Knowledge Acquisition, Validation, and Maintenance in a Planning System for Automated Image Processing

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Abstract

A key obstacle hampering fielding of AI planning applications is the considerable expense of developing, verifying, updating, and maintaining the planning knowledge base (KB). Planning systems must be able to compare favorably in terms of software lifecycle costs to other means of automation such as scripts or rule-based expert systems. Consequently, in order to field real systems, planning practitioners must be able to provide: 1. tools to allow domain experts to create and debug their own planning knowledge bases; 2. tools for software verification, validation, and testing; and 3. tools to facilitate updates and maintenance of the planning knowledge base. This paper begins by describing a planning application of automated image processing and our overall approach to knowledge acquisition for this application. This paper then describes two types of tools for planning knowledge base development: static KB analysis techniques to detect certain classes of syntactic errors in a planning knowledge base; and completion analysis techniques, to interactively debug the planning knowledge base. We describe these knowledge development tools and describe empirical results documenting the usefulness of these tools.

1 Introduction

A key bottleneck in applying AI planning techniques to a real-world problem is the amount of effort required to construct, debug, verify, and update (maintain) the planning knowledge base. In particular, planning systems must be able to compare favorably in terms of software lifecycle costs to other means of automation such as scripts or rule-based expert systems. An important component to reducing such costs is to provide a good environment for developing planning knowledge bases. Despite this situation, relatively little effort has been devoted to developing an integrated set of tools to facilitate constructing, debugging, verifying, and updating specialized knowledge structures used by planning systems.

While considerable research has focused on knowledge acquisition systems for rule-based expert systems (Davis, 1979) , and object-oriented/inheritance knowledge bases with procedures and methods (Gil and Tallis, 1995), little work has focused on knowledge acquisition for specialized planning representations. Notable exceptions to this statement are (DesJardins, 1994) which uses inductive learning capabilities and a simulator to refine planning operators and (Wang 1995) which uses expert traces to learn and a simulator to refine planning operators. However, in many cases a simulation capability is not available. In these situations the user needs assistance in causally tracing errors and debugging from a single example. This assistance is sorely needed to enable domain experts to write and debug domain theories without relying on AI people. Furthermore, planning knowledge base maintenance is often overlooked. Such tools are also invaluable in tracking smaller bugs, verifying KB coverage [1], and updating the KB as the domain changes. While these tools can draw much from causal tracking techniques used in rule-based systems (Davis, 1979), there are several aspects of planning systems which differentiate them from rule-based systems - their specialized representations and their temporal reasoning capabilities. Two specialized representations for planning are prevalent - task reduction rules and planning operators. These representations as well as the most common constraints (ordering and codesignation constraints) have evolved so that specialized reasoning algorithms must be adapted to support debugging.

Many types of knowledge encoding errors can occur: incorrectly defined preconditions, incorrectly defined effects, and incorrect variable specifications. Invariably the end result is a mismatch between the planners model of the legality of a plan and the model dictated by the domain (or domain expert). Thus, the end symptoms of a knowledge base error can be broadly classified into two categories.

Incorrect Plan Generation: This occurs when the planner is presented a problem and generates a plan which does not achieve the goals in the current problem context. In our experience, the current problem and faulty solution can focus attention in debugging the flaw in the knowledge base. By using the faulty plan to direct the debugging process, the user can often focus on the incorrect link in the plan (faulty protection or achievement) - allowing for rapid debugging.

Failure to Generate a Plan: This occurs when the planner is presented with a solvable problem, but the planner is unable to find a solution. In our experience this type of failure is far more difficult to debug. This is because the user does not have a particular plan to use to focus the debugging process. Thus, often a user would manually write down a valid plan based on their mental model of the domain, and then trace through the steps of the plan to verify that the plan could be constructed. Because our experience has been that detecting and debugging failure-to-generate-a-plan cases has been more difficult, our work focuses on: 1. verifying that a domain theory can solve all solvable problems; and 2. facilitating debugging of cases where the domain theory does not allow solution of a problem deemed solvable by the domain expert.

This paper describes two types of tools developed to assist in developing planning knowledge bases - *static analysis tools* and *completion analysis tools*. Static analysis tools analyze

[1] For work in verifying rule-based systems - see (O'Keefe and O'Leary, 1993). For work on rule base refinement using training examples (the analogue of a simulator for planning KB refinement) see (Ginsberg et. al., 1988).

the domain knowledge rules and operators to see if certain goals can or cannot be inferred. However, because of computational tractability issues, these checks must be limited. Static analysis tools are useful in detecting situations in which a faulty knowledge base causes a top-level goal or operator precondition to be unachievable - frequently due to omission of an operator effect or a typographical error.

Completion analysis tools operate at planning time and allow the planner to complete plans which can achieve all but a few focused subgoals or top-level goals. Completion analysis tools are useful in cases where a faulty knowledge base does not allow a plan to be constructed for a problem that the domain expert believes is solvable. In the case where the completion analysis tool allows a plan to be formed by assuming goals true, the domain expert can then be focused on these goals as preventing the plan from being generated.

The static analysis and completion analysis tools have been developed in response to our experiences in developing and refining the knowledge base for the Multimission VICAR Planner (MVP) (Chien, 1994a, 1994b) system, which automatically generates VICAR image processing scripts from specifications of image processing goals. The MVP system was initially used in December 1993, and has been in routine use since May 1994. The tools described in this paper were driven by our considerable efforts in knowledge base development, debugging, and updates to the modest sized knowledge base for MVP.

The remainder of this paper is organized as follows. Section 2 outlines the two planning representations we support: task reduction rules and operators. Section 2 also briefly describes how these representations are used in planning. Section 3 describes static analysis rules for assisting in planning KB verification and development. Section 4 describes completion analysis rules for assisting in planning KB development.

2 VICAR Image Processing

We describe the static and completion analysis tools within the context of the Multimission VICAR Planner system, a fielded AI planning system which automates certain types of image processing [2] (Lavoie et. al., 1989). MVP uses both task reduction and operator-based methods in planning. However, the two paradigms are separate, in that MVP first performs task reduction (also called hierarchical task network or HTN planning) and then performs operator-based planning. All of the task reduction occurs at the higher conceptual level and the operator-based methods at the lower level[3]. Consequently, MVP uses two main types of knowledge to construct image processing plans (scripts):

- decomposition rules - to specify how problems are to be decomposed into lower level subproblems; and

[2]We only briefly describe the MVP application due to space constraints. For further information on this application area, MVP architecture, and knowledge representation see (Chien, 1994a, 1994b, Chien and Mortensen, 1996).

[3]MVP first uses task reduction (Lansky, 1993) planning techniques to perform high level strategic classification and decomposition of the problem then uses traditional operator-based (Pemberthy and Weld, 1992) planning paradigms to plan at the lower level

- operators - to specify how VICAR programs can be used to achieve lower level image processing goals (produced by 1 above). These also specify how VICAR programs interact.

These two types of knowledge structures are described in further detail below.

A key aspect of MVP's integration of task reduction and operator-based planning is that first task reduction is performed, then operator-based planning. Because of the order in which these are performed, these two types of knowledge can be checked separately.[4]

2.1 Task Reduction Planning in MVP

MVP uses a task reduction approach to planning. In a task reduction approach, reduction rules dictate how in plan-space planning, one plan can be legally transformed into another plan. The planner then searches the plan space defined by these reductions. Syntactically, a task reduction rule is of the form:

LHS		RHS
GI = initial goal set/actions		GR= reduced goal set/actions
C0 = constraints	$\Rightarrow$	C1 = constraints
C2 = context		N = notes on decomposition

This rule states that a set of goals or actions GI can be reduced to a new set of goals or actions GR if the set of constraints C0 is satisfied in the current plan and the context C2 is satisfied in the current plan provided the additional constraints C1 are added to the plan. C0 and C1 are constraint forms which specify conjuncts of constraints, each of which may be a codesignation constraint on variables appearing in the plan, an ordering constraint on actions or goal achievements in the plan, a not-present constraint (which is satisfied only if the activity or goal specified does not appear in the plan and never appeared in the derivation of the plan), a present constraint (which is satisfied only if the activity or goal specified did appear in the plan or derivation of the plan), or a protection constraint (which specifies that a goal or set of goals cannot be invalidated during a specified temporal interval. Skeletal planning (Iwasaki and Friedland, 1985) is a technique in which a problem is identified as one of a general class of problem. This classification is then used to choose a particular solution method. Skeletal planning in MVP is implemented in by encoding decomposition rules which allow for classification and initial decomposition of a set of goals corresponding to a VICAR problem class. The LHS of a skeletal decomposition rule in MVP corresponds to a set of conditions specifying a problem class, and the RHS specifies an initial problem decomposition for that problem class.

MVP also uses decomposition rules to implement hierarchical planning. Hierarchical planning (Stefik, 1981) is an approach to planning where abstract goals or procedures are incrementally refined into more and more specific goals or procedures as dictated by goal or procedure decompositions. MVP uses this approach of hierarchical decomposition to refine the initial skeletal plan into a more specific plan specialized based on the specific

[4] A more recently developed planner (Chien et al, in preparation, Chien et al, 1996) completely integrates these two planning paradigms. While natural extensions of static and completion analysis to this integrated planning approach exist, we have not as of yet explored such possibilities.

current goals and situation. This allows the overall problem decomposition to be influenced by factors such as the presence or absence of certain image calibration files or the type of instrument and spacecraft used to record the image. For example, geometric correction uses a model of the target object to correct for variable distance from the instrument to the target. For VOYAGER images, geometric correction is performed as part of the local correction process, as geometric distortion is significant enough to require immediate correction before other image processing steps can be performed. However, for GALILEO images, geometric correction is postponed until the registration step, where it can be performed more efficiently.

This decomposition-based approach to skeletal and hierarchical planning in MVP has several strengths. First, the decomposition rules very naturally represent the manner in which the analysts attack the procedure generation problem. Thus, it was a relatively straightforward process for the analysts to articulate and accept classification and decomposition rules for the subareas which we have implemented thus far. Second, the notes from the decomposition rules used to decompose the problem can be used to annotate the resulting plan to make the output plans more understandable to the analysts. Third, relatively few problem decomposition rules are easily able to cover a wide range of problems and decompose them into much smaller subproblems.

2.2 Operator-based Planning in MVP

MVP represents lower level procedural information in terms of classical planning operators. These are typical classical planning operators with preconditions, effects, conditional effects, universal and existential quantification allowed, and with codesignation constraints allowed to appear in operator preconditions and effect conditional preconditions. For reasons of space constraints the operator representation is only briefly described here. (for a good description of a classical planning operator representation similar to ours see (Pemberthy and Weld 1992)). Thus, an operator has a list of parameter variables, a conjunctive set of preconditions, and for each effect (which is a conjunct) there is a (possibly null) set of preconditions.

```
Operator
    Parameters:    variable*
    Preconditions: Prec = Prop*
    Effects:       [Effecti = Prop* when Cpreci = Prop*]*
```

The above operator has the semantics that it can only be executed in a state in which all of the preconditions Prec are true. And when executed, for each effect set, if all of the conditional preconditions Cpreci are true in the input state, the effect Effecti occurs and all of the effects are true in the output state.

A description of the GALSOS operator is shown below.

```
operator GALSOS
        :parameters ?infile ?ubwc ?calc
        :preconditions
                the project of ?infile must be galileo
                the data in ?infile must be raw data values
```

:effects

reseaus are not intact for ?infile
the data in ?infile is not raw data values
missing lines are not filled in for ?infile
?infile is radiometrically corrected
the image format for ?infile is halfword
?infile has blemishes-removed
if (UBWC option selected) then ?infile is uneven bit wt. corrected
if (CALC option selected) then ?infile has entropy values calculated

2.3 An Overall Approach to Knowledge Acquisition, Validation, and Refinement for MVP

During development of the MVP knowledge base, we used an iterative refinement model in building the knowledge base. We began by eliciting representative problem classes and used these to direct the knowledge elicitation - both in terms of problem classes for the HTN rules and in terms of the causal structure underlying the operators. Concurrent with the development of this knowledge base, we attempted to elicit from expert analysts, declarative descriptions of the coverage of each of these problem classes - in terms of the legal combinations of goals and of initial states allowable.

When this knowledge base was relatively stable, it was tested against a holdback set of problems not used during the original elicitation process. This led to another round of refinement of the knowledge base and problem class descriptions.

In the operational version of MVP, this definition of legal problem classes is key. Before any problem is submitted to the planner from the interface, it is first checked against these problem class constraints. In the event that the submitted request does not pass the constraints, it is not submitted to the planner - rather the user is notified that the problem is not considered a valid request. If the user believes otherwise, they can submit a bug report at this time.

If the problem is considered a valid one, then if the planner is correct and sound, then the planner and knowledge base should be able to solve the problem correctly. While the MVP planner is not complete (it cannot backtrack across different decompositions in response to failures in operator-based planning), in actual usage, we have not yet encountered a problem in which this was the cause of a planner failure. Consequently, when the planner (and KB) are unable to solve a problem (e.g., the planner cannot find a solution either due to dead-ends in the search space or exceeding resource bounds), a KB bug is assumed and a bug report is automatically submitted. This bug report includes the requested goals, initial state, and image files are logged. Similarly, if the planner generates an incorrect plan, a bug report can be filed (manually) by the user. Figure 1 below graphically illustrates the acquisition and maintenance flows as described.

2.4 Different Tool Types and Representations

In order to facilitate this key process of knowledge acquisition and refinement we have been developing a set of knowledge-base editing and analysis tools. These tools can be categorized

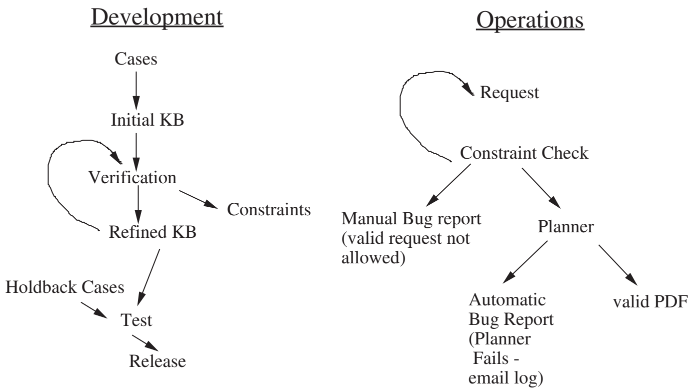

Figure 1: Initial Acquisition and Maintenance Processes for MVP Planning Knowledge Base

into two general types: (1) static knowledge base analysis tools; and (2) completion analysis tools. Because MVP uses two types of knowledge: decomposition rules and operator definitions, each of these tools can be used with each of these representations. Thus there are four types of tools:

- static rule analysis tools;
- static operator analysis tools;
- completion rule analysis tools; and
- completion operator analysis tools.

For each type of tool, it is possible to perform the analysis using propositional or full predicate checking. In propositional analysis, all actions and goals are considered optimistically only for the predicate or goal name. For example, when considering whether an operator could achieve a specific fact, "(radiometrically-corrected ?file1)", optimistic treatment means that any effect or initial state fact with the predicate "radiometrically-corrected" can be used. When considering whether an effect , "(radiometrically-corrected ?file1)", deletes a protected fact "(radiometrically-corrected ?file2)", one presumes that the arguments to the predicate can be resolved such that the conflict does not occur. Therefore the effect is not considered to delete the fact. The propositional analysis is used as a fast checking component to catch simple errors when debugging a knowledge base. The full static analysis is useful but restricted to more batch-like analysis due to its computational expense.

2.5 Problem Spaces for Knowledge Analysis

In our knowledge base development and refinement framework, the knowledge base is divided into a set of problem spaces. A problem space consists of a set of allowable sets of inputs and groundings. In the case of task reduction, conceptually the planner is reducing a set of abstract activities into more specific activities (although sometimes these specific activities can be mapped . Hence, in task reduction, the inputs are non-operational goals, groundings are operational goals, and the problem space corresponds to a class of non-operational goal

Figure 2: Problem Space Information

Problem Space	# operators	goals	typ. search
local correction	15	7	60
automatic navigation	20	4	150
manual navigation	24	4	300
photometric correction	5	2	60
registration	13	5	110
mosaicking	4	3	325
touch ups	10	3	325

sets which can be reduced into operational goals. In the case of operator-based planning, the planner is considering which how to achieve goal state requirements using a particular set of actions from certain initial states. In this case the problem space corresponds to a class of goal states which can be achieved from a general class of initial states. In both the task reduction and operator-based cases, the inputs are specified in terms of logical constraints over goals and groundings are specified in terms of a list of predicates which can be presumed true/operational.

These problem spaces represent a set of contexts in which the decomposition planner or operator planner is attempting to solve a general class of problems. Decomposing the overall problem solving process into these problem spaces and analyzing each in isolation dramatically reduces the complexity of the analysis process. Of course, this introduces the possibility that the knowledge base analysis is flawed due to a poor problem decomposition. Unfortunately, we know of no other way around this problem. While the tools we describe are of assistance in analyzing the impact of the problem space structure they do not directly assist in the definition of the problem spaces - which is a direct burden on the user.

Within a single problem space only one of the HTN and operator-based planner is being used. Hence in this case the system performing the analysis is complete and correct so that inability to solve a problem is interpreted as a flaw in the knowledge base.

Below in Figure 2 we list the problem spaces used in the current MVP knowledge base. For each problem space we describe the number of relevant planning operators, the number of top-level input goals, and the typical number of plans searched in the problem space.

3 Static Analysis Tools

3.1 Static Analysis Tools for Task Reduction Rules

Static analysis tools analyze the knowledge base to determine if pre-specified problem-classes are solvable. The static analysis techniques can be used in two ways: 1. fast run-time checking using propositional analysis (called propositional static rule analysis); and 2. off-line knowledge-base analysis to verify domain coverage (called full static rule analysis).

In the case of static rule analysis, the analysis process is to verify that all legal sets of input goals can be reduced into operational goals/facts/tasks. The set of allowable input goals is formally specified in terms of logical constraints on a set of goals produced by the interface. Figure 3 describes the static rule analysis algorithm. Below we show a simplified problem space description for the navigation problem space, and use this to illustrate static

Table 1: Propositional vs. Full Constraint Handling

Constraint type	Propositional Case	Full Case
codesignation	ignored	tracked
not-present	ignored	tracked
present	propositional	tracked
ordering	tracked	tracked
protection	ignored	tracked

rule analysis.
Input goals are all combinations of:

(attempt-to-FARENC ?files) (automatch ?files)
(manmatch ?files) (curve-verify ?files)
(display-automatch-residual-error ?files) (display-manmatch-residual-error ?files)
(update-archival-sedr ?files)

Subject to the constraint that:

¬((attempt-to-FARENC ?files ?files) and (automatch ?files))
¬(curve-verify ?files) or (attempt-to-FARENC ?files)
¬(display-automatch-residual-error ?files) or (automatch ?files)
¬(display-manmatch-residual-error ?files) or (manmatch ?files)

Generally, the allowable sets of input goals are of the form "all combinations of these 5 goals except that goal4 and goal3 are incompatible, and that every time goal 2 is selected goal 1 must have parameter X and so on.

The output legal set of goals/facts/tasks are defined in terms of a set of operational predicates. For example, in the relative navigation example used above has the operational predicates: construct-om-matrix, and display-om-error.

This means that any goal/activity/fact produced using one of these predicates is considered achieved. Static rule analysis runs the rules on these allowable combinations and verifies that the decomposition rules cover the combinations (this corresponds to exhaustive testing of the task reduction rules). As described in Section 2.1, there are several types of constraints used in the task reduction rules. Some of these constraints do not make sense for a propositional analysis; how constraints are handled in the propositional analysis is shown below.

The principal difference between the propositional and non-propositional cases is that when predicates are transformed to the propositional case, constraint resolution optimistically presumes variable assignments will remove conflicts. For example, consider the plan and reduction rules shown below.

Plan1: activities: (foo c216) (bar c216) constraints: .....

```
StaticRuleAnalyze(input-goals, operational-goals, rules)
initialize Q = (goals=input-goals, constraints={})
select a plan P from Q
    for each plan P' produced by reducing a goal in P using a
        task reduction rule w. constraints as below
        IF P' contains only operational goals return SUCCESS
        ELSE add P' to Q and continue
```

Figure 3: Static Rule Analysis Algorithm

Plan2: activities: (foo c216) (bar c211) constraints: .....

Reduction Rule1: if present: (bar ?a) not-present: (foo ?b)
Reduction Rule2: if present: (bar ?a) (foo ?a)

In the propositional case, both rule1 and rule2 apply to both plan1 and plan2. In the full case, rule 1 does not apply either plan1 or plan2. In the full case rule2 applies to plan1 but does not apply to plan2. Note that in the propositional case, in order to presume that variables resolve optimistically, the analysis procedure need not compute all possible bindings. Rather, the analysis procedure resolves present constraints by presuming matching if the predicate matches and by ignoring not- present constraints (and others as indicated above). To further illustrate, consider the following example from the MVP domain. The input goals, relevant decomposition rules, and operational predicates are shown below.

Input Goals: (automatch ?files) (manmatch ?files) (display-manmatch-error ?files)
Decomposition Rules:
Rule1 LHS (automatch ?f1) (manmatch ?f1)
RHS (construct-om-matrix ?f1 auto-man-refined)
Rule2 LHS (display-manmatch-error ?f2) present (automatch ?f2) (manmatch ?f2)
RHS (display-om-error ?f2 auto-man-refined)
Operational Predicates: construct-om-matrix, display-om- error

In both the propositional and full static rule analysis cases both rules would apply in the analysis. Thus, both analyses would indicate that the input goals can be reduced into operational facts/activities.

3.2 Static Analysis Tools for Operator-based Planning

The static analysis techniques can also be applied to the MVP's operator-based planner component. This is accomplished by generalizing the planning algorithm. Again, as with the static rule analysis, the static operator analysis is considering a general class of problems defined by a problem space. As with the static rule analysis, a problem space defines an allowable set of goals and a set of operational predicates which are assumed true in the initial state.

In the propositional static operator analysis case, in order to treat the domain theory optimistically, we must assume that all protection interactions can be resolved by variable assignments. Because of the absence of protection constraints, the propositional operator static analysis corresponds to the propositional rule-based static analysis. An operator with preconditions P and effects E maps onto a rule with LHS P and RHS E. Conditional effects extend analogously.

The non-propositional static analysis case is handled by modifying a standard operator-based planner. The planner is changed by adding an achievement operation corresponding to presuming any operational fact is true in the initial state. We are currently investigating using more sophisticated static analysis techniques to detect more subtle cases where goals are unachievable (Etzioni, 1993, Ryu and Irani, 1992). The full (e.g. non-propositional) operator static analysis algorithm is shown below in Figure 4. The * on Step 3 indicates that this is the key modification to a standard operator-based planning algorithm to perform static operator analysis.

```
StaticOperatorAnalyzeFull(input, operational, operators)
initialize plan queue Q to (goals=input, constraints={})
select a plan P from Q
    for each plan P' produced by achieving a goal G using the following methods:
        1. use an existing operator in the plan to achieve G
        2. add a new operator to the plan to achieve G
        3.* if the goal is operational assume it true in the initial state
    resolve conflicts in P' (protections)
    IF P' has no unresolved conflicts and no unachieved goals
    THEN return SUCCESS
    ELSE add P' to Q and continue
```

Figure 4: Static Operator Analysis Algorithm

Figure 5 shows the subgoal tree generated by performing full static analysis on the operator planner problem space defined by: Input Goals: (compute-om-matrix ?fl manmatch) (update-archival-sedr ?fl manmatch) and Operational Predicates: project, initial-predict-source.

4 Completion Analysis Tools

The second type of knowledge base development tool used in MVP is the completion analysis tool. In many cases, a knowledge engineer will construct a domain specification for a particular VICAR problem, test it out on known files and goal combinations. Two possible outcomes will occur. First, it is possible that the domain specification will produce an invalid solution. Second, it is possible that the planner will be unable to construct a solution for a problem that the expert believes is solvable.

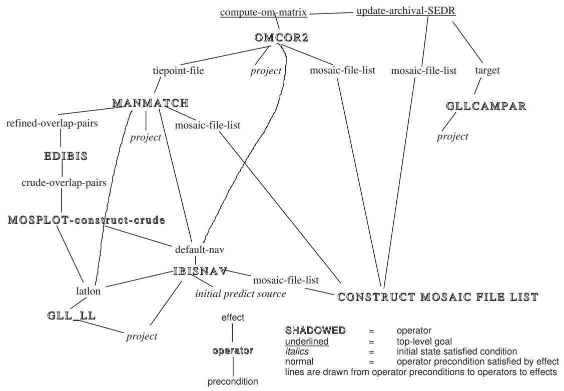

Figure 5: Subgoal Graph Indicating Static Operator Analysis for Navigation Goals

In the case that the planner constructs an invalid solution, the knowledge engineer can use the inconsistent part of the solution to indicate the flawed portion of the domain theory. For example, suppose that the planner produces a plan consisting of steps ABCD, but the expert believes that the correct plan consists of steps ABCSD. In this case the knowledge engineer can focus on the underlying reason that S is necessary. S must have had some purpose in the plan. It may be needed to achieve a top-level goal G or a precondition P of A, B, or C. Alternatively, if the ordering of operators or variable assignments is not valid in the produced plan, the knowledge engineer can focus on the protection or other constraint which should have been enforced.

The second possibility is that the domain specification fails to allow the desired solution. For example, the expert believes that the plan ABCD should achieve the goals, but the planner fails to find any plan to achieve the goals. In this case, detecting the flawed part of the knowledge base is more difficult, because it is difficult to determine which part of the domain specification caused the desired output plan to fail. In manually debugging these types of problems, the knowledge engineer would write out by hand the plan that should be constructed. The knowledge engineer would then construct a set of problems, each of which corresponded to a subpart of the failed complete problem. For example, if a failed problem consisted of achieving goals A, B, and C, the knowledge engineer might try the planner on A alone, B alone, and C alone, to attempt to isolate the bug to the portion of the knowledge base corresponding to A, B, or C, correspondingly.

Completion analysis tools partially automate this tedious process of isolating the bug by constructing subproblems. The completion analysis tools allow the decomposition or operator-based planner [5] to construct a proof with assumptions that a small number of goals or subgoals can be presumed achievable (typically only one or two)[6]. By seeing which goals,

[5] In the completion analysis for both the reduction planner and the operator-based planner there are choice points in the search in ordering plans in the search queue. In both cases, we use standard heuristics based on the number of outstanding goals and plan derivation steps so far. However, the static analysis techniques would work with any appropriate heuristic for this search choice.

[6] The number of goals assumable is kept small because allowing the planner to assume goals dramatically increases the search space for possible plans. It effectively adds 1 to the branching factor of every goal achievement node in the search space for the plan

if assumable, make the problem solvable, the user gains valuable information about where the bug lies in the knowledge base. For example, if a problem consists of goals A, B, and C, and the problem becomes solvable if B is assumed achievable, the bug is likely to be in the portion of the knowledge base relating to the achievement of B. Alternatively, if the problem is solvable when either B or C is assumed achievable, then the bug likely lies in the interaction of the operators achieving B and C. The completion analysis tool is used by running the modified planner algorithm until either: 1. a resource bound of the number of plans expanded is reached; or 2. there are no more plans to expand. The completion analysis algorithm for the reduction planner is shown below in Figure 6 .

```
CompletionReductionPlanner (input, operational, rules)
initialize Q = (goals=input, constraints=, assumptions=0)
IF resource bound return SOLUTIONS
ELSE select a plan P from Q
        for each plan P' produced by reducing P using a task reduction rule
            IF the constraints in P' are consistent
                    IF P' contains only operation goals/activities
                          THEN add P' to SOLUTIONS
                          ELSE add P' to Q and continue
                    ELSE discard P'
        for each plan P' produced by presuming the current goal achieved/operational
        IF P' contains only operation goals/activities
            THEN add P' to SOLUTIONS
            ELSE increment NumberOfAssumptions(P')
                    IF NumberOfAssumptions(P') ≤ bound
                          THEN add P' to Q
```

Figure 6: Completion Analysis for Reduction Rules

In the operator-based planner, completion analysis is permitted by adding another goal achievement method which corresponds to assuming that the goal is magically achieved. The completion analysis operator planner is then run until either 1. a resource bound of the number of plans expanded is reached; or 2. there are no more plans to expand. All solutions found are then reported back to the user to assist in focusing on possible areas of the domain theory for refinement. The basic completion analysis algorithm for the operator planner is shown below in Figure 7. The * on Step 4 indicates the principal modification to the standard operator-based planning algorithm made to perform operator-based completion analysis. The main drawback of the completion analysis tools is that they dramatically increase the size of the search space. Thus, with the completion analysis tools, we provide the user with the option of restricting the types of goals that can be presumed true. Currently the user can restrict this process in the following ways:

- allow only top-level (problem input) goals to be assumed;
- allow only goals appearing in a specific operators preconditions to be assumed;

```
CompletionOperatorPlanner(input, initial-state, operators)
initialize Q = (goals=input, constraints=, assumptions=0)
IF resource bound exceeded
  THEN return SOLUTIONS
  ELSE select a plan P from Q
        for each plan P' produced by achieving a goal using the following methods:
            1. use existing operator in the plan to achieve the goal
            2. add a new operator to the plan to achieve the goal
            3. use the initial state to achieve the goal
            4.* if the number of goals already assumed in P is less than the bound
                assume the goal true using completion analysis;
                the # of assumptions in the new plan is 1+ # in P;
                resolve conflicts in P' (protections);
        IF P' has no unresolved conflicts and has no unachieved goals
            THEN add P' to SOLUTIONS
            ELSE add P' to Q and continue
```

Figure 7: Completion Analysis for Operator Planner

- allow goals relating to an operator (appearing in its precondition or effects) to be assumed; and
- only allow certain predicates to be assumed.

Thus far, we have found these restriction methods to be fairly effective in focusing the search. Note that allowing certain goals to be presumed true corresponds to editing the problem definition (or domain theory) numerous times and re-running the planner. For example, allowing a single top-level goal to be assumed true for a problem with N goals corresponds to editing the problem definition n times, each time removing one of the top-level goals and re-running the planner each time. Allowing a precondition of an operator to be suspended corresponds to running the planner on the original problem multiple times, each time with a domain theory that has one of the operator preconditions removed. Manually performing this testing to isolate an error quickly grows tiresome. Furthermore, if multiple goals are allowed to be suspended, the number of edits and runs grows combinatorially. The completion analysis tools are designed to alleviate this tedious process and to allow the user to focus on repairing the domain theory. As a side effect, running the planner only once is also computationally more efficient than running the planner multiple times. This is because the planner need explore portions of the search space unrelated to the suspended conditions fewer times.

Thus, the completion analysis techniques are generally used in the following manner. MVP automatically logs any problems unsolvable by the task reduction planner (unreducable) or operator-based planner (no plan found). The user then specifies that one of the top-level goals may be suspended (any one of the top-level goals is a valid candidate - the planner tries each in turn. The completion planner then finds a plan which solves all but one of the top-level goals - focusing the user on the top-level goal which is unachievable. The user then determines which operator O1 that should be achieving the goal, and specifies that the completion planner may consider suspending preconditions of O1. The completion analysis planner runs and determines which precondition P1 of O1 is preventing application of this operator. Next, the user determines which operator O2 should be achieving this precondition P1 of O1, and the process continues recursively until the flawed operator is found. For example, it may be that a protection cannot be enforced, thus preventing a precondition P1 from being achieved. In this case, suppose another operator O2 should be able to achieve P1. But suspending its preconditions does not allow the problem to be solved. This might hint to the knowledge engineer that the problem is in the protection of P1 from O2 to O1. Alternatively, it may be that no operator has an effect that can achieve P (perhaps the knowledge engineer forgot to define the effect or operator). Or that the effect has a different number of arguments, or arguments in a different order, or arguments of a different type. These types of bugs can be easily detected once the bug has been isolated to the particular operator. Another possibility is that a conditional effect that should be used has the wrong conditional preconditions. Again, once the bug has been traced to a particular operator, the debugging process is greatly simplified.

In order to further explain how the completion analysis tools are used, we now describe a detailed example of how the completion analysis tools are used. The graph below in Figure 8 illustrates this process from an actual debugging episode which occurred in the development of a portion of the planning knowledge base [7] relating to a problem called relative navigation [8]. Each of the following steps in the debugging process is labeled P if the planner performed the step; U if the user/knowledge engineer performs the step; or C if the completion analysis tool performs the step.

1. (P) The planner is unable to solve the original problem.
2. (U) The user initiates the debugging process by invoking the operator-based completion analysis tool specifying that one top-level goal may be suspended.
3. (C) The completion planner constructs a plan achieving all of the goals but the top-level goal of (compute-om- matrix ?om-matrix ?file-list ?file-list).
4. (U) The user then determines that the OMCOR2 operator should have been able to achieve the goal (compute-om-matrix ?om-matrix ?file-list ?file-list). The user then continues the debugging process by invoking the completion analysis tool specifying that a precondition of the OMCOR2 operator may be suspended.
5. (C) In response to the user request, the completion planner finds a plan achieving all goals except the OMCOR2 precondition (tiepoint-file ?tp ?file-list manmatch).
6. (U) The user then determines that the precondition (tiepoint-file ?tp ?file-list manmatch) should be achieved by the MANMATCH operator, and invokes the operator completion analysis tool allowing suspension of one of the preconditions of the MANMATCH operator.
7. (C) The completion planner then finds a plan achieving all goals but the precondition (refined-overlap-pairs ?rop- file ?file-list) of the operator MANMATCH.

[7]Note that this is the operator portion of the knowledge base relating directly to the task reduction rules shown in the example for static rule analysis.

[8]For the interested reader, navigation of the image is the process of determining the appropriate transformation matrix to map each pixel from the 2-dimensional (line, sample) of the image space to a 3-dimensional (x,y,z) of some coordinate object space (usually based on the planet center of the target being imaged). Relative navigation corresponds to the process when determining the absolute position of each point is difficult to compute so that the process focuses on determining the correct positions of each point relative to other points in related images.

8. (U) The user then determines that the precondition (refined-overlap-pairs ?rop-file ?file-list) should have been achieved by the EDIBIS operator and invokes the operator completion analysis tool allowing suspension of an EDIBIS precondition.

9. (C) The completion planner finds a plan achieving all goals but the precondition (crude-overlap-pair ?cop-file ?file-list) of EDIBIS.

10. (U) The user then determines that this precondition (crude-overlap-pair ?cop-file ?file-list) should have been achieved by the MOSPLOT-construct-crude-nav-file. This results in another invocation of the completion analysis tool allowing suspension of a precondition for MOSPLOT-construct-crude-nav-file.

11. (C) The completion analysis tool then finds a plan achieving all goals but the precondition (latlon ?mf ?lat ?lon) for the operator MOSPLOT-construct-crude-nav-file.

12. (U) At this point, the user notices that the constructed plan for achieving the goals has assumed the instantiated goal (latlon &middle-file ?lat ?lon). This immediately indicates the error to the user because the user is expecting a file name as the second argument of the latlon predicate [9].

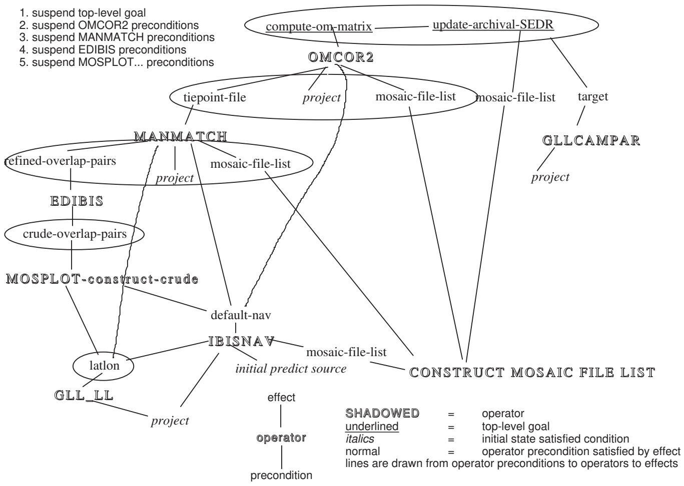

Figure 8: Subgoal Graph for Completion Analysis Debugging

Unfortunately, we have as of yet not been able to determine any heuristics for controlling the use of these completion tools that allows for more global search or allows for less user interaction. However, in their current form, the completion analysis tools have proved quite useful in debugging the MVP radiometric correction and color triplet reconstruction knowledge base.

4.1 Impact of Debugging

In order to quantify the usefulness of the completion analysis tools, we collected data from a 1 week phase of domain theory development for the relative navigation portion of the domain theory. During this week, we identified 22 issues raised by a domain expert analyst which at

[9]This is because the latlon goal is designed to refer to a specific image file (e.g., 1126.IMG). Correspondingly, the planning operators that had been defined to acquire information such as latlon presumed actual file names. Unfortunately, &middle-file refers to a VICAR variable which will be bound to an actual file name only at the time that the VICAR script is run (i.e. when the plan is executed). Thus, the bug lies in the mismatch between this precondition and the operators which can determine latlon information for a file. This bug was then fixed by defining operators which could utilize the VICAR variable information at runtime and perform the correct steps to compute the needed latlon information.

Table 2: Empirical Impact of Completion Analysis Tools

Set	Tools Applicable	Average Time	Tools Not Applicable	Average Time	Overall Average
Tool	7/11	10 min.	4/11	41 min.	21 min.
No Tool	6/11	43 min.	5/11	40 min.	42 min.

first guess appeared to be primarily in the decomposition rules or operators. For 11 of these 22 problems (selected randomly) we used the debugging tools in refining the domain theory. For the other 11 problems we did not use the debugging tools. When tools were allowed, we estimated that the tools were applicable in 7 out of the 11 problems. These 7 problems were solved in an average of 10 minutes each. The other 4 took on average 41 minutes. The total 11 problems where the tools were used took on average 21 minutes each to correct. In the 11 problems solved without use of the tools, after fixing all 11 problems, we estimated that in 6 out of the 11 problems that the debugging tools would have helped. These 6 problems took on average 43 minutes each to solve. The remaining 5 problems took on average 40 minutes to solve. The second set of 11 problems took on average 42 minutes to solve.

5 Discussion

One area for future work is development of explanation facilities to allow the user to introspect into the planning process. Such a capability would allow the user to ask such questions as "Why was this operator added to the plan?" and "Why is this operator ordered after this operator?", which can be answered easily from the plan dependency structure. More difficult (but also very useful) questions are of the form "Why wasn't operator O2 used to achieve this goal?" or "Why wasn't this problem classified as problem class P?". We are currently investigating using completion analysis tools to answer this type of question. The completion analysis techniques are related to theory refinement techniques from machine learning (Mooney and Ourston, 1994, Ginsberg et. al., 1988). However, these techniques presume multiple examples over which to induce errors. Additionally, reasoning about planning operators requires reasoning about the specialized planning knowledge representations and constraints. This paper has described two classes of knowledge base development tools. Static analysis tools allow for efficient detection of certain classes of unachievable goals and can quickly focus user attention on the unachievable goals. Static analysis techniques can also be used to verify that domain coverage is achieved. Completion analysis tools allow the user to quickly focus on which goals (or subgoals) are preventing the planner from achieving a goal set believed achievable by the knowledge base developer. These tools are currently in use and we have presented empirical evidence documenting the usefulness of these tools in constructing, maintaining, and verifying the MVP planning knowledge base.

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