neighboring path, heuristic choices and specific techniques leading to a systematic algorithm. We previously introduced a parameter $\Gamma$ in the neighboring computation functions (neighbor) and extension functions (extend). $\Gamma$ can be used to store a context that varies according to the chosen version of the algorithm. In the primitive version that is being presented in this paper, that context is not used.

3.3 Neighboring path

It seems to be a good idea to select a neighboring path $P'$ which does not have the drawbacks of the current path $P$ (recall that in path-repair, neighbors of path $P$ are computed iff $P$ is inconsistent). For example, it would be interesting to get to a consistent neighbor $P'$ i.e. such that $\text{obviousInference}(\Phi(C \cup C'_p)) = \text{allSolution}$. Obviously, that is not affordable to compute in the general case.

Therefore, we may prefer to get at least to a partially consistent neighbor $P'$ i.e. such that $\text{obviousInference}(\Phi(C \cup C'_p)) \neq \text{noSolution}$. Unfortunately, the only way to get there (without using computing resources) is to get back to an already explored node but, doing so, we would achieve a kind of backtracking mechanism, what is not wanted in the path-repair algorithm.

Nevertheless, what can be done is to avoid the neighbors that can already be known as inconsistent. Such an information can be extracted from an inconsistent path $P$. Indeed, inconsistency means that $\hat{C} \land \hat{C}_P \Rightarrow false$. It is possible to compute a subset of $C_P$ that is alone inconsistent with $C$. Such a subset will be called a nogood [7].

**Definition 1 (Nogood)** A nogood $k$ for a set of constraints $C$ and a path
\( P \), is a set of constraints such that: \( k \subset C_P \) and \( \hat{C} \land \hat{k} \iff false \).

As long as constraints in a computed nogood \( k \) remain altogether in a given path \( P' \), that path will remain inconsistent. Therefore, in order to get a path with some hopes to be consistent, we need to remove from the current path \( P \) at least one of the constraints in \( k \).

Note that if current path \( P \) is inconsistent, \( C_P \) is a valid nogood. Obviously, a strict subset will be much more interesting and will give a more precise neighborhood. A minimal (for the inclusion) nogood would be the best, but it is very expensive to compute one [28]. Therefore, non minimal nogoods will be computed in practice.

As for now, our neighborhood remains very general. In the following, more interesting neighborhoods are described. Our point here is to show that the concept of nogood is crucial for path-repair:

- nogoods allow relevant neighborhoods to be considered,
- nogoods can be used to derive efficient neighbor selecting heuristics for a non-systematic path-repair algorithm,
- nogoods can be used to derive a complete path-repair algorithm.

Nogoods are provided by the filtering algorithm as soon as it can prove that no solution exists in the subsequent complete paths derived from the current partial path. In filtering based constraint solving algorithms, a contradiction is raised as soon as the domain of a variable \( v \) becomes empty. Suppose that, for each value (or set of values) \( a_i \) removed from the domain of \( v \), a set of enumerating constraints \( k_i \subset C_P \) is given. \( k_i \) is called a removal explanation for \( a_i \) and is such that: \( \hat{C} \land \hat{k_i} \iff v \neq a_i \). If so, \( k = \bigcup_i k_i \) is a nogood since no value for \( v \) is allowed by the union of \( k_i \). Therefore, in order to compute nogoods, it is sufficient to be able to compute an explanation for each value (or set of values) removal for the domain of the failing variable.

Value removals are direct consequences of the filtering algorithms. Therefore, value removal explanations can be easily computed by using a trace mechanism within the filtering algorithm and memorizing the reason why a removal is done [16].

For example, let us consider two variables \( v_1 \) and \( v_2 \) whose domains are both \( \{1, 2, 3\} \). Let \( c_1 \) be the constraint: \( v_1 \geq 3 \) and let \( c_2 \) be the constraint: \( v_2 \geq v_1 \). Let us assume the used filtering algorithm is arc-consistency filtering. The constraint \( c_1 \) explains the fact that \( \{1, 2\} \) should be removed from \( v_1 \). Afterwards, \( c_2 \) forces to remove \( \{1, 2\} \) from \( v_2 \). An explanation of the removal of \( \{1, 2\} \) from \( v_2 \) will be: \( c_1 \land c_2 \) because \( c_2 \) makes that removal only because previous removals occurred in \( v_1 \) due to \( c_1 \).
3.4 Path-repair instances

3.4.1 Heuristic choice of neighbors

In a local search algorithm, the neighbor selection is very important. Many heuristics may be used. For path-repair it is the same, different heuristics can be used.

As for now, we have defined a neighbor of a path $P$ according to a nogood $k$ as a path that does not contain at least one constraint from $k$. Indeed, a more precise neighborhood can be computed. Let $c$ be a constraint to be removed from $C_P$. As long as all the constraints in $k \setminus c$ remain in the active path, $c$ will never be satisfiable. Thus, the negation of $c$ can be added in the new path.

A possible neighborhood for an inconsistent set of constraints $C_P$, according to a nogood $k \subset C_P$ is made from the sets of constraints $C_P$ different from $C_P$ by the negation of one constraint in $k$. Let us take an example. Let $P$ be the path $(c_1, c_2, c_3, \neg c_4, c_5)$. Let the nogood $k$ be the set $\{c_2, c_3, \neg c_4\}$. The neighborhood so defined is the set of the three paths $(c_1, \neg c_2, c_3, \neg c_4, c_5)$, $(c_1, c_2, \neg c_3, \neg c_4, c_5)$, and $(c_1, c_2, c_3, c_4, c_5)$.

Now, there remains to specify which neighbor to choose among the above defined neighbors. That degree of freedom for the choice of the constraint in $k$ to be negated allows the use heuristic techniques. In an initial version, we wanted to try to adapt the min-conflict heuristic [19] that minimizes the number of unverified constraints. But, when using a filtering algorithm such a mechanism may not be very efficient: the first unverified constraint stops the algorithm.

In our current implementation, an integer (weight) is associated with each constraint counting the number of times that the constraint appeared in a nogood. The heuristic consists in choosing to negate the constraint with the greatest weight. A similar approach counting the number of times that a constraint has not been verified has been successfully used for GSAT [24].

3.4.2 Tabu path-repair

The tabu version of path-repair uses a tabu list of a given size $s$. The $s$ last computed nogoods are kept in a list $\Gamma$. A valid neighbor is defined as a path that does not completely contain any of the nogoods in $\Gamma$. In other words, at least one constraint in each nogood of $\Gamma$ is not (or is negated) in the new neighbor. To compute such a neighbor in a reasonable time, a greedy algorithm can be used. Figure 2 shows an implementation of the neighbor function for tabu path-repair that has been used for solving scheduling problems. It chooses
function neighbor\( (P, k, \Gamma) \)
/* precondition: \( k \subseteq C_P \) */
add \( k \) to the list of nogoods \( \Gamma \)
if sizeOf\( (\Gamma) > s \) then
    remove the oldest element of \( \Gamma \)
\( L := \) ordered list (by decreasing weight) of constraints in \( k \)
repeat
    remove the first constraint \( c \) from \( L \)
    \( P' := P \) except that \( \neg c \) replaces \( c \)
    if \( C_{P'} \) covers all nogoods in \( \Gamma \) then
        return \( P' \)
until \( L \) empty
return stop (or extend the neighborhood)

Fig. 2. The \texttt{neighbor} function for \textit{tabu path-repair}

to negate the constraint with the greatest weight that, when negated, makes
the new path cover all the nogoods in \( \Gamma \). If such a constraint does not exist,
the neighborhood could be extended (for example, we may try to negate 2
constraints). In our implementation for open shop problems (see section 5),
this case is handled as a stopping criterion.

Note that, in the same way, the function \texttt{extend}(P, \Gamma) should use \( \Gamma \) in order
to correctly extend the partially consistent current path.

3.4.3 \textit{A systematic instance}

Backtracking-based approaches are interesting because they provide system-
atic search algorithms. Filtering techniques are then used for efficiency rea-
sons. Using filtering techniques is even more interesting within local search
algorithms: it can make them more efficient but also complete. Let’s see how
\textit{path-repair} can become a systematic algorithm.

Nogoods bring that completeness. The easy way is merely to keep all computed
nogoods. If during the resolution no valid neighbor exists, the considered prob-
lem does not have any feasible solution. Of course, this leads to potentially
exponential storage space in order to keep all the nogoods. It is possible to
avoid this problem and to keep a polynomial storage space. That is what is
done in algorithms such as \textit{dynamic backtracking} [10], \textit{partial order dynamic

Those algorithms work on an instantiation of the variables which is locally re-
paired using nogoods. The used recording mechanism requires only polynomial
space. For example, considering \textit{dynamic backtracking}:
• Only nogoods for which at most one constraint is not in the current path are kept in $\Gamma$;
• the neighbor to be processed is completely deterministic (the chosen enumerating constraint to be undone is the most recent one in the last encountered nogood).

In path-repair, such a nogood recording mechanism can be used thus providing a systematic search algorithm. Such algorithms can be found in a slightly different way in [16] for dynamic CSPs and [17] for numeric CSPs.

4 Related works

The path-repair algorithm takes its roots in many other works, among which [9] has probably been the most influential by highlighting the relationships between local and systematic search, and by the use of nogoods to guide the search and make it systematic.

Two algorithms have been designed that have similarities with the non-systematic path-repair algorithm (see section 3.4.2):

• The algorithm proposed by Schaerf [23] can be seen as an instance of the path-repair algorithm where
  • the enumerating constraints are instantiations,
  • there is no propagation and no pruning (the filtering algorithm $\Phi$ only consists in checking if the constraints containing only instantiated variables are not violated),
  • it does not make use of nogoods neither in the the neighbor function nor in the extend function.

The common idea, which already exists in previous works [15], is essentially to extend a partial instantiation when it is consistent, and to perform a local change when the partial solution appears to be a dead-end.

• The idea to use a filtering algorithm during the running of a local search has been also used in [26], where an extension to GENET, a local search method based on an artificial neural network aiming at solving binary CSPs, is introduced. This extension achieves what is called “lazy arc-consistency” during the search. The lazy arc-consistency filtering performs a filtering over the initial domains. The result is at most the one obtained by filtering the domains before any search. In path repair, the filtering is applied over the current domains at every step.

The way nogoods are computed by the filtering algorithm is a well-known technique that has already been used for different combinations of filtering algorithm with systematic search algorithms (forward checking + intelligent back-
tracking [21], forward checking + dynamic backtracking [29], arc-consistency + intelligent backtracking [5], arc-consistency + dynamic backtracking [16], 2B-consistency + dynamic backtracking [17]. Nevertheless, as far as we know, the tabu version of path-repair is the first time such a technique is used in combination with a local search algorithm.

5 Solving scheduling problems

Classical scheduling shop problems for which a set $J$ of $n$ jobs consisting each in $m$ tasks (operations) must be scheduled on a set $M$ of $m$ machines can be considered as CSPs upon intervals\(^7\). One of those problems is called the Open Shop problem\([13]\). For that problem, operations for a given job may be sequenced as wanted but only one at a time. We will consider here the building of non preemptive schedules of minimal makespan\(^8\). That problem is NP-hard as soon as $\min(n, m) \geq 3$.

Constraints on resources (machines and jobs) are propagated thanks to immediate selections from [4]. The consistency level achieved by that technique does not ensure the computation of a feasible solution. An enumeration step is therefore needed. For shop problems, enumeration is classically performed on the relative order on which tasks are scheduled on the resources. When every possible precedence has been posted, setting the starting date of the variable to their smallest value provides a feasible solution. Such a precedence constraint is therefore an enumerating constraint as defined in section 2.

One of the best systematic search algorithms developed for the Open Shop problem is the branch and bound algorithm presented in [3]. It consists in adding precedence constraints along the critical path of a heuristic solution in each node. As far as we know, although this is one of the best methods ever, some problems of size $7 \times 7$ remain unsolved.

Enumerating techniques used for the Open Shop problem are interesting for path-repair because they dynamically build independent sub-problems (by adding precedence constraints). We can suppose that path-repair will be able to make profit of that situation.

We first tested systematic versions of path-repair on the Open Shop problem. We obtained a very high improvement in terms of number of explored nodes comparing with the results of [3]. Moreover, a problem of size $10 \times 10$ has been solved for the first time. Those results have been presented in [14].

\(^7\) Variables are starting date of the tasks. Bounds thus represent the least feasible starting time and the least feasible ending time.

\(^8\) Ending time of the last task.
procedure minimize-makespan(C)
P := initial path
bound := +∞
lastSolution := failure
loop
    C := C ∪ “makespan < bound”
    Solution := path-repair(C)
    if Solution = failure then
        return lastSolution
    else
        bound := value of makespan in Solution
        lastSolution := Solution
end loop

Fig. 3. Algorithm used to solve Taillard’s problems

We also tested a tabu version of path-repair. Table 1 presents the results obtained on a series of 30 problems from Taillard [27]. In order to put in perspective our results, we recall results presented in [1,18]. Those papers present tabu searches specifically developed for the Open Shop problem. Those methods both use carefully chosen complex parameter values. Results presented in table 1 show that our simple approach which merely applies principles presented in this paper already gives very good results.

Our implementation uses a tabu list of size 15. The neighbor function is the one given in figure 2. The conditions of failure specifying the exit of the main loop (figure 1) are either “stop” returned by the neighbor function or 1500 iterations reached.

Taillard’s problems are optimization problems. This requires a main loop that calls the function path-repair until improvement is no longer possible (see figure 3). Improvements are generated by adding a constraint that specifies that the makespan is less than the current best solution found. The initial path for each call of the function path-repair is the latest path (which describes the last solution found).

6 Conclusion and future works

In this paper, we introduced a new solving algorithm for CSP: the path-repair algorithm. The two main points of that algorithm are: it makes use of a repair algorithm (local search) as a basis and it works on a partial instantiation in order to be able to use filtering techniques. We showed that the most useful tool to implement that algorithm was the use of nogoods.
Table 1
Results on Taillard’s problems – PR: results using path-repair restricted to 1500 moves without improvement, Dist. represents the distance to the optimum value. L: results obtained by Liauw with 50 000 moves without improvement and A: results obtained by Alcaide et al. with 100 000 moves without improvement. - : represents unknown values.

First experiments with both systematic versions (based upon a managing of the nogoods inspired from dynamic backtracking) and non systematic versions (using a tabu list) of path-repair have shown promising results.

References


