Computer Science
Technical Report

Colorado State University

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July 25, 1995

Technical Report CS-95-103

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Abstract

Partial order planners are very effective in solving simple problems. However, the search space in planning grows quickly with the number of subgoals and initial conditions, as well as less countable factors such as operator ordering and subgoal interactions. There are certain inherent features of these planners like flaw selection and threat resolution that causes this search space explosion. For partial-order planners to solve more than simple problems, the expansion of the search space will need to be controlled. This paper presents four new approaches to controlling search space expansion by exploiting commonalities in emerging plans and by effective threat resolution. These approaches are described in terms of their algorithms, their effect on the completeness and correctness of the underlying planner and their expected performance. The four new and two existing approaches are compared on several metrics of search space and planning overhead.

*This research was supported by a National Science Foundation Research Initiation Award #RIA IRI-9308573 and ARPA-AFOSR contract F30602-93-C-0100. The US Government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright notation hereof

1 Improving Search Efficiency in Planners

Partial order planning is becoming a common method of planning. Unfortunately, but hardly unexpectedly, the search space in partial order planning expands quickly as the problem size increases. Unfortunately, but less expectedly, search space expansion is dependent on a variety of factors, some of which are difficult to predict. A problem that was solved in short order may be made impossible to solve in reasonable time simply by adding an innocuous looking new goal, by changing the ordering of goals or even by adding a few more objects to the problem initial state.

The goal of this project was to determine why it could be so hard to design efficient problem descriptions for UCPOP, a partial order planner. We found that what seemed like trivial problems could not be solved in reasonable time. Indeed, minor variations on the same problem led to UCPOP's being unable to solve the new problem. Using a variety of analysis methods, (described in section 5.1) we determined that the fault lay in UCPOP's selection of flaws to repair and additions to the plan to repair the flaws. As a consequence, we focused on the search strategies employed for these phases of plan generation.

We used UCPOP because it is an easily available, domain independent partial order planner [6]. UCPOP plans by iteratively selecting and repairing flaws in the current plan. A flaw is repaired by adding steps and constraints to the plan. The search control strategy decides which partial plan to select for expansion. In general, UCPOP gives good results on small domains and problems in which subgoals are independent. For problems with interrelated subgoals or those requiring arithmetic, UCPOP often does not find a solution even with very large search limits.

The Least Cost Flaw Repair (LCFR) strategy [4] improved search control in UCPOP by selecting the flaw with the minimum repair cost. The repair cost of a flaw is defined as the number of plans generated to repair it. Open conditions and threats are treated alike. The main drawback of LCFR is the overhead incurred for flaw selection. The total time spent in planning with LCFR can be more than that for UCPOP, even though UCPOP examines far more plans than LCFR. However, LCFR reduces the search space more than other flaw selection strategies [7].

A variant on LCFR, QLCFR [4], assumes the cost of un-repaired flaws to be constant over time; it caches the results of estimating flaw repair costs and uses the cached cost as the estimate in subsequent flaw selection. QLCFR reduced the overhead of LCFR, but at a cost of solving fewer problems.

More graceful degradation of performance can be achieved by identifying aspects of the planner most susceptible to the problem changes and developing methods to ameliorate the search space expansion. This paper presents four new approaches for improving efficiency in a partial order planner by exploiting commonalities between proposed plans during two phases of planning: flaw selection and plan refinement. These approaches are described in terms of their algorithms, their effect on the completeness and correctness of the underlying planner and their expected performance when compared to two existing approaches. In addition for each modified approach its correctness and completeness are formally proven.

Finally, the new and existing approaches are compared on several metrics of search space and planning overhead.

2 Approach 1: Similar Flaws and LCFR (Templates)

LCFR is expensive because it estimates separately the cost of repair for every flaw in every potential extension to the current plan. However, in most problems, flaws can be similar; they involve the same type of condition and are amenable to repair by the same fix. For example, flaws in the Blocks World domain are commonly of the form `(on ?x ?y)` or `(clear ?x)`. The resolution of any flaw of these forms is likely to be the same (e.g., add an action to move the indicated block); hence, we can expect the cost of flaw repair to be *roughly* the same for flaws with similar forms.

Consequently, we exploit the similarity in flaws to reduce the number of repair cost estimates to be made. In particular, we assume that at a particular stage of plan refinement, the repair cost is the same for all similar flaws. Other than this approximation, repair cost is computed similar to LCFR scheme.

QLCFR also approximated the repair cost of flaws by estimating once and re-using the estimate. The difference between our approach and QLCFR is that QLCFR cached the estimate and re-used it in *subsequent* plan refinements rather than applying it to similar flaws at the same point in plan refinement. Our approach allows recently acquired information to be incorporated in estimating cost.

The first step in UCPOP towards deciding how to change a developing plan is to identify and group together identical open conditions in the plan. Two open conditions are said to be *similar* if they have the same predicate. For example, `(pred1 ?x)` and `(pred1 ?y)` are similar. A set of similar open conditions with predicate `p` are said to form a template `p`. All of the open conditions in a plan can be grouped into a set of templates.

We assume that when open conditions are similar, the order in which they are selected for repair does not matter. Thus, the repair cost of a template is estimated by finding the repair cost of the first member of the template.

This approach approximates only the cost of open conditions. Threats are not easily grouped because they do not involve variable bindings. Thus, similar threats often do not have similar resolutions and are often resolved as a side effect of repairing some other flaws. Consequently, a uniform repair cost would not be a reasonable approximation of the actual costs.

Open conditions are considered only if a plan does not have any threats. If a plan has threats, the one with the minimum repair cost is selected; otherwise, the first member of the template with the minimum repair cost is selected.

2.1 Expected Performance

We expected that the average number of plans examined before finding a solution in this scheme should be comparable to that of LCFR, while the overhead should be much less

than that of LCFR. Overhead is defined as the number of extra plans created in service of estimating flaw cost. Since only a subset of the open conditions are evaluated in the templating approach, on the average, its overhead should be less than that of LCFR. However, in the worst case, the templating approach can incur more overhead than LCFR when the estimate for one member of the template does not generalize to the rest; potentially causing additional backtracking. Empirical performance is reported in Section 6.

2.2 Correctness and Completeness

Because only flaw selection is modified, the correctness and completeness of UCPOP is maintained by the templating approach.

3 Approach 2: Templates with Repair Reuse

With Templates, open conditions are grouped to estimate repair cost. We extend this idea to the next step: selecting (or *reusing*) similar actions to add to repair similar flaws. Consequently, given that an action is added to the plan to repair a flaw of a particular type, another instance of the same action can be added, at the same time, to repair another flaw of the same type. This sense of reuse is much more limited and local than what is typically meant by plan reuse (e.g., [5]); it is constrained to reusing the occasional step within a plan being developed.

Consider a plan P with a set of flaws F. F can be grouped into a set of templates $T = \{T_1, T_2, \ldots T_m\}$. Each T_i consists of a set of similar flaws. Let T_{min} $(1 \leq min \leq m)$ be the template with the minimum repair cost. The first flaw in the T_{min} set, $f_{min,1}$, is selected for repair, and a set of new plans P' are generated. Let P'_s be a subset of P' such that each plan in P'_s includes a new plan step for repairing $f_{min,1}$. For each plan in P'_s, a set of new plans are generated in which some of the flaws of type T_{min} are repaired by adding another instance of an action added for $f_{min,1}$.

The plan refinement returns two values, the set of plans in which all flaws of type T_{min} are repaired by adding the same type of action, and the set of plans in which some but not all flaws are repaired this way. We require the second value to facilitate backtracking. As with the basic templating scheme, not all flaws of a similar type require the same cost or action for repair (e.g., some might be satisfied by initial conditions). Consequently, the first set of plans are added to the search queue and the second set is stored in the event of later backtracking.

3.1 Expected Performance

Two opposing factors were expected to affect the performance as measured by plans examined and overhead. If reuse is successful most of the time, then both plans examined and overhead will be less; however, if new threats are introduced due to reuse, repairing them will cost more in terms of plans examined as well as overhead. The worst case will occur when an early

attempt to reuse is inappropriate, leading to considerable backtracking. As a consequence, we expected the success of this approach to be highly problem/domain dependent.

3.2 Correctness and Completeness

Any newly added plan step may introduce threats; for each of the flaws in template T_{min}, a set of new threats could be introduced. However, all of these introduced threats will be detected. Thus, the final solution will still be correct. In addition, the backtracking facility insures that if a solution exists, it will eventually be found. Consequently, completeness and correctness are maintained.

4 Approach 3: Probabilistic Reuse

Templating and Reuse can be viewed as approaches in which plan repair reuse is applied with probability 0 and 1 respectively. Because we suspect that plan repair reuse is not always the best strategy (and cannot currently recognize when it is and is not the best strategy), we can define an approach in which reuse is applied with some probability p, $0 < p < 1$. Intuitively, some p exists for which the performance will be better than that of Templating or Reuse. This value can be determined empirically. Obviously, the value of p depends both on the problem and domain. We hypothesize that p should be small non-zero value, and so determined it empirically. For all tests, the same value of p, 0.2, was used.

5 Approach 4: Adding a New Construct to the Plan Language (Bang-UCPOP)

The previous approaches all altered the control of plan expansion within the planner only. One alternative is to make the plan language more expressive of constraints known by the user. A simple constraint is that multiple inclusions of the same operator within a single plan should be instantiated to *different* objects within the environment. This hard constraint is a simple form of the resource reasoning included in more sophisticated planning systems [8].

We developed this approach to address problems discovered when analyzing the behavior of UCPOP in Truckworld [2] (a simulator of trucks moving cargo between different destinations). UCPOP fails (i.e., could not find a plan even given a large search space) on apparently simple conjunctive subgoal problems in Truckworld. A typical example is "Bring 4 fuel drums from outside the truck and fill the fuel tank." Because the size of the search space increased dramatically with the order and number of identical subgoals, we hypothesized that the number of identical fuel drums needed and available might lead the planner to search unnecessarily for the *right* binding of fuel drums in the *right* order.

```
(defclip gf-openc (f plan)
        (
        :output-file "gf-openc.clasp"
        :trigger-event (UCPOP::handle-open :before)
        :components (current-plan flaws )
        )
        (values (gf-refines plan) f ))
```

Figure 1: clip for collecting plans created for repairing an open-condition

5.1 Experiments on Sub-goal Interactions

We studied the behavior of UCPOP in Truckworld by collecting execution traces of UCPOP working on Truckworld problems with similar conjunctive sub-goals. Using CLIP [1] (an instrumentation tool for defining and running data collection routines in a simulated environment), we collected data on what plans were generated, how certain open conditions were repaired, what threats were considered, and what variable bindings were used. From the initial experiments we made the following observations.

1. Number of plans examined depends on the size of problem *inits*. For instance, if the goal is to bring 3 identical fuel drums, and the world has several such drums. Then the number of plans examined increases greatly with increase in number of available fuel drums. For the same number of sub-goals and ordering the search space increased linearly with increase in number of fuel drums.

2. Reordering sub-goals affects the number of plans examined. For certain orderings, plans examined is minimum and for another arrangement it is maximum.

3. Increasing numbers of identical subgoals, lead to a non-linear increase in plans examined before reaching a solution Consider problems with goals to bring in 2, 3 and 4 fuel drums respectively. The increase in number of plans examined from 3 to 4 is much more than that from 2 to 3. The difference in increase is on the order of tens of thousands.

5.1.1 Execution Traces

The next step was to collect execution traces of UCPOP to analyze what plans are generated by UCPOP, how it repairs certain open conditions, what are the threats considered, and what are the variable bindings used. We wrote several *clips* to collect traces. Some of the clips we used are shown in figure 1 and figure 2.

We analyzed the data with a variety of methods, from simple eyeballing through dependency detection [3], and determined that, in effect, UCPOP was searching in circles: trying

```
(defclip gf-unsafe ( f plan)
        (
        :output-file "gf-unsafe.clasp"
        :trigger-event (UCPOP::handle-unsafe  :before)
        :components (current-plan flaws )
        )
        (values (gf-refines plan) f ))
```

Figure 2: clip for collecting new plans created by repairing an unsafe condition

```
(1 NIL A 0 ((GETFUELDRUM-FROM-OUTSIDE 5 16 ARM-2 5 0 50 40)
            (GETFUELDRUM-FROM-OUTSIDE 5 ?POS3 ARM-1 ?BIG3 1 ?CPT3 ?NCPT3)
            (ARM-MOVE-OUTSIDE ARM-2))
            #<UNSAFE link#<LINK 0 (AMOUNT-HELD FUEL-DRUM ?POS1 ?STORED-AMT1) 1> step3>)
(1 NIL A 0 ((GETFUELDRUM-FROM-OUTSIDE 5 ?POS3 ARM-1 ?BIG3 1 ?CPT3 ?NCPT3)
            (GETFUELDRUM-FROM-OUTSIDE 5 16 ARM-2 5 0 50 40)
            (ARM-MOVE-OUTSIDE ARM-2))
            #<OPEN (AMOUNT-HELD FUEL-DRUM ?POS3 ?STORED-AMT3) step3>
```

Figure 3: trying to repair the open condition causes a bogus threat

the same variable bindings over and over again. For example, consider the problem of picking up two identical fuel drums from a world which has five such drums. To repair the first open condition (i.e., picking up the first drum), a set of five possible plans are generated. For the second drum, a similar set of plans is generated, with one of them trying to reuse the first step to get the first drum. This results in a threat, which UCPOP tries to resolve by binding a new value for the first flaw. It continues to try pairs of identical bindings before it finds two unique binding values that can repair both the open conditions. Most of the search time is wasted in trying the same values for variables that require different values. A fragment trace that depicts the above case is shown in figure 3. When UCPOP adds the second instance of "GETFUELDRUM-FROM-OUTSIDE" to the plan to repair an open condition it sees that causal link it added for the previous step i.e (AMOUNT-HELD FUEL-DRUM ?POS1 ?STORED-AMT1) is threatened. This is indicated by marking " UNSAFE link".

Thus, the plan language needs a construct to indicate to UCPOP that it should use different variable bindings for certain variables, so that it can converge on the solution much faster.

```
(define (operator pick-drum)
   :parameters   (?amt ?!pos ?arm)
   :precondition (and (outside ?arm)
                      (drum-at ?!pos ?amt))
   :effect       (and (not (drum-at ?!pos ?amt))
      (amount-in-arm ?arm ?amt)))
```

Figure 4: UCPOP operator for Truck World that illustrates the use of a Bang variable, `?!pos`

5.2 Scheme Description

For this scheme, we introduce a new language construct that creates a "special variable". Bindings of such a variable are treated differently; in particular, the planner will *ensure* that if a binding value is needed for the special variable it will differ from that used in all previous instances of this operator in the current plan. Moreover, if more than one of such bindings are possible, only one plan using exactly one value is created; plans for other possible unique values are saved in the event of backtracking.

A special variable is denoted by the prefix '?!' (hence, the name *Bang-UCPOP* for this approach). Bang variables are treated differently only during binding. Currently, only one such variable per plan operator is allowed, in order to minimize the complexity of resolving which variable binding resulted in a threat. Another restriction is that two operators that clobber each other should not use the same type (as defined by the plan domain) of special variable.

Special variables have a curious but useful side effect on repairing threats. They cause the planner to ignore bogus threats. For example, given two instances $O_{si,1}$ and $O_{si,2}$ of the same operator O_{si} and let p_s be the special variable parameter in its operator, then the new scheme ensures that unique values will be used for p_s in $O_{si,1}$ and $O_{si,2}$. Under the normal planning process, an unsafe link may be introduced due to $O_{si,2}$, but now there is no threat. Hence, the planner marks this threat as bogus and removes it. This saves time that otherwise would be wasted on resolving such threats.

Figure 4 shows an example of an operator which uses a bang variable. The operator comes from the Truckworld domain and is one of the operators needed to refuel a truck. The bang variable, `?!pos`, indicates the position at which the fuel drum is stored. Multiple fuel drums are typically required to refuel a truck; thus, a plan may include multiple instances of this operator, each referring to a different fuel drum in a different location. A Bang variable is ideal for this situation because we do not wish to attempt to pick up the same fuel drum repeatedly during refueling; we can only gainfully empty it once. A general operator with special variables is shown in figure 5, where p_s is the special variable, $PC_{s,i}$ is the ith precondition using the special variable, $e_{s,i}$ is the i th effect using the special variable.

Unlike the other approaches, this approach required considerable change to the algorithm

Operator: O_s
Parameters: $p_1, p_2, ...p_s, ...$
Preconditions: $PC_1, PC_2, ...PC_{s,i}, ...$
Effect: $e_1, e_2, ..., e_{s,i}, ...$

Figure 5: General Operator using Bang variable, p_s

for linking in new actions to plans. To expedite backtracking, the algorithm caches alternative unique variable bindings and search control maintains two search queues. When a planning failure occurs, it moves a plan from the most recent backup list into the primary search queue and continues. The modified plan linking algorithm is shown in Figure 6. The parameters to the function represent the open condition to be repaired, the step to be added to repair it, and the current plan. In case no special variable is involved the new plans are added to plan-list. Otherwise, only one plan is added to plan-list and the rest to more-plan.

Plan language constructs for restricting search space are available in some hierarchical planners. For example, O-Plan2 [8] uses condition types, which allow the domain writer to restrict selection of actions as well as to bind variables. The 'only_use_for_query' condition type of O-Plan2 resembles the Bang scheme, but differs in the situations for which it is the best approach. The Bang scheme is most effective when the number of binding values is large and no one is preferred. Only_use_for_query cannot be applied in specific actions and does not look for previous bindings used in other instances of the current action. An over-indulging O-Plan2 condition type can result in the planner throwing away valid plans, whereas Bang stores all plans for later backtracking. The Bang scheme can be modified to selectively recognize bang variables at the problem level. In O-Plan2, the condition type information is built into the domain specification.

5.3 Expected Performance

Best case performance, in terms of the number of plans examined, occurs when problems have identical conjunctive subgoals and when the first variable bindings do not need to be retracted later. The worst case performance occurs when the unique values selected early do not satisfy all the subgoals, thus requiring backtracking. This approach is expected to do much better than other approaches for domains with many possible bindings to the same variables, as in the motivating Truckworld example. In other cases, this approach may incur additional backtracking and thus additional computation because the new constraint does not help.

The major drawback of this approach is that it requires user intervention. The user must know when to use bang variables in a domain description (e.g., when it is expected that problems will contain multiple conjunctive sub-goals involving the same types of objects).

```
PLAN-LINKING(open-cond, step, current)
plan-list := NULL
more-plans := NULL
; let V be the variable in open-cond to be bound.
While binding-exists(V)
    if (special-variable(V))
        ; find a binding not used in other instances
        B := unique-binding(V)
        ; if a binding can be found, generate plans
        if (B != NULL)
            current := make-plan(B,open-cond,current)
        else current := NULL
        ; add to plans for backtracking
        if (plan-list !=NULL)
            more-plans := add(current,more-plans)
            current := NULL
    else ; find a binding with normal methods
        B := binding(V)
        current := make-plan(B,open-cond,current)
    if (current != NULL)
        plan-list := add(current,plan-list)
; return current plan and list for backtracking
return plan-list, more-plans
```

Figure 6: Algorithm for linking in new plan actions under the Bang-UCPOP approach

5.4 Correctness and Completeness of Approach

To make sure that we have not violated the correctness and completeness of the underlying planner, we need to prove that when special variable operators are used, every answer is a correct solution to the planning problem and that if a solution exists it will eventually be found.

The proof consists of three parts:

1. Even though the algorithm is limited to only one binding value for a special variable, backtracking is still permitted and thus completeness is preserved.

2. When special variables are bound to values from goal terms, then correctness is preserved.

3. When special variables are bound to particular unique values, marking threats as bogus when they are due to different instances of the same special variable operator does not affect correctness.

The correctness and completeness of UCPOP has already been proven [6], so we will show that all these cases are reducible to UCPOP. If UCPOP cannot find a solution (e.g., if enough unique values do not exist), then neither can our modification.

5.4.1 Proof

To give a complete proof we need certain definitions.

Definition 1: Special Variable A special variable directs the UCPOP to use exactly one unique value and return other plans using other unique values as a backup list. A value is unique if it has not been used in previous instances of the same operator.

Definition 2: Special Variable Operator A special variable operator is one that uses a special variable as a parameter. Only one special variable per operator is allowed.

Definition 3: Same Special Variables Two special variables are same, or same type, if they bind to same type of constant values like block, ferry, vehicle, position.

Definition 4: Independence on Special Variable Two special variable operators using same type of special variable are "independent on the special variable" if one does not clobber the effect of other. This is a required criterion for Bang scheme.

Lemma 1: Using special variables does not affect backtracking.

Proof Let F_s be the search control function. Let F_d be the function that refines the current plan (i.e, the adjacent states generator).

Let I be the current state, selected for expansion.

F_s maintains two search queues, Q_1 and Q_2.

Function F_d returns two values C_1 and C_2. If *Plan-linking* has to bind values for a special variable V_s, in an open condition, F_d returns in C_1 one plan using a unique value for V_s and in C_2 returns rest of plans using other unique binding values possible for V_s.

F_s adds C_1 to Q_1 and C_2 to Q_2. F_s removes a plan from Q_1, generates children to it using F_d and adds it to Q_1 and Q_2. If at a stage C_1 and Q_1 are NULL, F_s takes a plan from Q_2 (if Q_2 also is not empty), adds it to Q_1 and proceeds. We will show this enables backtracking when required.

Let I be the state selected from Q_1 by F_s. If F_d uses one of $O_1, ...O_m$ for generating next plans, it will return all possible plans in C_1, and C_2 will be null. In which case Q_1 will have all possible plans possible using $O_1, ...O_m$, and hence when a current plan does not reach goal state, backtracking to other plans using other operators or other bindings for $O_1, ...O_m$ is provided. In short, this is same as unmodified UCPOP. If F_d uses $O_{s1}, ...O_{sn}$ for generating next states, only one plan will be added to Q_1 each time. However the rest will be in Q_2. If a plan using one particular binding for one of O_{sj} fails, and no more plans exist in Q_1, it indicates other plans in Q_2 should be tried. That is a different binding value for O_{sj} should be used. This is done by moving a 'latest' generated state (plan) from Q_2 to Q_1 and proceeding. This essentially is back tracking.

Corollary 1.1: From the above proof we see that 'Completeness of UCPOP ' is maintained. That is if a solution exists UCPOP will find it.

Lemma 2: When special variables are bound to values from goal terms, the special variable operator is used just like other operators.

Proof The algorithm *Plan-Linking* generates binding values for variables in a open condition. If certain values are bound in goal term itself, it need not bind values for these variables. Hence no 'exception' is identified and it is reduced to un-modified *Plan-Linking.*

By the same reasoning, *Handle-Unsafe* procedure will not see the specialty since the variable is not bound by *Plan-Linking.* All threats recognized will be handled in original way and none is marked bogus. Hence this reduces to un-modified *Handle-Unsafe.* Since these are the two procedures which are modified, from above discussion we see that modified UCPOP will behave the same as the unmodified one for this case.

Corollary 2.1: The correctness of UCPOP is maintained when special variables are bound to values from goal terms.

Proof: From lemma 2 this case is reducible to UCPOP not using special variable operators at all, the correctness of which is already proved.

Lemma 3: When *Plan-Linking* function binds unique values for special variable in an operator O_{sj} then we can safely mark the threat posed by one instance of O_{sj} on another instance as bogus in *Handle-Unsafe* function and still maintain the correctness.

Proof: We will have to prove the correctness in two cases

- when no backtracking to saved plans occurs.
- when backtracking occurs.

Handle-Unsafe identifies one instance of an O_{sj} the special variable operator that is a threat to another instance of it. The threats may involve the bang variable that is bound by *Plan-Linking*. A threat on the same bang variable in two different special variable operators won't occur since we assumed the operators are pairwise independent. By induction on the number of instances of a special variable operator we can prove that *Plan-Linking* will ensure all instances of any O_s will use a unique binding value for the special variable and hence the threats can be safely marked as bogus.

Basis For the first instance added it is trivially true.

Induction Hypothesis Let us assume that unique values are bound for first n instances of O_s.

Induction Step For n+1 th instance *Plan-Linking* will use a value not used in any of n instances and hence the plan with n+1 instances will also have a unique value. If no unique value exists for n+1 th instance it will not be added at all . Again all the instances will have unique binding values. Note that this may be a plan failure but it will be reported even by UCPOP. If another binding value is found we have the following sub cases.
Case i:
If *Plan-Linking* is able to find a unique value for a special variable for each instance of a O_{sj}, then each instance of O_{sj} will be accommodated in the plan. In which case no instance will be a threat to other. By the induction hypothesis, n values are unique and n+1st value is guaranteed to be different from all n values. Hence we can safely mark the threat by O^r_{si} on all $O^1_{si}, O^2_{si}, ...O^l_{si}$ as bogus.

On the other hand if *Plan-Linking* is not able to find a unique binding value it returns nil, in which case plan failure will be detected by F_s, and no need to go through *Handle-Unsafe*.

Case ii:
Plan-Linking generates a second list (backup list) of children. All the plans in this list also have a unique value for the special variable. If backtracking to saved unique value plans occurs then also the proof holds.

Now if backtracking by using a plan from Q_2 is necessitated, the plan moved from Q_2 to Q_1 will also have the uniqueness property due to *Plan-Linking*. Let us assume we backtracked to a plan I_b with following instances for an O_{sj},

$O^1_{sj}, O^2_{sj}, ...O^l_{sj} < 2 >$. The $< 2 >$ indicates using the second possible binding value in O_{sj}. Let V_{sj} be the special variable in a O_{sj}. The current plan with $O^1_{sj}, O^2_{sj}, ..., O^l_{sj}, ...O^k_{sj}$ has no children and also the search queue is empty. This is why I_b is selected.

$O^l_{sj} < 2 >$ in I_b indicates for the l th instance of O_{sj} in I_b another possible unique value for the special variable is used. So in I_b there is no instance of O_{sj} that uses the first possible value for V_{sj}. This value is now available for *Plan-Linking* for the generation of next instance of O_{sj}. Note that in plan I, $l < 2 >$ could have been used in l+1 th instance of O_{sj}. But since we backtracked, l+1 th instance is generated anew and *Plan-Linking* maintains its uniqueness. Hence we can still mark the threat as Bogus. In all the cases the new algorithm is reducible to the old one. Hence the correctness and completeness of the UCPOP algorithm is maintained.

6 Comparison of Approaches

In this paper, we have defined four extensions to two current approaches (vanilla UCPOP and LCFR in UCPOP) for controlling plan search in a partial order planner. We expected the new approaches to perform significantly better than LCFR or UCPOP in some domains/problems. The goal of the comparison was to determine which of the six approaches works best in some common planning problems.

Three performance metrics were collected: number of plans examined before reaching a solution, overhead incurred in terms of the number of plans created for flaw selection, and CPU time. On average, we expected that the four new approaches, templating, reuse, probabilistic reuse and Bang-UCPOP, would compare favorably to LCFR on plans examined but would have less overhead and so require less CPU time.

6.1 Experiment Design

The six approaches were tested on 40 problems in ten domains. The same set of problems without any modification is used for all versions. Most of the problems are from the example domains provided with UCPOP and tested in Joslin and Pollack's research with LCFR. Four of the problems are from the Truckworld domain [2], all of which require picking up fuel drums; the four differ in the number of subgoals and arm positions. In all the domains, some of the operators were modified to include a special variable parameter for Bang-UCPOP. Because most of the domains are small in size, only one special variable operator was used.

Domains	Total	UCPOP	LCFR	App-1	App-2	Prob Reuse	Bang
Blocks World	4	4	4	4	3	4	4
Truck World	4	3	4	4	4	4	4
Robot Domain	2	2	2	2	2	2	2
Monkey and Banana	3	2	2	2	2	2	2
Briefcase World	4	4	4	4	4	4	4
Russells Tire World	6	4	5	5	6	6	5
Fridge Domain	2	1	2	1	0	0	1
Strips World	2	0	1	0	1	1	0
Office Domain	7	7	7	7	7	7	7
Other Domains	6	3	6	6	6	6	6
TOTAL	40	30	37	35	35	36	35

Table 1: Number of problems solved by the search control strategies.

All trials were run on the same SPARC IPX workstation in the same version of Common Lisp.

For all cases, the search limit was restricted to 10000 plans examined. A failure was reported only when no possible plan could be found within that limit.

6.2 Results

The results are reported in Tables 1 thru 4. Table 1 presents the number of problems within each domain that were solved by each approach. The domains were: Blocks World (A), Truck World (B), Robot Domain (C), Monkey and Banana (D), Briefcase World (E), Russell's Tire World (F), Fridge Domain (G), Strips World (H), Office Domain (I), and Others (J). Table 2 lists the minimum, average and maximum number of plans examined by each approach in problems within each test domain; this corresponds to how much of the space was explored during plan refinement. Table 3 lists the average number of plans created for flaw selection (which included those created to estimate cost) for each approach in each problem domain; UCPOP and Bang are not included because they do not create any plans for flaw selection. Finally, as a crude estimate of both factors incorporated in the previous two measures and those not, average CPU time is provided in Table 4.

Table 1 shows that LCFR solves the largest number of problems. However, the four new approaches solve all but one or two of those solved by LCFR. All approaches solve considerably more problems than UCPOP.

In terms of number of plans examined, we expected the performance of the four new approaches to be comparable on average to LCFR and better than UCPOP. In addition the two reuse and the bang approaches are problem dependent, the worst case performance for these three approaches are expected to be worse than LCFR and possibly even UCPOP in particular problems. The data (in Table 2) shows that the average case performance is comparable in about half the domains, with the "best" average (numbers in boldface) for

Domains	UCPOP	LCFR	App-1	App-2	Prob	Bang
Blocks World	24	16	21	32	21	31
	854	69	1784	42	1346	2880
	2969	160	6958	47	5169	5397
Truck World	93	43	148	68	148	42
	1013	700	784	598	589	549
	2488	2333	2520	1733	1733	1938
Robot Domain	21	22	26	26	26	20
	4088	310	1096	201	68	321
	8155	597	2165	375	110	612
Monkey Domain	26	27	40	40	40	67
	274	197	270	270	270	180
	521	366	500	500	500	293
Briefcase World	10	10	10	61	10	20
	98	104	533	296	386	1919
	248	196	1820	846	1229	7105
Russells Tire World	10	10	10	10	10	10
	17	23	76	506	506	1050
	23	44	310	2701	2701	2457
Fridge Domain	448	52	271	8952	-	208
	-	63	-	-	-	-
	-	73	-	-	-	-
Strips World	-	761	-	583	928	-
	-	-	-	-	-	-
	-	-	-	-	-	-
Office Domain	32	8	8	8	8	9
	285	32	63	64	64	1065
	1099	66	193	193	193	5560
Other Domains	61	43	36	23	16	42
	101	112	120	154	159	506
	187	335	208	427	314	1063

Table 2: Number of Plans Examined. Successful Problems Only. Best, Ave and Worst Data.

Domains	LCFR	Approach-1	Approach-2	Prob UCPOP
Blocks World	1669	6566	6157	5265
Truck World	28772	11802	1872	2529
Robot Domain	8076	3535	1034	322
Monkey and Banana	105518	5558	5558	5558
Briefcase World	1645	847	563	647
Russells Tire	59008	11036	3760	2547
Fridge Domain	9754	15075	42466	42466
Strips Domain	258897	79230	48030	79230
Office Domain	459	257	267	267
Other Domains	78080	11697	11789	11625

Table 3: Average Overhead, number of plans created for all problems.

each domain distributed among the approaches. Similarly, the minimum(best) and maximum (worst) cases appear highly domain dependent, with the four new approaches in general having higher maximum values. In all but a few cases, LCFR and the four new cases offer either a comparable number of plans examined or a reduction over UCPOP.

While plans examined was expected to be comparable or worse than LCFR, we expected the overhead to be significantly lower for the new approaches. In fact, the overhead (Table 3) and CPU time (Table 4) data suggest that LCFR is quite costly in comparison to the other approaches. The difference in the overhead incurred is well illustrated in the figure 7. For problems with no solution, LCFR expends the most effort before reporting a failure. All other approaches report failure as early as possible. This causes the LCFR to expend very high CPU time as shown in figure 8. Only in the Blocks World problems does LCFR out-perform the other approaches.

In terms of overhead, the performance of the probabilistic reuse scheme is usually lower or comparable to the approaches other than Bang. This implies that if proper criteria, mostly likely domain and problem dependent, for reuse can be determined then the search space can be reduced greatly.

Bang-UCPOP incurs no overhead; its CPU time is the minimum in all but three domains. However, it appears to be problem dependent, rather than specifically domain dependent and so should be applied based on the type of problem rather than applying it for every problem in the domain. The primary cost of Bang-UCPOP is the storage of certain nodes to allow back tracking. If the unsuitability of certain plans can be detected very early, the search space explosion to support backtracking can be controlled.

Our template scheme assumes that the order in which similar open conditions are selected for repair does not matter. We tested this assumption by running experiments in which flaw selection from a template is randomized. The results showed no significant difference between open conditions selected randomly versus simply taking the first flaw from the template.

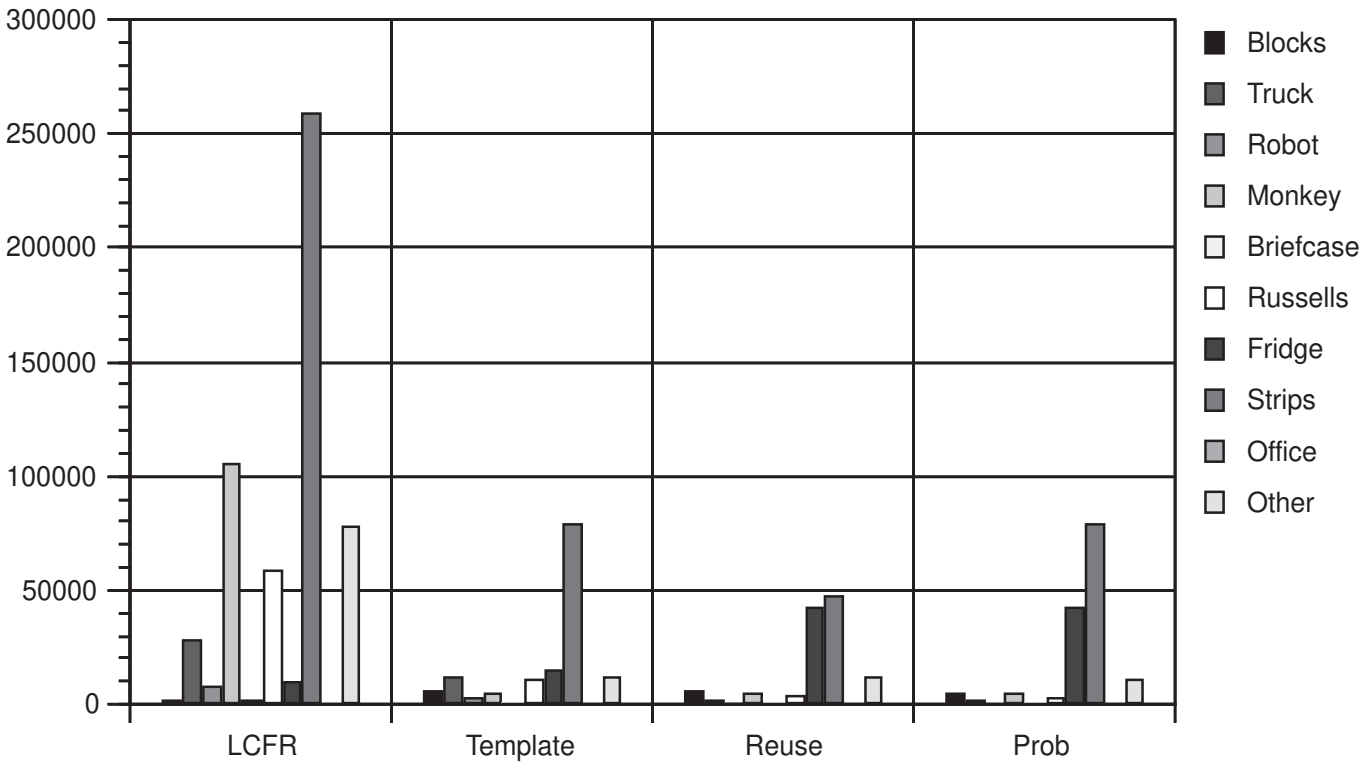

Figure 7: Differences in Overhead

Domains	UCPOP	LCFR	App-1	App-2	Prob	Bang
Blocks World	15.6	7.75	46.45	49.49	37.13	11.34
Truck World	33.58	106.76	48.12	11.93	13.00	1.89
Robot Domain	47.37	56.23	34.03	6.35	1.97	1.99
Monkey and Banana	81.79	2021.41	89.27	90.23	89.4	31.43
Briefcase World	0.85	8.78	8.06	4.90	6.37	14.45
Russell Tire	37.80	556.43	97.05	54.25	40.95	15.93
Fridge Domain	43.56	30.44	98.55	305.50	289.74	30.44
Strips World	181.17	2975.12	967.71	567.23	956.16	73. 54
Office Domain	2.94	2.22	1.61	2.22	1.57	1 0.69
Other Domains	43.60	363.45	58.85	75.36	56.65	1 4.65

Table 4: Average CPU time in seconds, all problems.

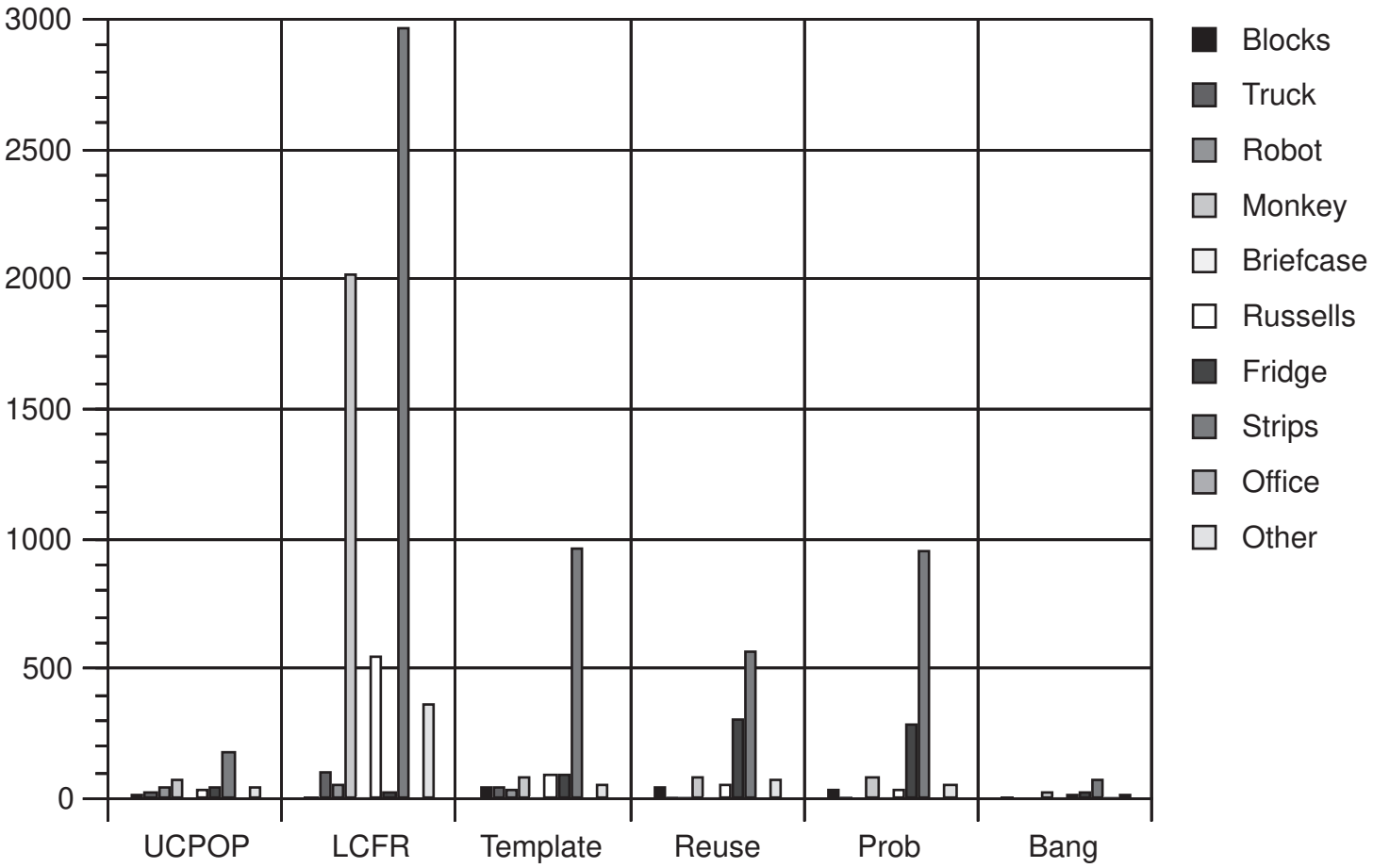

Figure 8: Differences in CPU time

7 Conclusion

Not too surprisingly, no one approach seems to be best, solving all possible problems as efficiently as possible. Each solution seems to have its pros and cons, favoring some domain or problem within a domain. Though LCFR is able to solve many problems with far fewer plans examined than UCPOP, the cost of doing so, in terms of overhead, can be quite high. The four approaches described in this paper solved more problems than UCPOP, almost as many problems as did LCFR, and usually incurred far less overhead than LCFR. Additionally, the results of Bang-UCPOP suggest that flaw selection alone is not adequate for efficient planning.

However, these approaches and this comparison are barely a first step. We need to model *why* different approaches work better in different domains and problems. Such models will help determine which approaches to apply in which situations and to design new methods. For example, from the execution traces of UCPOP, we observed that reordering sub-goals or operators in the domain strongly affects the amount of search required to solve problems; in particular, some orderings lead quickly to a solution while others appear to cycle. A flaw selection strategy partly eliminates this problem, but at great expense. If we can identify what plans or orderings will lead to cycles, then we can modify plan refinement to prune those plans early in the planning process.

The two limited reuse approaches performed well on problems with related sub-goals. One simple improvement to probabilistic reuse could be to make the probability a function of the number of flaws in the plan with reused steps. For example, if the number of threats introduced by applying reuse is more than that introduced by solving the minimum cost flaw, the probability of reuse should be reduced. A better way is to use more knowledge about the domain and problem to decide on step reuse rather than applying reuse with some probability. We should be able to identify long sequences (sub-plans) and solve similar flaws together rather then considering them separately. For example, in Truckworld, when the truck tries to pick up fuel drums to fill its fuel tank, it can pick up other objects it needs since the sequence of steps are same.

Considering the time reported to solve even a simple problem, the problem of scaling up to larger problems is daunting. Based on this small exploration of methods for improving plan generation efficiency, we need additional methods for constraining the search space in partial order planning and language constructs to incorporate known constraints. Most importantly, we need to know how domain dependent problem characteristics lead to inefficient exploration of the search space.

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