Sharing Meta-Information to Guide Cooperative Search among Heterogeneous Reusable Agents

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CMPSCI Technical Report 94-48

June 1994

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Index terms: reusable agents, information (knowledge) sharing, distributed search, multiagent systems, mechanical design, distributed artificial intelligence

Abstract

A *reusable agent* is a self-contained computational system that implements some specific expertise and that can be embedded into diverse applications requiring that expertise. Systems composed of heterogeneous reusable agents are potentially highly adaptable, maintainable, and affordable, assuming that integration issues such as information sharing, coordination, and conflict management can be effectively addressed. In this article, we investigate the effectiveness of sharing meta-level search information to improve system performance, specifically with respect to how sharing affects the quality of solutions and the runtime efficiency of a reusable-agent system.

We first give a formal description of shareable meta-information in systems where agents have private knowledge and databases and where agents are specifically intended to be reusable. We then present experimental results from a mechanical design system for steam condensers that demonstrate performance improvements related to information sharing and assimilation. Finally, we discuss the practical benefits and limitations of information sharing in application systems comprising heterogeneous reusable agents. Issues of pragmatic interest include determining what types of information can realistically be shared and determining when the costs of sharing outweigh the benefits.

This work was supported by ARPA contract N00014-92-J-1698, and NSF contract CDA 8922572. The content of the information does not necessarily reflect the position or the policy of the Government and no official endorsement should be inferred.

1 Introduction

The computational equivalent to a team of human specialists is the *reusable-agent system*, a multiagent system in which expert agents are dynamically selected from an existing library and integrated with minimal customized implementation. With reusable-agent systems, diverse information can be applied in situations that were not explicitly anticipated at agent-development time. The benefits of this type of system to an application builder are potentially large: for example, agents can be flexibly and inexpensively added to or deleted from a system in response to changes in specifications, resources, and technology; agents will be more reliable over many uses; and the cost of building an agent can be amortized over multiple uses. However, in order to participate in an application system, reusable agents must be technically capable of effective interaction. They must be able to communicate information about the state of problem solving, to coordinate actions, and to resolve conflicts stemming from inconsistent or incomplete knowledge and evaluation criteria.

As noted by Neches et. al. [18], software reuse in any form is difficult and is impeded by the lack of tools available to foster information sharing. Concurrent investigations of languages, ontologies, and protocols for agent interaction such as KQML [7] complement our research but focus on the development of enabling technologies for information sharing rather than on the effect of shared meta-information on problem solving. In this article, we investigate how the communication of specific information among agents affects the quality of solutions and the efficiency of a reusable-agent system. Our goal is to show that reusable agents involved in distributed search can improve their joint performance by sharing meta-information with other agents, assimilating shared information from other agents, and using this information to refine their local views of the global solution space.

1.1 Shared Meta-Information

Multiagent systems generally assume some form of *result-sharing* [24], i.e., the sharing of partial solutions to facilitate global coherence. In our experiments, result-sharing is an integral part of problem solving—agents are able to examine, evaluate, and extend others' proposed partial solutions. However, our focus is on the sharing of a different type of information; namely, information that describes some abstraction of an agent's solution space rather than a specific solution instance. This will be referred to as *meta-information*.[1]

To illustrate the use of meta-information, consider a generic example of meeting scheduling. (Sen and Durfee investigate the effectiveness of various forms of shared information in a meeting scheduling domain in [22]). Assume two agents, $\mathcal{A}$ and $\mathcal{B}$, are seeking a mutually acceptable meeting time. A simple result-sharing approach would be for $\mathcal{A}$ to examine its local schedule and propose a time based on its constraints: "How about Monday at 3:00?" $\mathcal{B}$ responds with "No good. How about Tuesday at 9:00?", $\mathcal{A}$ responds with "Maybe Monday at 3:30?" and so on until one of the agents suggests a mutually acceptable time. In contrast, the use of meta-information is seen in the following exchange. $\mathcal{A}$ again begins with "How

[1]In the following text, *information* and *meta-information* are used interchangeably where it is clear from the context that this is the case.

about Monday at 3:00?", but now $\mathcal{B}$ responds: "No good. I'm tied up all day Monday. I've got some time Tuesday morning though and I'm free most of Thursday." Often some combination of a specific proposal and meta-information is offered, e.g., $\mathcal{B}$ would say ''...I'm free most of Thursday. How about Thursday at 10:00?". The goal of sharing meta-information is not to pinpoint a specific solution, but to guide other agents in their search for a solution.

1.2 Distributed Search

We explore the use of shared meta-information using a prototype application system, `STEAM`, that represents a class of cooperative distributed search systems for parametric design. Search systems are historically described in the Artificial Intelligence literature as comprising three components: a *state space* describing the current state of the search, a set of *operators* used to manipulate the state space, and a *control strategy* used for deciding what to do next, specifically, deciding what operator to apply and where to apply it [2]. When all operators reside in a single program or logical entity and have access to a central store of knowledge and databases, the search is centralized. In this article, we are concerned with the problem of distributed search as described in [16]:

> A distributed search involves partitioning the state space and its associated operators and control regime so that multiple processing elements can simultaneously perform local searches on different parts of the state space; the (intermediate) results of the local searches are shared in some form so that the desired answer is produced in a timely manner.

The partitioning of the state space in a reusable-agent system is induced by the *a priori* division of expertise of agents in the agent set. The set of operators available at an agent is also an *a priori* attribute of the agent. The control strategy used for a solving a particular problem should be tailored to the problem but must be chosen from the set of strategies known to the agents in the system. The selection of operators and control strategies for distributed search are addressed elsewhere in [14, 15].

1.3 The `STEAM` Application System

Throughout the article, we will augment the presentation of concepts with examples from a seven-agent system, `STEAM`, that performs parametric design of steam condensers. Figure 1 shows the general form of a steam condenser. The agents in `STEAM` each take responsibility for either: 1) designing some component of a steam condenser; or 2) critiquing some aspect of the condenser. The agent set in `STEAM` is:

{`pump-designer`, `heat-exchanger-designer`, `motor-designer`,
`platform-designer`, `vbelt-designer`, `shaft-designer`,
`system-frequency-critic`}

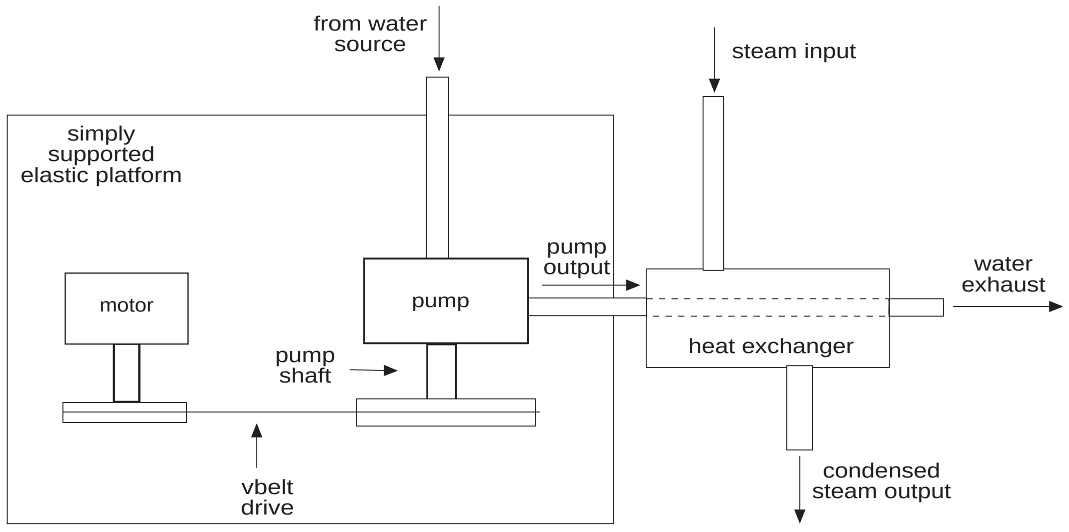


Figure 1: *A Steam Condenser*

1.4 Globally Cooperative Systems

The `STEAM` system is a *globally cooperative* system, meaning that there is assumed to be a global measure of system performance that overrides any local measures. This is generally true for design problems: there is some measure of the quality of a design that is distinct from the quality of any subcomponents of that design. An important aspect of globally cooperative systems is that it is not useful for agents to attempt to maximize their local payoffs for solutions by withholding information from other agents. The overriding goal of the system is to maximize the global, rather than local, payoff for solutions. In this situation, sharing information is not restricted by selfish or adversarial motives of agents as in some multiagent domains [25, 27].

Another example of a globally cooperative multiagent system is given by de Souza and Talukdar in [4], which describes the Asynchronous Team (A-Team) approach to solving a class of problems where multiple partially satisfactory algorithms exist but no completely satisfactory algorithm is known (such as the Traveling Salesman Problem). In the A-Team approach, each agent represents one of the known algorithms and the goal is to cooperate in such a way that the agent set produces better results as an organization than any one agent would produce alone. In this work, the only information shared among agents is in the form of partial solutions and the emphasis of the research is on how intermingling of the control flow of the agent organization improves performance.

In contrast, our emphasis is on the communication and assimilation of meta-information among reusable agents, the influence of shared information on an agent's ability to focus its search efforts, and the resulting performance improvements within an application system. In Section 2 we give a formal description of shareable meta-information in reusable-agent systems. The next section, Section 3, presents experimental results from `STEAM` that substantiate our hypothesis that meta-information sharing can improve solution quality and problem-solving efficiency. Section 4 discusses what costs are involved in sharing meta-information and what the practical limitations of the technology are from an application-system perspective. We conclude with a summary of observed results and some speculation as to the significance of these results within the `STEAM` system and within the more general realm of multiagent systems.

2 Solution Spaces

When discussing the solution spaces of agents, we distinguish between the *local* space of an agent and the *composite* space of the system. A local space is one that is private to an agent, the composite space is one that is shared by all agents.[2] In a parametric design application, the *local solution space* of an agent is defined by the parameters that are assigned values by an agent in its local solutions, i.e., its output parameters. An agent's initial view of the *composite solution space* is equivalent to its local solution space. However, this local view is unlikely to be effective in finding solutions that are mutually agreeable to all agents (solutions in the composite space). A primary goal of communication among agents, therefore, is for each agent to end up perceiving the closest approximation possible to the part of the composite solution space that contains its local output parameters. In nontrivial cases, it is unlikely that a complete and correct global view can be achieved at every agent. However, to the extent that its local view approaches the global view, an agent is likely to be more effective at proposing solutions that will be mutually acceptable.

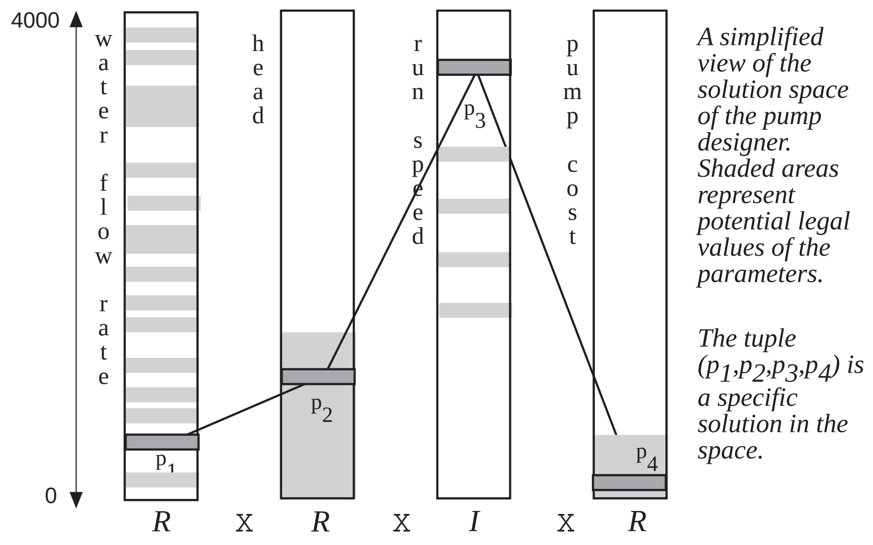
2.1 Defining a Local Solution Space

We will use examples from the `STEAM` system to illustrate the concepts being discussed. Figure 2 shows a simplified version of the solution space of `pump-designer`. This figure is simplified both in the number of parameters and the specification of the parameters' domains. The set of parameters in the solution space of an agent α is $\mathcal{P}^{\alpha}$, the *parameter set* of α. The parameter set of `pump-designer`, as shown in Figure 2, is {water-flow-rate,head,run-speed,pump-cost}.

The set of legal values for a parameter θ at agent α is its *parameter space*, $\mathcal{V}^{\alpha}_{\theta}$. To illustrate, the parameter space of `run-speed` from Figure 2 is the set of integers {1200,1800,2400, 3000,3600}. The parameter space of an agent can be defined over various domains including integers, reals, numeric intervals of the form $\{(min,max),\ min,max \in \mathcal{R}\}$, or discrete labels such as {*model-1, model-2,. . . ,model-n*}.

A solution in the solution space of α is a tuple $s^{\alpha}_{j} = (p_1, p_2, \ldots, p_n)$ such that $p_x \in \mathcal{V}^{\alpha}_{x}$ and such that any constraining relationships on or between the $p_x \in s^{\alpha}_{j}$ are satisfied. A parameter space may be constrained by explicit constraints on solutions such as (`run-speed` $\geq$ 1200) or through implicit constraints that are embedded in the functions an agent uses to search for solutions. As a trivial example of an *implicit constraint*, consider the following

[2] Spaces may also be shared by some subset of agents, but not the entire agent set [13]. These *common* spaces are outside the scope of this article, however, and we will not discuss them further here.



4000
0
water flow rate
head
run speed
pump cost
p1
p2
p3
p4
R x R x I x R
A simplified view of the solution space of the pump designer. Shaded areas represent potential legal values of the parameters.
The tuple (p1,p2,p3,p4) is a specific solution in the space.

Figure 2: *The Local Solution Space Of Pump-Designer from the* `STEAM` *System*

loop in pseudo-code:

```
head :== 0;
DO  water-flow-rate = 0 to 500
  new-head :== calculate-head water-flow-rate;
  head :== select-best new-head head;
END DO;
```

An agent using this code implicitly constrains the parameter space of `water-flow-rate` to be the set of integers from 0 to 500, although it may not declaratively represent this anywhere. In reality, functions tend to be more complex and the implicit constraints more difficult to discern. In the above example, the value of `head` is tacitly constrained by the implicit constraint on `water-flow-rate`. However, the effect of this implicit constraint on the parameter space of head is not determinable without a deeper understanding of the constraining relationship.

The existence of implicit constraints, goals, and heuristics must be expected in the general case of expert agents. Implicit meta-information cannot normally be shared since it is an integral part of an agent's expertise and cannot be easily extricated.[3] Unshareable information strongly affects properties of the agent sets in which it is embedded. For example, in [11], Khedro and Genesereth present a distributed-search model in which agents provably converge on a globally satisfactory solution if one exists. However, the property of convergence can only be guaranteed if all constraining information can be explicitly exchanged. When implicit constraints are added, this desirable property no longer holds.

[3]It is possible that some agents may be able to share either code or some form of abstracted explanation of implicit information. However, this requires specialized capabilities on the part of both the sending and receiving agents. Although it is possible to support these capabilities in specific situations, generalized code exchange and assimilation among heterogeneous reusable agents is not a realistic option.

Explicit (declaratively represented) meta-information can be shared and, as will be discussed in Section 3, this sharing can greatly enhance the effectiveness and coherence of the agent set. In `STEAM`, shareable information is limited to simple boundary constraints with the basic form (`water-flow-rate` < 800) that specify minimum or maximum values for a parameter (see Section 3.1 for a more complete explanation of shareable constraints). This limitation is not mandated by either our model of shareable information or the `STEAM` system, but rather was chosen due to its simplicity and accessibility. The costs of information sharing increase as agents apply more sophisticated techniques. Restricting information to boundary constraints may result in lower efficiency or lower-quality solutions than could be achieved by sharing more complex forms of information. However, the associated overhead costs are low and these constraints provide a manageable, first-cut view of the composite solution space. In Section 5, we will further discuss the tradeoffs inherent in supporting the sharing and assimilation of more complex forms of information; namely, the tradeoff between improved system performance due to better-informed agents and degraded system performance due to the overhead associated with sharing.

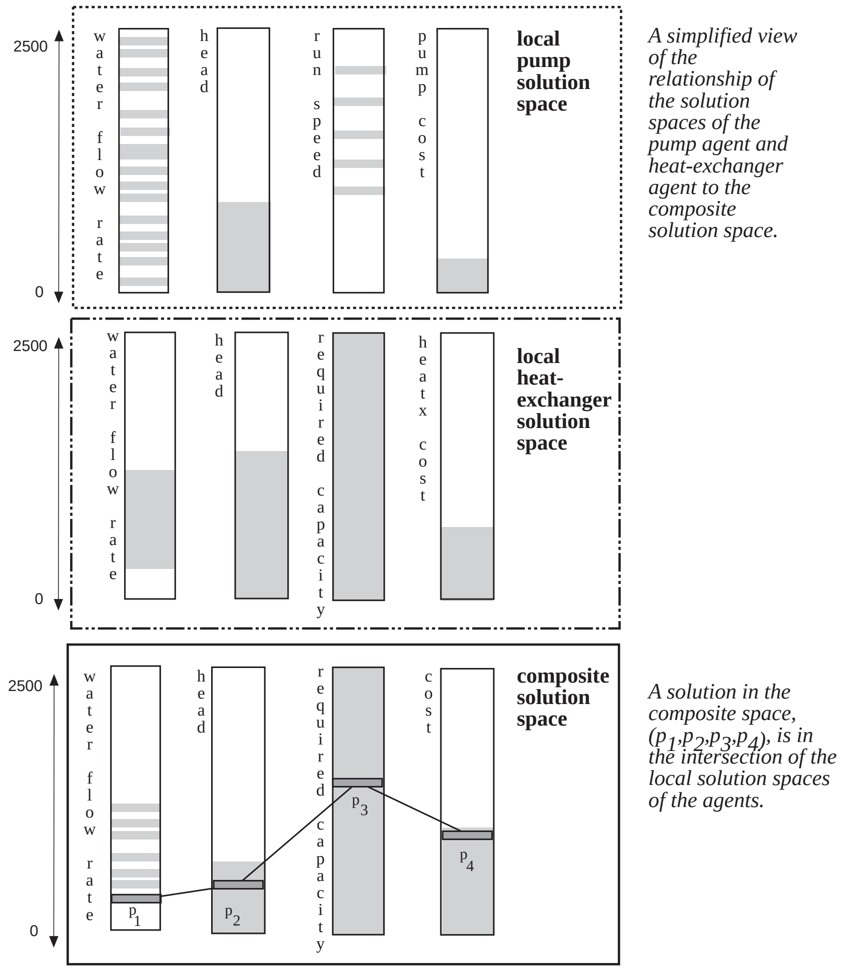
To include explicit boundary constraints in the definition of a solution space, we use the following notation: let c_j^α be a declaratively represented boundary constraint of agent α in the set of all explicit boundary constraints of α, $\mathcal{C}^\alpha$. Then, let the notation $\{c_j^\alpha : s_k^\alpha\}$ mean that c_j^α is satisfied with respect to a particular solution, s_k^α. For example if c_1^α is $(p_1 \leq 10)$ and $s_1^\alpha = (9, 5, 3, 7)$, then c_1^α is satisfied with respect to s_1^α, $\{c_1^\alpha : s_1^\alpha\}$. When c_j^α is neutral with respect to s_k^α (it does not constrain any parameters in s_k^α), it is considered to be satisfied.

Using this notation, the shareable solution space of agent α can be defined by specifying the parameter set of α, $\mathcal{P}^\alpha$ and the set of explicit constraints over those parameters, $\mathcal{C}^\alpha$. This shareable solution space is an approximation of the actual local solution space since it does not represent any implicit solution requirements that are embedded in the agent. We formally describe the shareable local solution space of agent α as follows: $\delta^\alpha = \{(p_1, p_2, \ldots, p_n) \mid (p_\theta \in \mathcal{V}_\theta^\alpha), (\forall c_j \in \mathcal{C}^\alpha, \{c_j : (p_1, p_2, \ldots, p_n)\})\}$. In nontrivial cases, δ^α will be a superset of the valid solutions of agent α since it does not take implicit constraints into account.

2.2 Defining the Composite Solution Space

Given a set of agents, $\mathcal{A}$, and a problem that they are cooperating to solve, the desired composite solution must derive its parameter values from the local solution spaces of the agents. However, the parameter set of the composite solution space, $\mathcal{P}^C$, is not necessarily the union of the parameter sets in the local solution spaces, as can be seen in Figure 3.

In this figure, the solution space of agent p (the pump agent) contains the parameters *water-flow-rate*, *head*, *run-speed*, and *pump-cost*. The solution space of agent h (the heat-exchanger agent) contains the parameters *water-flow-rate*, *head*, *required-capacity*, and *heatx-cost*. We find in Figure 3 that the parameters *water-flow-rate* and *head* are common to both agents while *run-speed*, *pump-cost*, *required-capacity*, and *heatx-cost* represent parameters unique to individual agents. The composite solution space shown in Figure 3 contains the shared parameters *water-flow-rate* and *head*, the parameter *required-capacity* from agent h, and also a unique parameter, *cost*. *Cost* is not local to either agent p or agent h, but



2500
0
water flow rate
head
run speed
pump cost
local pump solution space
A simplified view of the relationship of the solution spaces of the pump agent and heat-exchanger agent to the composite solution space.
2500
0
water flow rate
head
required capacity
heatx cost
local heat-exchanger solution space
2500
0
water flow rate
head
required capacity
cost
composite solution space
A solution in the composite space, (p_1,p_2,p_3,p_4), is in the intersection of the local solution spaces of the agents.
p_1
p_2
p_3
p_4

Figure 3: *Constructing a Composite Solution from the Local Solutions of Agents*

represents a transformation on local parameters of those agents, i.e., the sum of *pump-cost* and *heatx-cost*. To summarize, each parameter in the composite solution space is local to either agent p or agent h, local to both agent p and agent h, or is a unique parameter whose value can be derived from parameters local to agent p and/or agent h.

The *run-speed* output parameter of `pump-designer` does not appear in the composite solution. In this application system, *run-speed* can be characterized as a throw-away parameter: one that does not appear in a composite solution and is not used as an input parameter by any other agent. Throw-aways are a common occurence in reusable-agent systems since the agents are constructed without any foreknowledge of what output information will be required for any specific application system. Therefore, there is no guarantee that the set of output parameters chosen by the agent implementor will be exactly what is needed for any particular application.

In Figure 3, notice that the constrained set of values (the shaded areas) of the shared parameters, *water-flow-rate* and *head*, are not identical for the two agents. If we are looking only at constraint-satisfaction problems, problems in which all constraints must be satisfied or no solution can be found, the constrained composite parameter space of a shared parameter is the intersection of the constrained local parameter spaces. For example, the shared composite parameter space of *water-flow-rate* from Figure 3 is the intersection of the local *water-flow-rate* parameter spaces of the two agents p and h. We denote the composite *water-flow-rate* parameter space as w^C. If w^C is empty, no solution exists that will be mutually acceptable to agents p and h.

As discussed earlier, an agent's perception of w^C will not be identical to the actual composite parameter space in the general case. Formally, let w^C_α be an agent's perception of the composite parameter space, w^C. After all shareable information has been communicated and assimilated, agent α perceives some superset of w^C as defined by the explicit constraints of other agents and its own explicit and implicit constraints. If w^C_α is not empty, there are two possibilities: 1) a mutually acceptable composite solution, $s^C_x = (p_1, p_2, \ldots, p_n)$, exists with $p_w \in w^C$; or 2) no composite solution exists because there implicit constraints at other agents that exclude values in w^C, but that do not exclude values in w^C_α. Therefore, because of the possibility that implicit constraints exist, it is impossible to tell by looking at w^C_α whether or not a mutually acceptable solution exists. An example of the discrepancy between an agent's local solution space and other agents' perceptions of that space based on transmitted constraints is shown in the next section in Figure 5.

Intersection of the fully constrained local solution spaces of agents (spaces constrained by both implicit and explicit constraints) defines the composite solution space in a constraint-satisfaction problem. However, in a *constraint-optimization* problem, not all constraints must be satisfied in a solution. Instead an attempt is made to satisfy constraints to the fullest extent possible. Constraints may have differing amounts of flexibility: some may be *hard*, meaning that they must be satisfied in any legal solution, while others may be *soft*, meaning that they can be relaxed if necessary. Soft constraints again can have different degrees of flexibility: some can be "softer" than others. In these types of problems, composite solutions must lie within the intersection of the local parameter spaces under the set of hard constraints, but not necessarily under all soft constraints. The order in which constraints are relaxed can strongly affect system performance and solution quality [9, 17, 19]. A discussion of these issues is beyond the scope of this article, however, in [13], we present the algorithms used by `STEAM` agents to determine which constraints to relax in conflict situations and in situations where problem-solving progress has stalled.

In this section, we have defined the local, composite, and locally perceived composite solution spaces of a system of heterogeneous reusable agents. In complex application systems, the composite solution space is an amalgam of local spaces, each of which may be constrained in ways that cannot be articulated outside of the local context. Information sharing is viewed as a mechanism for reducing the difference between agents' local perceptions of the composite solution space and the actual space. The hypothesis is that as agents begin to understand the 'big picture' they become more effective at generating high-quality solutions quickly. In the next section, we investigate this hypothesis through experimental observation of how information-sharing affects solution quality and processing time in the `STEAM` system.

3 Empirical Analysis of Information Assimilation

In this section we empirically demonstrate the effectiveness of sharing potentially useful information among agents during distributed search. The experiments reported below were run in the `STEAM` system with the seven active agents listed in Section 1.3. There were two categories of experimental trials: *non-assimilation trials* and *assimilation trials.* For the assimilation trials, three agents instantiate the capabilities required for information assimilation: the *pump designer*, *motor designer*, and *heat-exchanger designer* agents. The other agents do not attempt to assimilate information as will be explained in Section 4.1. In the non-assimilation trials, the assimilation capabilities are not active at any agent.

In these experiments, agents transmit boundary constraints directly in response to conflict situations rather than transmitting information that is anticipated to be potentially useful. In other words, a boundary constraint is shared only when it conflicts with a proposed solution. The relative benefits of reactive information sharing and proactive information sharing are not explored here.

The system was run on each of 100 different feasible problem specifications, once with active assimilation capabilities and once without. The problem specifications were generated by randomly choosing a feasible value for each of the steam condenser attributes, {*required capacity, maximum platform deflection, platform side length*}, for each specification. The complete set of input problem specifications and observed data from the experiments are tabulated in [13].

In order for an agent to use information received from an external source to guide its local processing (i.e., *learn* about other agents' requirements for solutions), the agent must be able to receive constraining information sent from other agents, translate that information into a locally usable form, and store the translated information into a local knowledge base so that it can be easily retrieved and applied. We call this process *information assimilation.* Notice, however, that with reusable agents, the usefulness of shareable information cannot be determined at agent-development time since it is dependent on capabilities and interests of other agents that may eventually be integrated into a joint agent set. Therefore, not all shared meta-information will be assimilated by all agents.

Assimilated information is used by the assimilating agent to guide its search for local solutions. We have developed mechanisms that extend or replace the traditional retrieval capability of an agent to extract relevant constraining information from its knowledge base. These mechanisms were developed specifically to enable reusable agents to handle potentially conflicting information that has been received from external sources since there is no guarantee that shared external information will be consistent with internal information. The goal of the retrieval process is to find the most restrictive, but non-conflicting, set of known constraints on solutions for the current problem using both local and assimilated information. This set of constraints defines the closest possible approximation of the composite solution space in which globally acceptable solutions must lie. However, it requires that intelligent conflict-resolution capabilities be applied to select which constraints to relax when conflicts do occur. Although we do not address specific techniques for conflict management in this article, it is an important and encompassing problem. Work describing computational conflict-management techniques includes [1, 12, 15, 21, 22, 26, 27].

3.1 Information Shared in the `STEAM` System

The information shared in these experiments was limited to simple boundary constraints of the form {`constraint-form, flexibility`}. A `constraint-form` is a single clause with the syntax $(x < n)$, $(x <= n)$, $(x > n)$, or $(x >= n)$, as previously discussed in Section 2.1. x is a shared numeric parameter and n is some numeric value although the concepts could be extended to processing sets of labels as well. These constraints define an n-dimensional 'box' in the solution space, where each dimension represents a parameter in the parameter set of the agent α, $\mathcal{P}^{\alpha}$. Ignoring for the moment the `flexibility` attribute, Figure 4 shows the boundary constraints derived by two agents to represent their local solution spaces. The accuracy of the representation is dependent upon characteristics of the space. For example, when the solution space is sparse, as in Figure 4a, the shareable view defined by boundary constraints will not be highly accurate, as shown in Figure 4c.

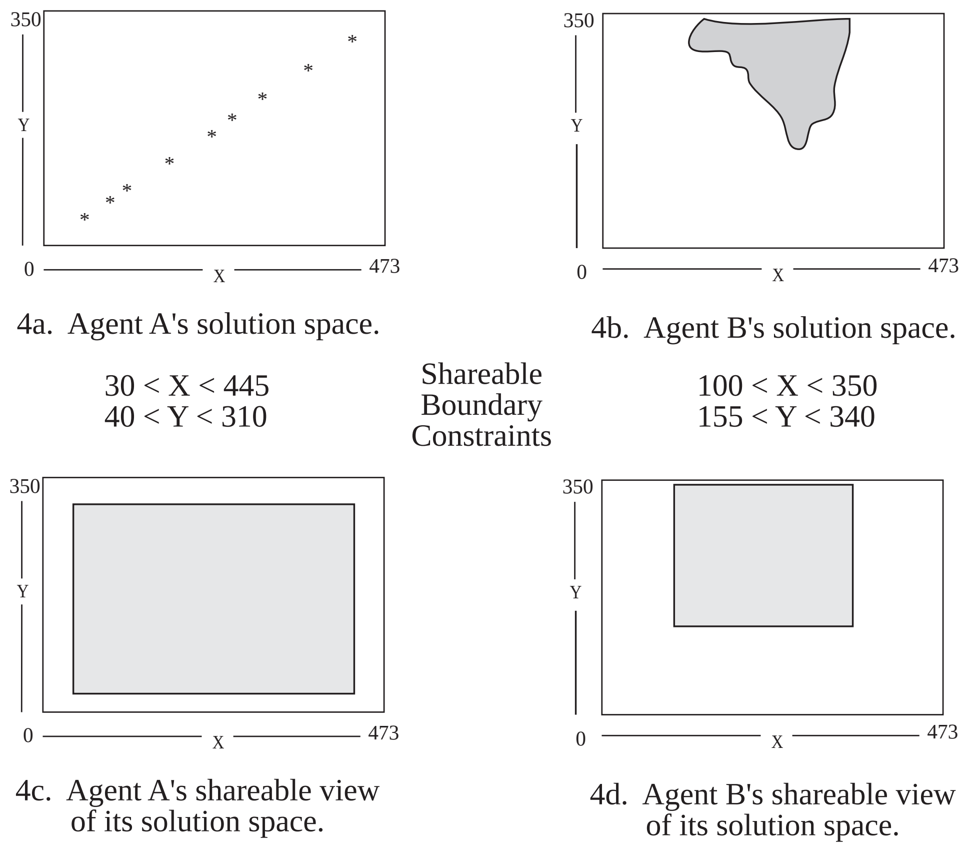

350
Y
0
X
473
4a. Agent A's solution space.
4b. Agent B's solution space.
30 < X < 445
40 < Y < 310
Shareable Boundary Constraints
100 < X < 350
155 < Y < 340
4c. Agent A's shareable view of its solution space.
4d. Agent B's shareable view of its solution space.

Figure 4: *Shareable Views of Agent Solution Spaces Built using Boundary Constraints*

Continuing the example in Figure 4, Figure 5 shows the perceived situation from each agent's perspective after the boundary constraints have been transmitted, along with the actual composite space.

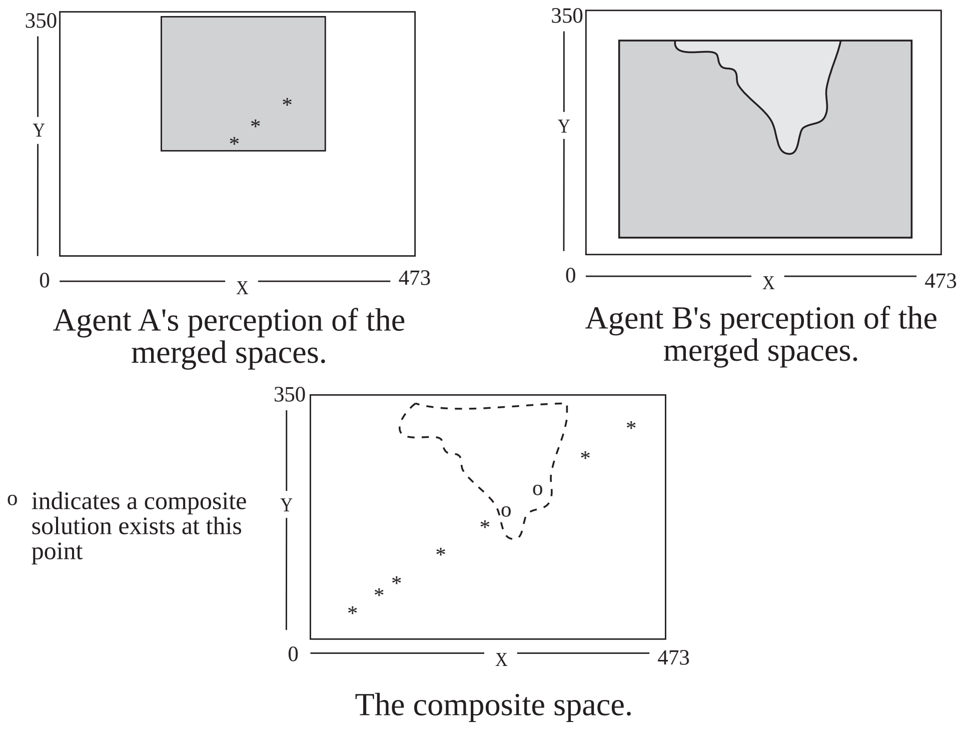

350
Y
0
X
473
Agent A's perception of the merged spaces.
350
Y
0
X
473
Agent B's perception of the merged spaces.
o indicates a composite solution exists at this point
350
Y
0
X
473
The composite space.

Figure 5: *Perceived Solution Spaces Contrasted with the Actual Space*

Agent A has a much more accurate perspective than Agent B because, as noted earlier, Agent B's boundary constraints more accurately represent its solution space. Therefore, it is important to note that when boundary constraints are used as the primary mechanism for information sharing, it is possible to either predict (through agent analysis) or learn which agents have the best global perspective. This is the basis of work that has been done by Lander [13] on making effective assignments of roles to agents within an agent set. It also provides the foundation for ongoing work in building reusable-agent sets that can automatically adjust role assignments for effective problem solving without requiring knowledge-based analysis of agent characteristics [20].

Returning to our discussion of how boundary constraints represent shareable perspectives of agents' solution spaces, notice that in some situations an agent may choose its boundary constraints such that some local solutions are excluded from the shared information. For example, if there are spurious outlying points, it may be advantageous to the entire system to exclude those points. By excluding them, the area that needs to be searched can be made much smaller, although this may result in missing valid or even optimal solutions. This idea is similar to that of relaxing the admissibility condition in $A*$ search whereby $h*$ is allowed to overestimate the distance to the goal, resulting in less search but a possibly non-optimal solution. If an agent intentionally misstates its boundaries, whether its motives are benevolent or malicious, issues of deception arise. Deception in multiagent environments is an important and ongoing area of research [5, 10, 28] that must be addressed in the larger scope of multiagent systems in general; however, in the `STEAM` system, agents are assumed to never lie.

In addition to the `constraint-form` clause of a constraint, the boundary constraints used by the `STEAM` agents include a `flexibility` attribute, loosely based on the notion of *utility* suggested by Fox [8]. `flexibility` is represented as an integer from 0 to 4. A flexibility of 0 specifies a hard (nonrelaxable) constraint that must be met by any feasible solution. A flexibility of 4 implies that solutions satisfying the constraint are of high quality. The use of a flexibility attribute on boundary constraints defines a set of n-dimensional boxes in the solution space, each representing an equivalence class of solutions of a given quality. For example, the box circumscribed by an agent's boundary constraints at flexibility 4 contains solutions that satisfy the most demanding local constraints of the agent. In contrast, the box circumscribed by an agent's boundary constraints at flexibility 0 contains solutions that are feasible but not necessarily desirable. For example, pump-designer specifies a soft constraint, $\{(\textit{water-flow-rate} < 175), 4\}$, meaning that all pumps rated as *excellent* will have a water-flow-rate less than 175. It also specifies a hard constraint, $\{(\textit{water-flow-rate} < 415), 0\}$, that indicates any value >= 415 will result in an infeasible solution. Figure 6 illustrates possible

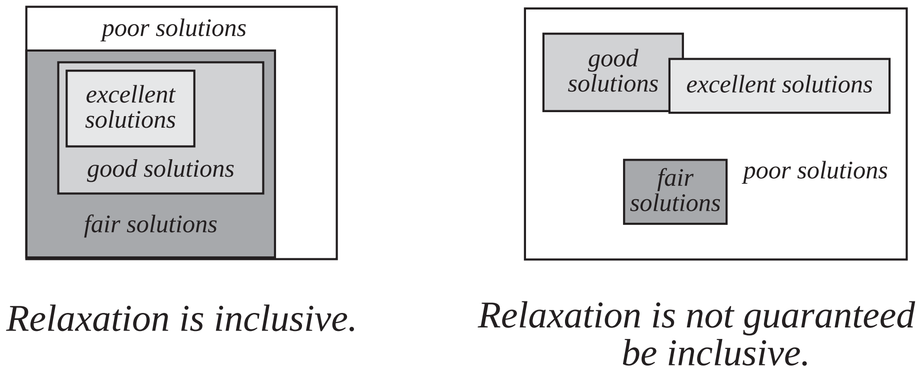


Figure 6: *Quality Equivalence Classes within an Agent's Local Solution Space*

partitionings of a two-dimensional solution space according to the flexibility values of known boundary constraints on the space, one in which the partitionings are *inclusive* and one in which they are not.

In `STEAM`, solution quality classes are inclusive. In other words, all *:excellent* solutions fall within the boundary constraints of the *:good* class so that searching for a solution in one quality class does not preclude the possibility of finding a solution of higher quality (as in Figure 6a). This need not be true in the general case however. Figure 6b illustrates a set of quality classes that is only partially inclusive. This distinction is only important from an agent implementation standpoint: conceptually it does not affect problem solving but it does affect the algorithms used for constraint manipulation and search.

The boundary constraints described above are only one form of information that can potentially be shared. They will not be adequate or appropriate in all domains. However, one result of our work has been the recognition that they are adequate to significantly improve processing in our domain. There is a high degree of complexity inherent in building heterogeneous agents that can understand each other well enough to positively affect mutual work. As the type of information to be shared increases in sophistication, the design and implementation of agents needs to be more tightly coordinated to support effective generation and assimilation of shared information. Even the simple form of sharing shown here requires some uniform mechanisms across agents for representing, assimilating, and applying constraints. A primary principle in the development of reusable agents is that the degree of coordination required among agent implementors should be kept as small as possible. These constraints provide a minimal basis for interaction that can be shown to positively influence the overall search activity of the agent set.

There are two measures of system performance in the `STEAM` system: solution quality and runtime. We expected to see that extra costs associated with sharing information would be balanced, in the majority of cases, by improvements in performance. In the following sections, we first present the results from the information-sharing experiments on solution quality and runtime. We then discuss the underlying mechanisms in the `STEAM` system that produce the results: what is it about the agents that is affected by having external information available?

3.2 Solution Quality

We compared the results of running the system when agents assimilated constraining information and when they did not. In `STEAM`, solution quality is determined by the monetary cost of each solution: the minimum-cost acceptable design is considered the most highly rated. The results of the 100 experimental trials are graphically summarized in Figure 7. In this figure, the results are sorted into ascending order based on cost in the assimilation trial.

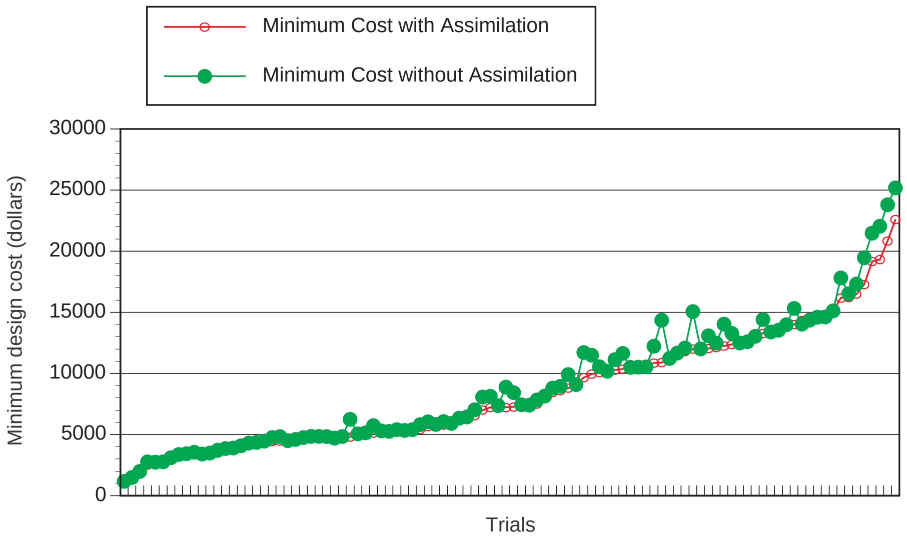


Figure 7: *Solution Quality Results in Assimilation Experiments*

For the 100 problem specifications tested, the mean cost in the assimilation trials was \$8504.77, in the non-assimilation trials, it was \$9020.43. The mean cost improvement with assimilation operators enabled was 5.72%, meaning that the monetary cost of the most highly rated solution in an assimilation trial was 5.72% lower on average than that in the associated non-assimilation trial under the identical problem specification. We had hypothesized that enabling assimilation would lower the cost of a design (thereby improving solution quality) and the experimental results appeared to support this hypothesis. To statistically confirm this result, we applied a paired difference t-test. In this type of test, the results from two matched trials are compared—in our case non-assimilation trials are compared to assimilation trials performed under the same problem specification. For each paired trial, the difference between the resulting design costs is calculated. Then the mean of the differences is computed over the entire set of trials. The null hypothesis in this case is $H_o : \mu_D = 0$ (the population mean of the differences is 0), meaning that the results of the two types of trials are not significantly different. The alternative hypothesis is $H_a : \mu_D > 0$ (the population mean of the non-assimilation trial results minus the assimilation trial results is greater than 0), meaning that the cost of designs in the non-assimilation trials are higher than those in the assimilation trials. Applying the paired t-test results in a t-score of 6.455, which allows us to reject the null hypothesis with a confidence of more than 99%. We can thus say with a high level of confidence that when `STEAM` agents apply assimilation capabilities, the average quality of solutions improves.

An inherent characteristic of the `STEAM` domain is that good solutions are easy to find under many problem specifications (the solution space is dense). We believe that there is a significant *floor effect* in the domain, meaning that minimum-cost designs are easy enough to find even in the non-assimilation trials that it is difficult to dramatically improve solution quality. However, the ability to consistently lower design costs approximately 5.72% by sharing simple boundary constraints is compelling evidence that information sharing and assimilation is an important technique for improving solution quality in multiagent systems. Furthermore, if it is the case that a floor effect is influencing our results, larger improvements could be expected in some domains.

The 5.72% figure given above for the improvement in solution quality may understate the significance of the improvement if the assimilation trials are approaching optimality. For example, assume that our average figures of \$8504.77 and \$9020.43 represent the results of a matched pair trial. If the optimal solution in this trial was actually \$8300, the assimilation run is suboptimal by \$204.77 while the non-assimilation run is suboptimal by \$720.43. With respect to the optimal solution, then, the assimilation run shows approximately a 72% improvement over the non-assimilation run.

3.3 Runtime

Runtime is directly measured in these experiments as the elapsed real time from the invocation of the system until termination of the system.[4] The average runtime with assimilation is 121.98 seconds, without assimilation the average runtime is 132.67 seconds. The assimi-

[4]These experiments were run on a TI Explorer II. Incremental garbage collection was turned off during the runs. However, the recorded time includes time spent on process and memory management tasks. Therefore, recorded times varied slightly across identical runs.

lation runtimes are, on average, 8.06% lower than the non-assimilation runtimes. However, direct comparison of the runtimes of assimilation and non-assimilation trials is somewhat misleading.

STEAM is a *satisficing* system [23]: there is no way to determine if an optimal solution has been achieved, and it is difficult to decide when to stop looking for a better solution. In any satisficing system, some policy must be generated that defines under what conditions the system will terminate processing. The termination policy used in the STEAM system is that when three acceptable solutions are found, the system enters a termination phase. The rationale behind creating at least three alternative solutions is that alternative solutions represent various design tradeoffs, and the user should have the opportunity to decide which of the tradeoffs is best for her needs. Furthermore, instead of halting immediately with the first three completed acceptable solutions, STEAM finishes all remaining acceptable partial solutions (as long as they remain acceptable). This policy is appropriate for the STEAM domain since solution quality and user participation are higher priorities than runtime.

Due to the focused search that occurs when information is shared, there are likely to be more acceptable solutions produced per run in the assimilation trials than in the non-assimilation trials. We found that this is indeed the case: more of the solution paths that are started in the assimilation trials turn out to result in acceptable solutions. Therefore, one result of the termination policy used in STEAM is a bias in which direct runtime measures favor non-assimilation trials. In those trials, the system doesn't complete as many solutions as it does in the matching assimilation trial because many of the solutions it tries are unacceptable and need not be completed.

To make runtime comparisons more meaningful, we divided the runtime of each trial by the number of solutions completed during that trial, resulting in a *runtime-per-solution* measure. The results obtained using this method are graphed in Figure 8.

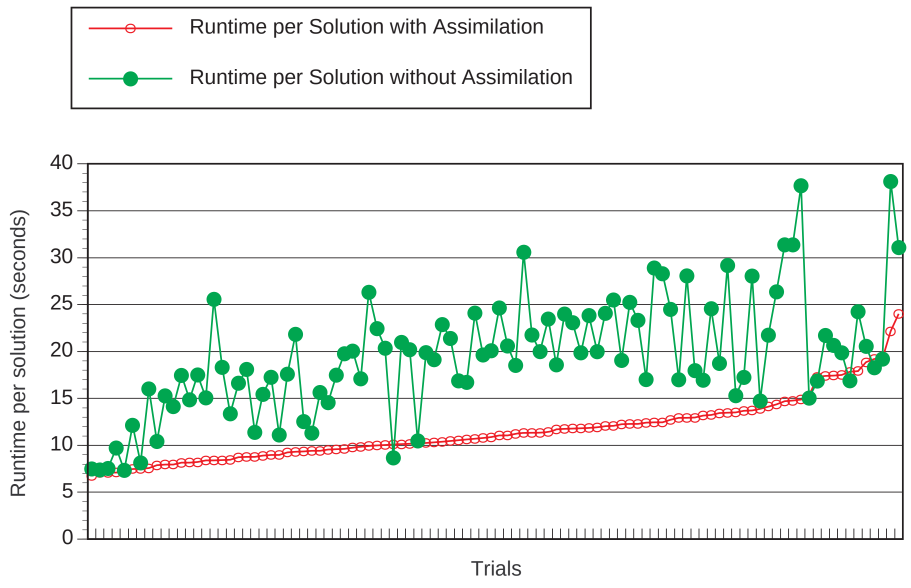


Figure 8: *Runtimes-per-Solution Results in Assimilation Experiments*

The *runtime-per-solution* observations in the assimilation and non-assimilation trials were averaged over the 100 experiment sets for comparison. The average runtime per solution in the assimilation trials was 11.58 seconds and in the non-assimilation trials it was 19.50 seconds. The average percent improvement achieved by the assimilation trials over the non-assimilation trials in runtime-per-solution was 40.62%. In addition to highlighting the improvement in system efficiency in the assimilation trials, this indicates that the system could be tuned for faster runtime at the expense of solution quality by changing the termination policy to halt without finishing partial acceptable solutions.

3.4 Understanding the Effect of Shared Meta-Information on System Performance

We stated above, based on the t-test analysis of solution quality, that when `STEAM` agents apply assimilation capabilities, the average quality of solutions improves. However, knowing that quality improves is not equivalent to understanding why it improves.

As described earlier, the goal of meta-information sharing is to improve agents' local perceptions of the composite solution space in order to make local search more productive. The more accurate the view of the composite solution space, the less time is wasted in producing solutions that are locally, but not globally, acceptable. Therefore, we expected to see runtime measurements improve in the assimilation trials because agents would waste less time in unproductive tasks. This expectation was fulfilled in the experiments performed.

Though it seems clear that system runtime would be affected by information sharing, it is not as easy to see why solutions would improve in quality as well. To understand the relationship between solution quality and information assimilation in the `STEAM` system, it is necessary to understand the relationship between constraint relaxation and solution quality. In this section, we describe the mechanisms of constraint relaxation that are affected by information sharing and that, in turn, affect the quality of solutions produced.

In any non-trivial agent environment, there will be conflicts among the boundary constraints of different agents. These conflicts are often *soft conflicts*, meaning conflicts that occur over soft constraints. In order to find any solution in the composite solution space, these soft conflicts must be resolved by relaxing one or more of the conflicting constraints. In the `STEAM` domain, there is an approximate mapping between the degree of local constraint satisfaction and the quality of a solution. In general, the more relaxation has occurred in the environment, the lower the quality of solutions produced. This is an approximate mapping because the global evaluation of a design in a globally cooperative system is not necessarily a direct function of local agent evaluations. For that matter, a local agent evaluation is not necessarily a direct function of local constraint satisfaction. However, it is usually the case that there is a relationship between constraint satisfaction and solution quality and, in the `STEAM` domain, this is a reasonable assumption.

There are three primary types of constraint relaxation used in `STEAM`: unilateral, responsive, and automatic [13]. *Unilateral* relaxation occurs at an agent in direct response to a problem specification—the agent will relax local soft constraints in order to meet requirements imposed by the specification. Unilateral relaxation is not dependent on information sharing and will not be further discussed.

Responsive relaxation occurs when there are explicit conflicts between an agent's constraints and some other agent's constraints. In responsive relaxation, an agent that has received conflicting constraints from another agent determines which of its own constraints to relax or which of the received constraints to ignore based on some conflict-management criteria. In this case, relaxation is used to remove a conflict and it is specifically enabled by information sharing.

Automatic relaxation occurs in response to a lack of problem-solving progress. Because not all relevant information is shareable, it is sometimes the case that problem solving stalls over implicit conflicts without any agent being able to pinpoint the cause. One way to handle this situation is to set up the system so that one or more agents must select and relax a local constraint after some amount of time has gone by. Decisions about which agent should relax which constraint are not discussed here—this is a complex problem and in general these decisions are highly domain-dependent and agent-set specific. However, the basic rationale for automatic relaxation is that unless it is possible to directly attribute any lack of problem solving progress to a particular constraint, there must be a mechanism for selecting and relaxing arbitrary constraints until the obstacle is removed. This basic idea has been part of the DAI literature for some time. For example, in the Hearsay-II speech understanding system developed in the late 1970s, a group of hypotheses for words were generated and rated, and the most highly rated hypotheses were passed to the word-sequence level of processing that would then try to build multiword sequences. If problem solving stagnated at that level, rating thresholds were relaxed at the word level in order to provide more breadth in the word-sequence search space [6].

Given this brief introduction to constraint relaxation, we now return to our discussion of how information sharing and assimilation affects global solution quality in a globally cooperative system. Without information sharing, the default form of constraint relaxation is automatic relaxation: basically a blind search for the source of a problem. In the course of 'fixing' the problem, other non-problematic constraints are also often relaxed. This leads to lower standards for solutions and, ultimately, lower quality solutions. In contrast, responsive relaxation supports the agents in making globally beneficial decisions about which constraints to relax. By providing an agent with specific knowledge about the source of the problem, information sharing enables the agent to make an intelligent decision about the most appropriate solution to the problem. Knowledge that can be brought to bear in deciding which constraint to relax includes power relationships between agents and the flexibility of the constraints involved in the conflict.

Automatic constraint relaxation is also influenced by information sharing and assimilation. The general effect of automatic relaxation policies is that the local quality of proposed solutions degrades over time as requirements become less stringent. Because of this, the timing of solution generation is important—it is important that each agent quickly focus its local search as narrowly as possible. Because information assimilation and sharing accomplishes precisely that, the quality of solutions improves simply because good solutions are proposed before any arbitrary relaxation occurs.

3.5 Summary

The results presented in this section demonstrate that information sharing can positively affect both solution quality and runtime in a heterogeneous reusable-agent system. However, there are costs associated with information sharing and, in fact, the more sophisticated information sharing becomes, the higher the costs are likely to become. In the following section, we discuss the costs involved in information sharing with an eye toward determining how sophisticated it is practical to become.

4 Information-Sharing Costs

Sharing information has five primary costs (where cost is measured in time):

1. *Generation*: the cost of generating shareable information at the sending agent specifically intended to be transmitted to other agents to guide their local searches;

2. *Determination*: the cost of determining what information to share at a given point in problem solving;

3. *Transmisssion*: the actual costs associated with the physical transmission of messages among agents;

4. *Translation*: the cost of translating shared information either directly from one agent's language to another's or from the local language to a shareable format at the sending agent and then from the shareable format into a local language at the receiving agent;

5. *Local Management*: the cost of managing shared information at the receiving agent; determining the applicability of received information (sorting, filtering, detecting conflicts and locally resolving those conflicts) and managing the greater volume of information that results from accumulating received information (storage and retrieval costs).

In the timing analysis described below, we do not include transmission costs (those associated with the physical transfer of information from one agent to another). This is consistent with the current implementation of `STEAM` in which all agents reside on the same machine and run in the same process, making transmission costs virtually nil. This exclusion of transmission costs should not be extended to the general case however.

The list above summarizes the types of costs incurred as a direct result of information sharing. We next give a more complete description of those costs and present observed data from their measurements in the `STEAM` system. We then move on to discussing the relevance of our observations in the more general context of reusable-agent systems. We conclude with some thoughts on how agent reusability affects information sharing, discussing both the positive and negative issues that arise.

Generation: The costs listed as *generation* costs should represent only the time an agent spends generating shareable information that would not otherwise be declaratively represented. This can potentially entail a great deal of 'self-analysis'. Types of information that can be used to focus other agents' searches include: 1) constraints that are completely independent of the specific problem being addressed (*independent* constraints); 2) constraints that are dependent only on the problem specification without regard to any particular solution (*problem-dependent* constraints); and 3) constraints that are dependent on existing instantiated parameters for a particular solution (*solution-dependent* constraints). These different categories are explained in more detail in [13].

In the timing studies reported here, we investigated the use of problem-dependent constraints. In other words, we measure the time it takes to construct boundary constraints that are dependent on a particular problem specification. For example, a problem specification in `STEAM` includes a fixed value for the required capacity of the desired steam condenser. Required capacity is an input parameter to the *heat-exchanger-designer* and affects the mapping between parameter value and solution quality of other local parameters. Therefore, each time a new problem specification is provided to the system, heat-exchanger designer must recompute the boundary constraints on any parameters affected by the assigned value of required capacity.

Costs associated with generating independent constraints are not considered to be part of the normal cost of developing a solution because these constraints can be generated in a one-shot preprocessing procedure.

Solution-dependent constraints are not used in `STEAM` although, in some domains, it is possible to exploit these constraints. If the agents in an application system (or some subset of the agents) have a limited number of local alternative solutions, it may be effective to develop guiding information that relates specifically to a single solution. For example, say an agent, $\mathcal{Z}$, in a globally cooperative system has only two alternative local solutions, either *proposal 1* or *proposal 2*. Any global solution will therefore incorporate one of the those two proposals. In this situation, it might well be worthwhile to specify solution-dependent constraints such as {if $x = \textit{proposal1.x}$, then $y > 10$}. Even though deriving this constraint might entail considerable runtime analysis, it will be applicable 50% of the time. However, assume instead that $\mathcal{Z}$ has 100,000 alternative solutions. In this case, the above constraint is only applicable in .001% of the potential solutions and it is unlikely that the time spent in generating the constraint will be recovered by its effect on focusing the composite search. In their work on multistage negotiation, Conry et. al. have developed a formalism that generates solution-dependent constraints for a set of subplans through iterative agent interactions. These constraints focus the system and enable it to determine that no solution exists when no non-conflicting constraint set can be found [3]. However, solution-dependent constraint generation and manipulation techniques are not useful in the `STEAM` domain because of the size of the solution spaces at each of the agents.

Determination: An agent must decide what information to transmit. In `STEAM`, agents transmit information directly in response to conflict situations rather than transmitting information that is anticipated to be potentially useful. Therefore, only constraints that are in direct conflict with an existing solution are transmitted. The costs of retrieving potentially conflicting constraints and checking each constraint to see if it conflicts with the existing solution are reported in this measure.

Notice that in some domains, agents might be more proactive than reactive with respect to when information is transmitted. For example, an agent might broadcast some of its strongest constraints without waiting for a conflict to occur, thereby facilitating conflict avoidance rather than conflict resolution. No matter when transmission occurs, however, the agent must still determine what to send.

Translation: In the general case of heterogeneous reusable-agent systems, local information can be represented at an agent in any form that is appropriate for that agent but some mechanism must be provided to ensure that agents are able to understand each other. When translation is necessary, the cost can vary greatly depending on exactly what is entailed. Some agents may share a language and have no translation costs, others may translate using simple syntactic procedures, and others may require complex semantic translation. In STEAM, the local representation of an agent's information is unrestricted, but in order for information to be shared, it must be translated into a globally specified language. All agents use the same simple syntactic procedures for translation between local and global formats. Translation costs, therefore, do exist but are relatively small.

Local Management: Conflict between local and assimilated information is one factor that potentially mitigates the benefits of information sharing: what happens when an agent receives information that contradicts something it already knows? With logically heterogeneous agents, it must be assumed that conflict will occur. In the `STEAM` system, the costs of managing conflicts between inconsistent local and external information are categorized as local management. Other local management costs include costs that accrue from the greater volume of information that must be stored and retrieved due to assimilated information.

4.1 Observed Information-Sharing Costs in `STEAM`

In these experiments, the costs attributed to sharing information are broken down into the categories: 1) generation (for problem-dependent constraints); 2) determination; 3) translation; and 4) local management, as described earlier. The observed costs for each of these categories over the 100 problem specifications are summarized in Figure 9 (the complete set of data is tabulated in [13]).

The approximate average time spent in constraint generation per problem is 7.3 seconds, constraint transmission is .4 seconds, translation is .5 seconds and local management is 4.2 seconds, for an average total time for information assimilation of approximately 12.4 seconds per run (out of 121.98 seconds average runtime). The average total percentage of time spent in information sharing in these trials is 10.17%. These figures are highly domain-dependent and each of the different areas could be more or less expensive in other situations. For example, if more elaborate constraints were being generated or if a more sophisticated analysis of the local search space was performed, the constraint generation time would be higher and consume a larger proportion of the processing time. Likewise, if translation were more difficult and involved some semantic interpretation as well as strict syntactic replacement, it would take more time. The question that must be asked is not whether information sharing and assimilation takes time—it does. Rather, the questions to ask are:

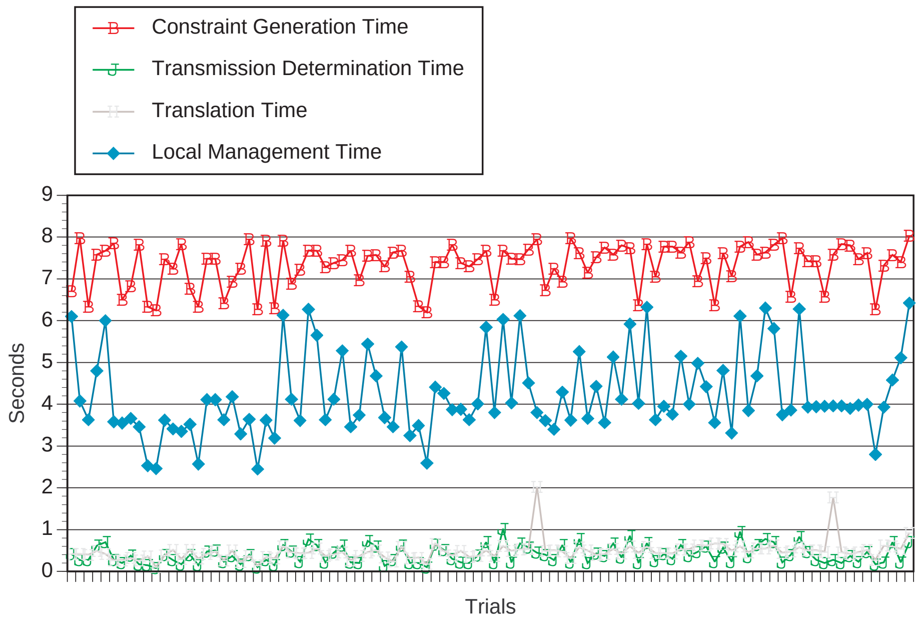


Figure 9: *Information-Sharing Costs in* `STEAM`

1. What information can be shared and assimilated by each agent?
2. For each type of information that can potentially be shared, will sharing it decrease the processing time of the system?
3. For each type of information that can potentially be shared, will sharing it improve solution quality in the system?

It is possible to empirically answer the second and third questions for a particular system and, therefore, to tune the system to appropriate tradeoffs in quality and processing time based on information sharing, either manually or automatically using machine learning techniques. The first question cannot be answered in any general way when agent reusability is an issue.

In the assimilation experiments described above, only three of the seven agents instantiated information-assimilation capabilities. The primary reason for this is that implementing these capabilities is very difficult. For each agent, the implementation is unique and requires a thorough understanding of the information requirements and search mechanisms of that agent. This suggests that it must be done by the agent implementor at the time the agent is built. The agent implementor cannot be responsible for determining what local information will be relevant in a particular application system since the agent may be embedded in different systems. However, the agent implementor must determine what local information will be shareable. Furthermore, the agent developer must anticipate the types of information that may become available to the agent during problem solving and build into the agent the capabilities required to effectively apply that information.

We demonstrate the difficulty inherent in implementing effective information assimilation through an example. Say that the `pump designer` receives a constraint from the

heat-exchanger designer that restricts a parameter called *run-head* of pumps proposed by the pump agent. This constraint is not directly applicable during the search for candidate pumps because the value of *run-head* is computed after the specific pump is chosen: it is an output parameter rather than an input parameter. However, once a candidate pump has been generated, the *run-head* for that pump can be computed and the constraint can be applied as a filtering mechanism to eliminate non-viable candidates. If *pump-designer* does apply the filtering constraint, it will still have to iteratively generate and test candidate pumps locally, but will eliminate infeasible ones before other agents are asked to respond to them. Therefore, by appropriately applying assimilated information, it can reduce the workload of other agents.

The point here is that it is not only necessary to understand the language of received information, it is also necessary that the agent know how to apply it. Applying the information appropriately can be subtle—it may have to be applied differently than the agent's own local information, for example, as a post-search filter as described above. This implies that an agent must anticipate the kinds of information it may receive and have internal procedures available to effectively use that information.

5 Conclusions

In this article, our objective was to clarify the costs and benefits that are attributable to information sharing in systems of heterogeneous reusable agents. The experiments in Section 3 demonstrated that the ability of agents to share and assimilate information about the composite solution space positively affects both solution quality and runtime. When external information is assimilated by an agent, that agent is able to focus its search efforts in areas of its local solution space that are more likely to be contained in the composite solution space as well. By focusing its search in areas that are likely to be mutually acceptable, the agent's work is more productive and will tend to improve both solution quality and system performance. However, there are implementation and performance costs associated with information sharing and, in some situations, these costs may outweigh the benefits.

After empirically demonstrating the benefits of information assimilation in multiagent problem solving, we took a detailed look at the costs of assimilation. We classified the costs of information sharing as involving: the generation of information to share; the translation of information into and out of a shared language; the determination of what information to communicate at any given time; the transmission of information[5]; and local management (storage, retrieval, and use of potentially conflicting assimilated information). We observed these costs within the `STEAM` system and found them to total approximately 10.17% of the overall runtime. Although this is not a trivial figure, in this domain, the time spent in sharing information is more than balanced by the productivity enhancement that comes from focusing on mutually acceptable areas of the composite solution space. With these costs

[5]Although we recognize that transmission of information will add to the cost of information sharing, it was not included as one of the categories in our experiments. Because of the physical environment in which our experiments were run, this cost was trivial.

included, we recorded mean improvements in solution quality of 5.72% and in runtime-per-solution of 40.62% and can conclude with a high probability that these results are significant.

Our experience with information assimilation suggests some conflicting perspectives on achieving information sharing in systems of heterogeneous reusable agents. On the one hand, the experiments showed that information sharing and assimilation can be highly effective in improving system performance, both in terms of solution quality and runtime. On the other hand, we found sharing and assimilation difficult to actualize because they require in-depth understanding of the domain characteristics of individual agents. The application-system developer that is responsible for integrating a set of reusable agents into a system cannot be expected to have a deep enough understanding of individual agent domains to install the necessary mechanisms into the agents post-implementation.

Sharing meta-information requires that each agent know: 1) what information it can share; 2) what information it can assimilate; and 3) how information that is assimilated from external sources is to be applied. When the mechanisms required for information sharing are installed at agent-implementation time, the implementor will not know whether shared information will ever be used, whether anticipated information will ever arrive, or whether functional capabilities for applying certain types of information will ever be applied. If the agent is implemented with highly sophisticated information-sharing capabilities, it must be expected that in any given application system, these capabilities may be beyond what is required or even usable for the domain. The price of generality goes beyond implementation costs for the agent, since there may be system-wide runtime repercussions based on the transmission of unusable information, or on applying assimilated information that degrades system performance rather than enhancing it.

Can reusable-agent search systems be built without giving agents the ability to exchange meta-information? The answer depends on what is required. Multiagent search without meta-information reduces to blind search or possibly search guided by local heuristics in the composite search space. In small, simple application systems, this may be enough. However, reusable agents that cannot coherently focus their search are unlikely to be effective in complex application systems. And because agent reusability implies that the agent developer does not know the nature of potential application systems, it also implies that agents must be prepared for at least an a system of "average" complexity. Future research in reusable-agent systems should examine questions of balancing the information-sharing capabilities of agents with the benefits of sharing various types of information. It may be that some general guidelines will emerge that can be applied by agent implementors to decide what capabilities are likely to be most beneficial and cost-effective in an agent.

In conclusion, we have shown that information sharing and assimilation can enhance system performance in the `STEAM` system. Although there is no basis on which to generalize any specific figures outside of `STEAM`, the `STEAM` domain is typical of a class of small-scale globally cooperative design domains and our results indicate that information sharing and assimilation can improve performance in this class of systems. Furthermore, the categories of information-sharing costs hold across all domains. Both the empirical evidence demonstrated here and intuitive arguments for the benefits of focused search suggest that information sharing and assimilation will be effective in more complex domains.

Although sharing meta-information is potentially beneficial, it is not particularly easy to achieve. Most of the work must be done at agent-implementation time when nothing is known about the application system(s) into which the agent will be embedded. The costs of making agents that are highly proficient in sharing and using assimilated information may outweigh the benefits that accrue from those capabilities. Future work may clarify the boundaries of benefit versus hindrance based on types of information and the capabilities required by agents to use those various types. However, it is clear that information sharing and assimilation should be considered a potential source of performance enhancement when designing distributed-search systems comprising heterogeneous reusable agents.

Acknowledgements

We thank Nagendra Prasad and Daniel Corkill for their assistance and suggestions.

References

[1] M.R. Adler, A.B. Davis, R. Weihmayer, and R.W. Worrest. Conflict-resolution strategies for non-hierarchical distributed agents. In L. Gasser and M.N. Huhns, editors, *Distributed Artificial Intelligence, Volume 2*, Research Notes in Artificial Intelligence, pages 139–161. Pitman, London, 1989.

[2] A. Barr and E.A. Feigenbaum. *The Handbook of Artificial Intelligence, Volume 1.* William Kaufmann, Inc., 1981.

[3] S.E. Conry, K. Kuwabara, V.R. Lesser, and R.A. Meyer. Multistage negotiation for distributed satisfaction. *IEEE Transactions on Systems, Man and Cybernetics*, 21(6):1462–1477, November/December 1991.

[4] P.S. de Souza and S. Talukdar. Asynchronous organizations for multi-algorithm problems. In *Proceedings of the ACM Symposium on Applied Computing*, Indianapolis, Indiana, February 1993.

[5] E. Ephrati and J.S. Rosenschein. The Clarke Tax as a consensus mechanism among automated agents. In *Proceedings of the Ninth National Conference on Artificial Intelligence*, pages 173–184, Anaheim, California, July 1991.

[6] L.D. Erman, F. Hayes-Roth, V.R. Lesser, and D.R. Reddy. The Hearsay-II speech-understanding system: Integrating knowledge to resolve uncertainty. *Computing Surveys*, 12(2):213–253, June 1980.

[7] T. Finin, R. Fritzson, D. McKay, and R. McEntire. KQML: A language and protocol for knowledge and information exchange. Technical report, Universitiy of Maryland, Baltimore, MD, 1994.

[8] M.S. Fox. *Constraint-Directed Search: A Case Study of Job Shop Scheduling.* Research Notes in Artificial Intelligence. Pitman Publishing, London, 1987.

[9] M.S. Fox, B. Allen, and G. Strohm. Job-shop scheduling: an investigation in constraint-directed reasoning. In *Proceedings of the National Conference on Artificial Intelligence*, pages 155–158, Pittsburgh, Pennsylvania, August 1982.

[10] P.J. Gmytrasiewicz and E.H. Durfee. Toward a theory of honesty and trust among communicating autonomous agents. *Group Decision and Negotiation*, 2(3):237–258, 1993.

[11] T. Khedro and M.R. Genesereth. Progressive negotiation for resolving conflicts among distributed heterogeneous cooperating agents. In *Proceedings of the Twelfth National Conference on Artificial Intelligence*, Seattle, Washington, July/August 1994.

[12] M. Klein. Supporting conflict resolution in cooperative design systems. *IEEE Transactions on Systems, Man, and Cybernetics*, 21(6):1379–1390, November/December 1991.

[13] S.E. Lander. *Distributed Search and Conflict Management Among Reusable Heterogeneous Agents*. PhD thesis, University of Massachusetts, Amherst, Massachusetts, May 1994.

[14] S.E. Lander and V.R. Lesser. Customizing distributed search among agents with heterogeneous knowledge. In *Proceedings of the First International Conference on Information and Knowledge Management*, pages 335–344, Baltimore, Maryland, November 1992.

[15] S.E. Lander and V.R. Lesser. Understanding the role of negotiation in distributed search among heterogeneous agents. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pages 438–444, Chambery, France, August/September 1993.

[16] V.R. Lesser. An overview of DAI: Viewing distributed AI as distributed search. *Journal of the Japanese Society for Artificial Intelligence*, 5(4):392–400, July 1990.

[17] T. Moehlman, V. Lesser, and B. Buteau. Decentralized negotiation: An approach to the distributed planning problem. *Group Decision and Negotiation*, 1(2):161–192, 1992.

[18] R. Neches, R. Fikes, T. Finin, T. Gruber, R. Patil, T. Senator, and W.R. Swartout. Enabling technology for knowledge sharing. *AI Magazine*, 12(3):36–56, Fall 1991.

[19] Y. Nishibe, K. Kuwabara, and T. Ishida. Effects of heuristics in distributed constraint satisfaction: Towards satisficing algorithms. In *Workshop on Distributed Artificial Intelligence*, pages 285–302, Michigan, February 1992.

[20] M.V.N. Prasad and V.R. Lesser. Learning decision-analytic control in a heterogeneous multi-agent system. Technical report, University of Massachusetts, Amherst, MA, 1994. (In preparation.).

[21] A. Sathi and M.S. Fox. Constraint-directed negotiation of resource reallocations. In Les Gasser and Michael Huhns, editors, *Distributed Artificial Intelligence, Volume 2*, chapter 8, pages 163–193. Pitman Publishing, London, 1989.

[22] S. Sen and E.H. Durfee. A formal study of distributed meeting scheduling: Preliminary results. In *Proceedings of the Conference on Organizational Computing Systems*, pages 55–68, Atlanta, Georgia, November 1991.

[23] H.A. Simon. *The Sciences of the Artificial*. The M.I.T. Press, 1969.

[24] R.G. Smith and R. Davis. Frameworks for cooperation in distributed problem solving. In Alan H. Bond and Les Gasser, editors, *Readings in Distributed Artificial Intelligence*. Morgan Kaufmann, 1988.

[25] K. Sycara. *Resolving Adversarial Conflicts: An Approach Integrating Case-Based and Analytic Methods*. PhD thesis, Georgia Institute of Technology, Atlanta, Georgia, June 1987. Also published as Technical Report GIT-ICS-87/26.

[26] K. Sycara. Resolving goal conflicts via negotiation. In *Proceedings of the Seventh National Conference on Artificial Intelligence*, pages 245–250, Saint Paul, Minnesota, August 1988.

[27] G. Zlotkin and J.S. Rosenschein. Cooperation and conflict resolution via negotiation among autonomous agents in noncooperative domains. *IEEE Transactions on Systems, Man and Cybernetics*, 21(6):1317–1324, November/December 1991.

[28] G. Zlotkin and J.S. Rosenschein. A domain theory for task oriented negotiation. In *Proceedings of the Thirteenth International Joint Conference on Artificial Intelligence*, pages 416–422, Chambery, France, August 1993.