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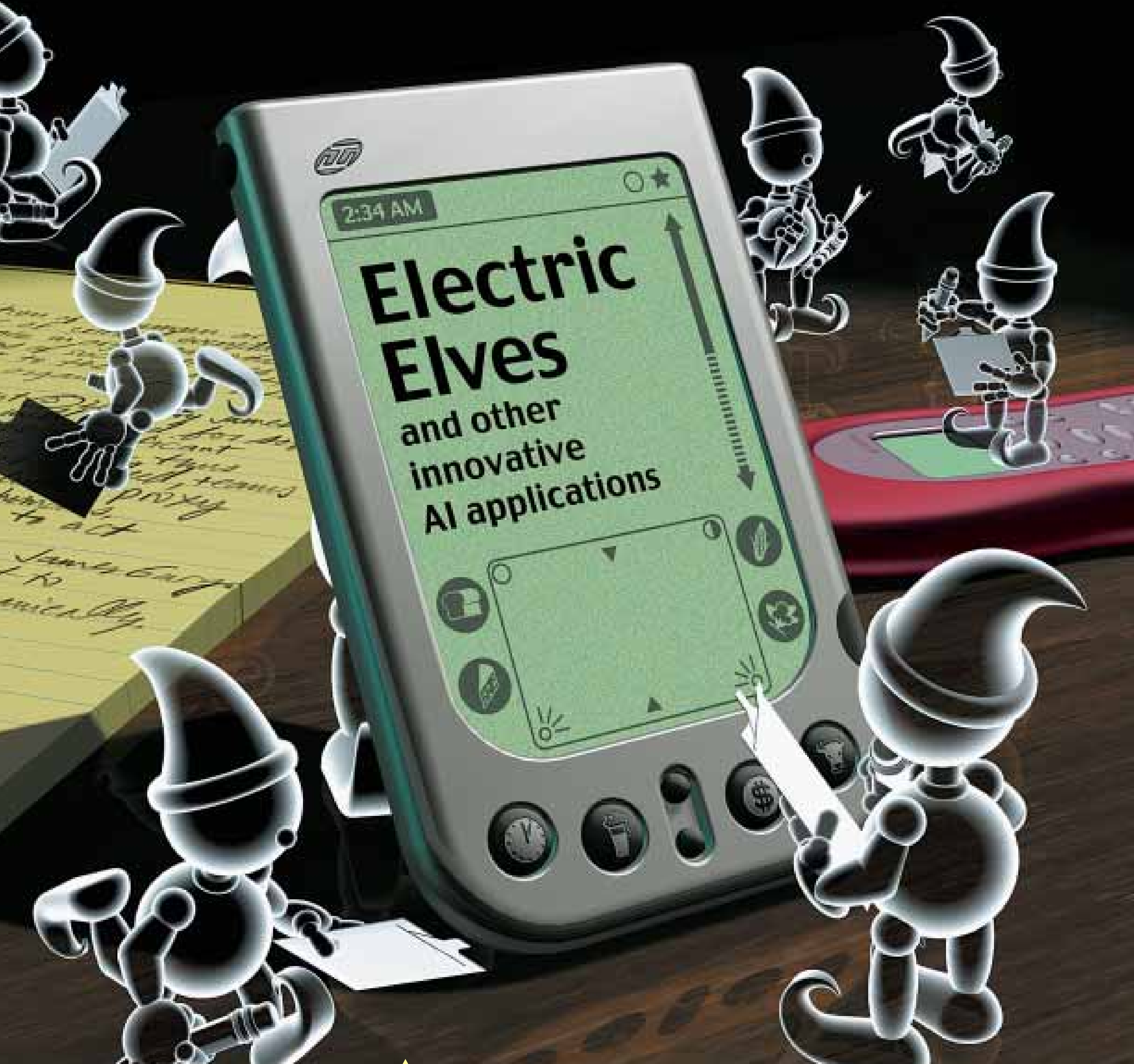

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ELECTRIC ELVES
Agent Technology for Supporting Human Organizations

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■ The operation of a human organization requires dozens of everyday tasks to ensure coherence in organizational activities, monitor the status of such activities, gather information relevant to the organization, keep everyone in the organization informed, and so on. Teams of software agents can aid humans in accomplishing these tasks, facilitating the organization's coherent functioning and rapid response to crises and reducing the burden on humans. Based on this vision, this article reports on ELECTRIC ELVES, a system that has been operational 24 hours a day, 7 days a week at our research institute since 1 June 2000.

Tied to individual user workstations, fax machines, voice, and mobile devices such as cell phones and palm pilots, ELECTRIC ELVES has assisted us in routine tasks, such as rescheduling meetings, selecting presenters for research meetings, tracking people's locations, organizing lunch meetings, and so on. We discuss the underlying AI technologies that led to the success of ELECTRIC ELVES, including technologies devoted to agent-human interactions, agent coordination, the accessing of multiple heterogeneous information sources, dynamic assignment of organizational tasks, and the deriving of information about organization members. We also report the results of deploying ELECTRIC ELVES in our own research organization.

The operation of a human organization involves dozens of critical everyday tasks to ensure coherence in organizational activities, monitor the status of such activities, obtain information relevant to the organization, keep everyone in the organization informed, and so on. These activities are often well suited for software agents, which can devote significant resources to perform these tasks, thus reducing the burden on humans. Indeed, teams of such software agents, including proxy agents that act on behalf of humans, would enable organizations to act coherently, attain their mission goals robustly, react to crises swiftly, and adapt to events dynamically. Such agent teams could assist all organizations, including the military, civilian disaster response, corporations, and universities and research institutions.

Within an organization, we envision agents assisting in all its day-to-day functioning. For a research institution, agents can facilitate activities such as meeting (re)scheduling, selecting presenters for research meetings, composing papers, developing software, and deploying people and equipment for out-of-town demonstrations. For a disaster response organization, agents can facilitate the teaming of people and equipment to rapidly respond to crises (for example, earthquakes), monitor the progress of any such elements for rapid response, and so on. To accomplish such goals, each person in an organization will have an agent proxy. For example, if an organizational crisis requires an urgent deployment of a team of people and equipment, then agent proxies could dynamically volunteer for team membership on behalf of the people or resources they represent and ensure that the selected team collectively possesses sufficient resources and capabilities. The proxies must also manage efficient transportation of such resources, the monitoring of the progress of individual participants and of the mission as a whole, and the execution of corrective actions when goals appear to be endangered.

Based on this vision, we developed a system called ELECTRIC ELVES that applies agent technology in service of the day-to-day activities of the Intelligent Systems Division of the University of Southern California Information Sciences Institute. ELECTRIC ELVES is a system of some 15

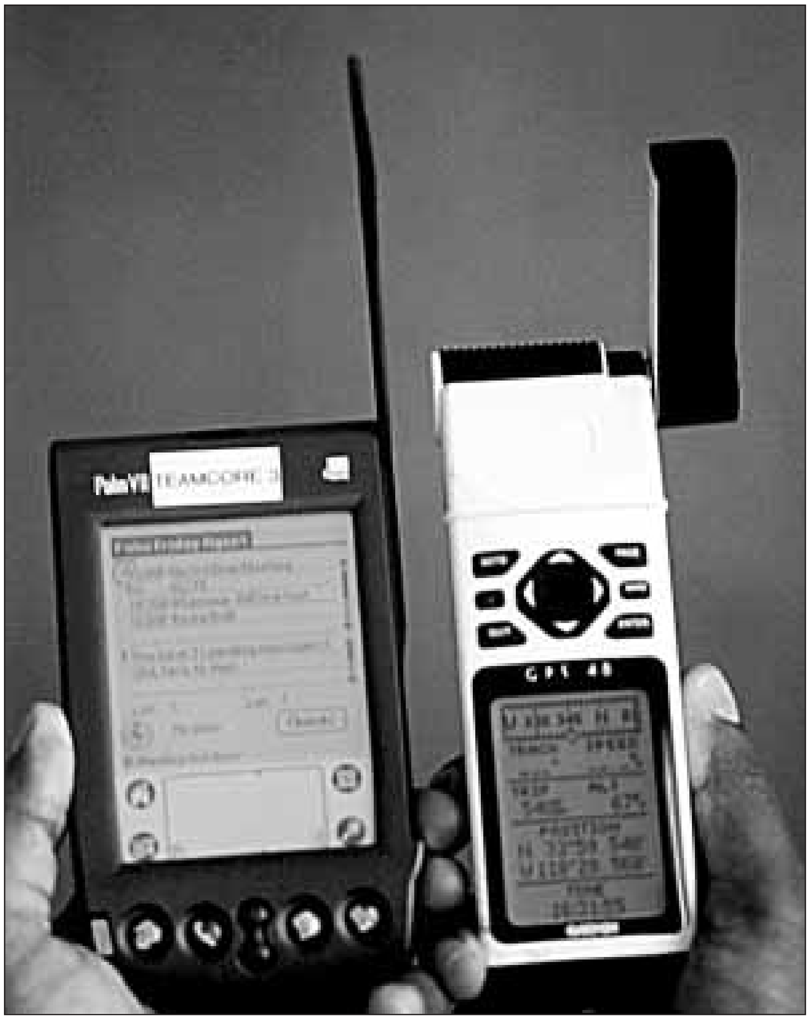

Figure 1. A Palm VII Personal Digital Assistant with Global Positioning System Receiver.

agents, including 9 proxies for 9 people plus 2 different matchmakers, 1 flight tracker, and 1 scheduler running continuously for the past several months. This article discusses the tasks performed by the system, the research challenges it faced, and its use of AI technology in overcoming these challenges.

One key contribution of this article is outlining the challenges faced in deploying agents to support organizations. In particular, the complexity inherent in human organizations complicates all the tasks that agents must perform. First, because agents must interact with humans, issues of adjustable autonomy become critical. In particular, agents acting as proxies for people must automatically adjust their own autonomy, for example, avoiding critical errors, possibly by letting people make important decisions while autonomously making the more routine decisions. Second, to accomplish their goals, agents must be provided reliable access to information. Third, people have a variety of capabilities, interests, and preferences and engage in many different tasks. To enable teaming among such people for crisis response or other organizational tasks, agents acting as their proxies must represent and reason with such capabilities and interests. We thus require powerful matchmaking capabilities to match both interests and capabilities. Fourth, coordination of all these different agents, including proxies, is itself a significant research challenge. Finally, the entire agent system must scale up: (1) it must scale up in the sense of running continually 24 hours a day, 7 days a week (24/7) for months at a time and (2) it must scale up in the number of agents to support large-scale human organizations.

The ELECTRIC ELVES

In any organization, there are dozens of small, mundane tasks that every individual performs on a daily basis, such as scheduling meetings, arranging lunch, and locating other people. Many of these tasks require looking up information, monitoring information, and keeping people informed. As such, they are well suited to software agents, which can devote the resources to perform these tasks in a way that would be impractical for people to perform them. For example, most people would consider it unreasonable to ask their secretary to check their flight every few minutes to see if it is delayed or to monitor their current global positioning system (GPS) location to ensure that they will arrive in time for the 8 AM meeting. However, we have the resources and technology today to give everyone his/her own personal agents to help with these everyday tasks.

In the ELECTRIC ELVES project, we have developed technology and tools for deploying agents into human organizations to help with organizational tasks. We describe the application of the ELECTRIC ELVES to two classes of tasks. First, we describe the problem of coordinating activities within an individual research project. These tasks must tightly be coordinated, and a significant amount of information is known in advance about the participants and their goals and capabilities. Second, to demonstrate the capabilities of the system in a more open environment, we applied the system to the problem of meeting planning with participants outside the organization where some of the necessary information about participants is not known in advance.

Coordinating Project Activities

Our agents help coordinate the everyday activities of a research project: They keep the project running smoothly, rescheduling meetings when someone is delayed, ordering food for meetings or someone working late, and identifying speakers for research meetings. Each person in the project is assigned his /her own personal proxy agent, which represents this person to the agent system.

A *proxy agent* keeps track of a project member's current location using several different information sources, including his/her calendar, GPS device when outside the building (figure 1), infrared communications within the building, and computer activity. When a proxy agent notices that someone is not attending a scheduled meeting or that they are too far away to make it to a scheduled meeting in time, it springs into action. Their agent sends them a message using a wireless device (that is, a cell phone or palm pilot) asking if he/she wants to cancel the meeting, delay the meeting, or have the meeting proceed without him/her. If a user responds, the decision is communicated to the other participants of the scheduled meeting. If they are unable to respond, the agent must make a decision autonomously.

For weekly project meetings, the agents coordinate the selection of the presenter and arrange food for the meetings. Once a week, an auction is held, where all the meeting participants are asked about their capability and willingness to present at the next meeting. Then the system compiles the bids, selects a presenter, and notifies all the attendees who will be presenting at the next project meeting. The agents also arrange food for lunch meetings. They order from a set of nearby restaurants, select meals that were highly rated by others, and fax the orders directly to the restaurant with instructions for delivery. We have begun relying on our agents so heavily to order lunch that one local Subway restaurant owner even remarked: "...more and more computers are getting to order food...so we might have to think about marketing [to them]."

When a visitor is coming to visit a project, the agents monitor the flight that the person is arriving on. If a visitor is arriving the day of the meeting, the agents track his//her flight status and send a notification once the visitor arrives. If he/she is late, the agents will delay the scheduled meetings. If he/she is arriving the day before a visit, then the agents will send a welcome fax to the hotel where the visitor is staying with a list of highly rated restaurants nearby.

Some of the technical challenges in building this application are in determining how much autonomy the agents should assume on behalf of the user, dynamically building agent teams, determining how to assign the organizational tasks (for example, presentations), and providing access to online data such as calendars and restaurants.

Organizing External Meetings

To demonstrate how the technology supports less structured environments, we also applied the ELECTRIC ELVES to the task of planning and coordinating ad hoc meetings at conferences and workshops involving individuals across different organizations. The system identifies people that have similar research interests, coordinates scheduling a meeting with these people, locates a suitable restaurant for a meeting that takes into account dietary constraints, and makes a reservation using an online reservation service.

To identify individuals with related interests, the agents use an online bibliography service that provides a list of the papers written by an individual. When a person is going to a meeting, his/her agent can check an online source to locate individuals going to the same meeting and then build a model of the research interests of the different participants based on their publications. Using this information, the user selects the participants for the meeting, and the agent sends out an invitation to each of the potential attendees. If they are part of the ELECTRIC ELVES network, the invitation is sent to their own agent. Otherwise, the invitation is sent by fax or e-mail with instructions on how to confirm (or decline) the meeting.

Once the agent has finalized the set of participants for a meeting, it selects an appropriate place to have the meeting. It does this by checking for any known dietary restrictions and uses this information to identify suitable cuisine types. Next, the agent goes out to an online restaurant reservation site to find the set of restaurants closest to the given location and matches up these restaurants with a restaurant review site to select the high-quality restaurants. The user selects from a small set of close, recommended restaurants, and the agent then makes a reservation for the meeting using the online reservation system.

This application highlights two additional technical challenges: (1) gathering information about people from other organizations and (2) ensuring the robustness of the interaction with online sources that change frequently.

Underlying Technologies

In this section, we describe how we addressed some of the technical challenges, namely, the issues of interacting with human users within an organization, providing reliable access to organization-related data, dynamically assigning organizational tasks, deriving knowledge about the participants in an organization, and coordinating agent teams.

Agent Interactions with Human Users

ELECTRIC ELVES agents must often act on behalf of the human users. Specifically, a user's agent proxy (named FRIDAY after Robinson Crusoe's servant and companion) can take autonomous actions to coordinate collaborative activities (for example, meetings). FRIDAY's decision making on behalf of a person naturally leads to the issue of adjustable autonomy. An agent has the option of acting with full autonomy (for example, delaying a meeting, volunteering the user to give a presentation, ordering a meal). However, it might act without autonomy, instead asking its user what to do. Clearly, the more decisions that FRIDAY makes autonomously, the more time and effort it saves its user. However, given the high uncertainty in FRIDAY's knowledge of its user's state and preferences, it could potentially make very costly mistakes when it acts autonomously. For example, it might order an expensive dinner when the user is not hungry or volunteer a busy user to give a presentation. Thus, each FRIDAY must make intelligent decisions about when to consult its user and when to act autonomously.

Our initial attempt at adjustable autonomy was inspired by CAP (Mitchell et al. 1994), an agent system for advising a user on scheduling meetings. As with CAP, each FRIDAY tried to learn its user preferences using decision trees under C4.5 (Quinlan 1993). One problem became apparent when applying this technique in ELECTRIC ELVES: A user would not grant autonomy to FRIDAY in making certain decisions, but he/she would sometimes be unavailable to provide any input at decision time. Thus, a FRIDAY could end up waiting indefinitely for user input and not coordinate with its teammates. We therefore modified the system so that if a user did not respond within a fixed time limit, FRIDAY acted autonomously based on its learned decision tree. Unfortunately, when we deployed the system in our research group, it led to some dramatic failures. For example, one user's proxy erroneously volunteered him to give a presentation. C4.5 had overgeneralized from a few examples to create an incorrect rule. Although FRIDAY tried asking the user at first, because of the time-out, it had to eventually follow the incorrect rule and take the undesirable autonomous action.

It was clear, based on this experience, that the team context in ELECTRIC ELVES would cause difficulties for existing adjustable-autonomy techniques (Dorais et al. 1998; Ferguson, Allen, and Miller 1996; Mitchell et al. 1994) that focused on solely individual human-agent interactions. Therefore, we developed a novel, decision-theoretic planning approach that used Markov decision processes (MDPs) (Puterman 1994) to support explicit reasoning about team coordination. The MDPs used in our framework (Scerri, Pynadath, and Tambe 2001) provide FRIDAY with a novel three-step approach to adjustable autonomy: (1) before transferring decision-making control, an agent explicitly weighs the cost of waiting for user input and any potential team miscoordination against the likelihood and cost of erroneous autonomous action; (2) when transferring control, an agent does not rigidly commit to this decision, but it instead flexibly reevaluates when its user does not respond, sometimes reversing its decision and taking back autonomy; and (3) rather than force a risky decision in situations requiring autonomous action, an agent changes its coordination arrangements by postponing or reordering activities to potentially buy time to lower decision cost-uncertainty. Because these coordination decisions and actions incur varying costs and benefits over time, agents look ahead over the different sequences of possible actions and plan a policy that maximizes team welfare.

The agent follows the first step of our approach through team-related components within its MDP model of the costs and benefits of its available actions. Thus, the MDP's decision-theoretic selection of optimal policies balances individual preferences against the team's needs. The policies generated from the MDP support the second step of our approach by providing the necessary flexibility and responsiveness in autonomy decisions. The agent can immediately respond to any change of state by following the policy's specified action for the new state. The agent's decision making is an ongoing process rather than a single decision because the agent acts according to its MDP policy throughout the entire sequence of states it finds itself in. We achieve the third step of our approach by having each agent consider the different costs, both present and future, of team miscoordination versus erroneous actions. In the meeting scenario, changes in coordination are essentially delaying actions. Such changes in coordination could, among other things, buy time to reduce the uncertainty or cost.

```
"agents that can discuss Phosphorus"
    ((capability (discuss (obj Phosphorus-project)))
     (agents (gil surya chalupsky russ)))

"agents that can setup an LCD projector in a meeting room"
    ((capability (setup (obj (?v is (inst-of lcd-projector)))
                         (in (?r is (inst-of meeting-room)))))
                   (agents (itice)))
```

Figure 2. Specification of Human Agent Capabilities.

MDPs are especially suitable for producing such a plan because they generate policies while they look ahead at all the possible outcomes.

We have implemented MDPs that model FRIDAY's decisions on rescheduling meetings, volunteering its user to give a presentation, and selecting which user should give a presentation. For example, consider one possible policy generated from an MDP for the rescheduling of meetings. If the user has not arrived at the meeting five minutes prior to its scheduled start, this policy specifies "ask the user what to do." If the user does not arrive by the time of the meeting, the policy specifies "wait," so the agent continues acting without autonomy. However, if the user still has not arrived 5 minutes after the meeting is scheduled to start, then the policy chooses "delay by 15 minutes," which the agent then executes autonomously.

In the future, we plan to apply our MDP-based framework to other decisions (currently performed without any autonomy) within ELECTRIC ELVES, such as ordering meals, accepting meeting invitations, and selecting restaurants. In addition, the current MDP framework supports some learning of likelihoods (for example, the probability that the user will arrive to the meeting on time), but we are planning to extend the role of learning to allow further personalization.

Flexible Assignment of Tasks

The human agents and software agents in our organization perform a variety of tasks that are often interrelated. Agents often need to delegate a subtask to another agent capable of performing it (for example, reserve a meeting room), invoke another agent to gather and report back necessary information (for example, find the location of a person), or rely on another agent to execute some task in the real world (for example, attend a lunch meeting). Simple agent matchmaking is sufficient in many multiagent systems where agents perform one (or at most a few) kind of task, and their capabilities are designed by the system developers to fit the interactions anticipated among the agents. In contrast, our agents are complex and heterogeneous, and the agents that issue a request cannot be expected to be aware of what other agents are available and how they are invoked.

We have developed an agent matchmaker called PHOSPHORUS (Gil and Ramachandran 2001), which builds on previous research on matching problem-solving goals and methods in EXPECT (Gil and Gonzalez 1996; Swartout and Gil 1995). The main features of this approach are (1) a declarative language to express task descriptions that includes rich parameter-type expressions to qualify task types; (2) task descriptions are fully translated into description logic to determine subsumption relations among tasks; and (3) task descriptions are expressed in terms of domain ontologies, which provide a basis for relating and reasoning about different tasks and enables reformulation of tasks into subtasks.

Agent capabilities and requests are represented as verb clauses with typed arguments (as in a case grammar), where each argument has a name (usually a preposition) and a parameter. The type of a parameter can be a specific instance, an abstract concept (marked with spec-of), an instance type (marked with inst-of), and extensional or intensional sets of these three types. Figure 2 gives some examples of capabilities of some researchers and project assistants.

Requests are formulated in the same language and can ask about general types of instances (for example, what agents can set up any kind of equipment for giving research presentations in a meeting room).

Description logic and subsumption reasoning are used to relate different task descriptions. Both requests and agent capabilities are translated into LOOM (MacGregor 1991). LOOM's classifier recognizes that the capability to "set up equipment" will subsume one to "set up LCD projector" because according to the domain ontologies, equipment subsumes LCD projector.

PHOSPHORUS performs task reformulation when there are no agents with capabilities that subsume a request. In this case, it might be possible to fulfill the request by decomposing it into subtasks, allowing a more flexible matching than if one required a single agent to match all capabilities in the request. PHOSPHORUS supports set reformulation (breaking down a task on a set into its individual elements) and covering reformulation (decomposing a task into the disjoint subclasses of its arguments). For example, no single agent can discuss the entire ELECTRIC ELVES project because no single

```
(COVERING -name ARIADNE-PROJECT
                -matches KNOBLOCK MINTON LERMAN
          -name PHOSPHORUS-PROJECT
                -matches GIL SURYA CHALUPSKY RUSS
          -name TEAMCORE-PROJECT
                -matches
                   (COVERING
                   -name ADJUSTABLE-AUTONOMY-PROJECT
                        -matches TAMBE SCERRI PYNADATH
                   -name TEAMWORK-PROJECT
                        -matches TAMBE PYNADATH MODI)
          -name ROSETTA-PROJECT
                -matches GIL CHALUPSKY)
```

Figure 3. Complex Query Answer.

Because no one person can satisfy the query, a set of alternatives that collectively provide the necessary capabilities is returned.

researcher is involved in all the aspects of the project. However, PHOSPHORUS can return a set of people who can collectively cover the topic based on the subprojects (figure 3).

Figure 3 shows our flexibility: The requesting agent did not need to be aware of the details of the ELECTRIC ELVES project but still gets from the reply subsets of agents that are able to fulfill complementary parts of the request.

The SHADE matchmaker (McGuire et al. 1993) also matched agent capabilities using logic descriptions, but the basic matching operation was done by unification and did not exploit domain ontologies to relate different terms. In RETSINA (Sycara et al. 1999), description logic is used only to match the parameters of the capability descriptions, but PHOSPHORUS translates the entire expression for a more thorough match.

Many additional challenges lay ahead regarding capability representations for people within the organization. For example, although anyone has the capability to call a taxi for a visitor (and will do so if necessary), project assistants are the preferred option. Depending on upcoming deadlines, a researcher might be capable but not willing to participate in a visitor's schedule. Extensions to the language are needed to express additional properties of agents, such as reliability, efficiency, and invocation guidelines.

Reliable Access to Information

Timely access to up-to-date information is crucial to the successful planning and execution of tasks in the ELECTRIC ELVES organization. Agents making decisions on behalf of human users need to extract information from multiple heterogeneous information sources, including organizational databases (personal schedules, staff lists) and external web sites, such as airline schedules, restaurant information, traffic, and weather updates. To pick a restaurant for a scheduled lunch meeting, the agents access the Restaurant Row site to get the locations of restaurants that meet the specified criteria, for example, dietary restrictions. *Wrappers* enable web sources to be queried as if they were databases by other applications, such as the ELECTRIC ELVES agents. A critical part of a wrapper is a set of extraction rules that enable the wrapper to quickly locate the beginning and end of the data to be extracted from a web page in response to some query.

The ARIADNE component (Knoblock et al. 2001, 2000) of ELECTRIC ELVES learns wrappers from pages in which relevant data have been labeled by the user. Previous research has focused on applying machine learning techniques to rapidly generate wrappers (Kushmerick 2000; Muslea, Minton, and Knoblock 2000), but few attempts have been made to validate data, detect failures (Kushmerick 1999), or repair wrappers when the source pages change in a way that breaks the wrapper. Automatically monitoring external information sources and repairing wrappers when errors are detected is a critical part of a robust dynamic organization.

We address the problem of wrapper verification by applying machine learning techniques to learn a set of patterns that describe the content of the extracted data. Because the information for a single data field can vary considerably, the system learns a statistical distribution of patterns. Wrappers can be verified by comparing newly extracted data to the learned patterns. When a significant difference is found, we can launch the wrapper repair process.

The learned patterns represent the structure of data as a sequence of words and wild cards. *Wild cards* represent syntactic categories to which words belong—alphabetic, numeric, capitalized, and so on. For example, a set of street addresses all start with a pattern "_Number_ Capitalized_": a number followed by a capitalized word. The algorithm we developed (Lerman and Minton 2000) finds all statistically significant starting and ending patterns in a set of positive examples of the data field. A pattern is significant if it occurs more frequently than would be expected by chance if the tokens were generated randomly and independently of one another. Our approach is similar to work on grammar induction (Carrasco and Oncina 1994), but our pattern language is better suited for capturing the regularities in small data fields (as opposed to languages). For verification, we learn the patterns from training examples (data extracted by the wrapper that is known to be correct). Next, the wrapper generates a set of test examples from pages retrieved using the same or similar set of queries. If the patterns describe statistically the same proportion of the test examples as the training examples, the wrapper is deemed correct; otherwise, it has failed.

The most common causes of wrapper failure are changes in web site layout. Even minor changes can break the wrapper's data-extraction rules. However, because the content tends to remain the same, it is often possible to automatically repair the wrapper by learning new extraction rules. We exploit the learned patterns to find correct examples of data on the new pages. The Restaurant Row wrapper allows us to retrieve several examples of restaurant addresses, and the verification algorithm learned that some of the examples start with the pattern "_Number_ Capitalized_" and end with the pattern "Avenue." If Restaurant Row changes to look more like the Zagat web site, the wrapper will no longer extract addresses correctly. In the verification phase, we will detect the failure because the extracted data are not described by the patterns. However, because restaurant addresses still start with "_Number_ Capitalized_" and end with "Avenue," we should be able to find addresses on the changed pages. Once the desired information has been found, these examples and the new pages are sent to the wrapper generation system to learn new data-extraction rules. We use prior knowledge about the content of data, as captured by the learned patterns, along with a priori expectations about the data, to identify correct examples on the changed pages. We can expect the same data field to appear in roughly the same position and in a similar context on each page; moreover, we expect at least some of the data to remain unchanged. Of course, some information, for example, traffic and flight arrivals, changes on a regular basis, although we might still rely on patterns to identify it.

Our approach can be extended to automatically create wrappers for new information sources using data extracted from a known source. Thus, once we learn what restaurant addresses look like, we can use this information to extract addresses from any yellow pages–type source and use it to create a wrapper for this source.

Knowledge from Unstructured Sources

As mentioned earlier, an agent-assisted organization crucially depends on access to accurate and up-to-date information about the humans it supports as well as the environment in which they operate. Some of this information can be provided directly from existing databases and online sources, but other information—people's expertise, capabilities, interests, and so on—will often not be available explicitly and might need to be modeled by hand. In a dynamic environment such as ELECTRIC ELVES, however, manual modeling is only feasible for relatively static information. For example, if at some conference, we want to select potential candidates for a lunch meeting with Yolanda Gil based on mutual research interests, it is not feasible to manually model relevant knowledge about each person on the conference roster before such a selection can be made.

For supporting team-building tasks such as inviting people for a lunch meeting, finding people potentially interested in a presentation or research meeting, and finding candidates to meet with a visitor, we developed a matchmaking service called the INTEREST MATCHER. It can match people based on their research interests but also take other information into account, such as involvement in research projects, present and past affiliation, and universities attended. To minimize the need for manual modeling in a dynamic environment, we combined statistical match techniques from the area of information retrieval with logic-based matching performed by the POWERLOOM knowledge representation system. The information-retrieval techniques work well with unstructured text sources available on the web, which is the form in which information is typically available to outside organizations. POWERLOOM facilitates declarative modeling of the decision process, modeling of missing information, logical inference, explanation, and customization.

The matchmaker is built on top of the POWERLOOM knowledge representation system, which is the successor to LOOM. POWERLOOM uses a variant of KIF (Genesereth 1991) as its language, and its inference, explanation, and partial-match capabilities are important to support the matchmaking task. POWERLOOM's inference, explanation, and partial-match capabilities are important to support the matchmaking task. The matchmaker's knowledge base contains an ontology of research topic areas and associated relations; rules formalizing the matchmaking process; and manually modeled, relatively static information about staff members, research projects, and so on. To perform a particular matchmaking task, a requesting agent sends a message containing an appropriate POWERLOOM query to the INTER-

```
(defrelation should-meet ((?p1 Person) (?p2 Person))
  :<= (or (interests-overlap ?p1 ?p2)
          (institution-in-common ?p1 ?p2)
          (school-in-common ?p1 ?p2)))

(defrelation interests-overlap ((?p1 Person) (?p2 Person))
  :<=> (exists (?interest1 ?interest2)
          (and (research-interest ?p1 ?interest1)
               (research-interest ?p2 ?interest2)
               (or (subset-of ?interest1 ?interest2)
                   (subset-of ?interest2 ?interest1)))))
```

Figure 4. Definition of the Should-Meet and the Interests-Overlap Relations.

EST MATCHER. For example, the following query finds candidates for lunch with Yolanda Gil:

(retrieve all ?x (should-meet ?x Gil))

The should-meet relation and one of its supporting relations are defined in figure 4 in POWERLOOM.

To answer more specific questions, any of the more basic relations composing should-meet, such as interests-overlap, could be queried directly by a client. Using a general-purpose knowledge retrieval system as the matching engine provides us with this flexibility. Note that for interests-overlap, we only require a subsumption relationship; for example, interest in planning would subsume (or overlap with) interest in hierarchical planning.

To answer the previous query, the matchmaker generates the set of people in its knowledge base satisfying the should-meet relation and returns it as a result (usually, the candidate set is further constrained and does not include everybody in the knowledge base). In an ideal world, the matchmaking knowledge base would be complete. In the real world, this will usually not be the case, particularly when the organization interacts with outsiders such as conference attendees. To deal with incompleteness of the knowledge base, we allow a requesting agent to introduce new individuals, and then the INTEREST MATCHER automatically infers limited structured knowledge—their research interests—by analyzing relevant unstructured text sources on the web.

The key idea is that people's research interests are implicitly documented in their publication record. We make these interests explicit by associating each research topic in the POWERLOOM topic ontology with a statistical representation of a set of abstracts of research papers representative of the topic. These topic sets are determined automatically by querying a bibliography search engine such as CORA or the NEC RESEARCHINDEX with seed phrases representative of the topic (access to such web sources is facilitated by ARIADNE wrappers). We then query the same search engine for publication abstracts of a particular researcher and then classify them by computing statistical similarity measures between the researcher's publications and the topic sets determined before. When the similarity surpasses an empirically determined threshold, an appropriate interest assertion is added to the matchmaker knowledge base that can then be exploited in the matchmaking process described earlier.

We use a standard information-retrieval vector space model to represent document abstracts and compute similarity by a cosine measure and by weighting terms based on how well they signify particular topic classes (Salton and McGill 1983). We also use our own aggressive stemmer to reduce the number of features that need to be considered for similarity computations. The dynamic derivation of interests from unstructured online sources sets our approach apart from the one described in Sycara and Zeng (1996) that relies solely on manually specified interests.

Extending knowledge retrieval with information retrieval can increase robustness for the case of an incomplete topic ontology because we can use a direct statistical match of researchers' publications. Conversely, information-retrieval matching can benefit from knowledge retrieval matching in cases where two researchers do not have similar publication records but can be related by similarity to a common or hierarchically related topic. The smooth combination of statistical and logical reasoning is a nontrivial problem, however, and still provides room for further research and improvement.

Coordination of Component Agents

The diverse agents in ELECTRIC ELVES must work together to accomplish the complex tasks of the whole system. For example, to plan a lunch meeting, the INTEREST MATCHER finds a list of potential attendees, the FRIDAY of each potential attendee decides whether he/she will attend, the capability matcher identifies dietary restrictions of the confirmed attendees, and the reservation site wrapper identifies possible restaurants and makes the final reservation. In addition to low-level communication issues, there is the complicated problem of getting all these agents to work together as a team. Each of these agents must execute its part in coordination with the others, so that it performs its tasks at the correct time and sends the results to the agents who need them.

However, constructing teams of such agents remains a difficult challenge. Current approaches to designing agent teams lack the general-purpose teamwork models that would enable agents to autonomously reason about the communication and coordination required. The absence of such teamwork models makes team construction highly labor intensive. Human developers must provide the agents with a large number of problem-specific coordination and communication plans that are not reusable. Furthermore, the resulting teams often suffer from a lack of robustness and flexibility. In a real-world domain such as ELECTRIC ELVES, teams face a variety of uncertainties, such as a member agent's unanticipated failure in fulfilling responsibilities (for example, a presenter is delayed), members' divergent beliefs, and unexpectedly noisy communication. It is difficult to anticipate and preplan for all possible coordination failures.

In ELECTRIC ELVES, the agents coordinate using TEAMCORE, a domain-independent, decentralized, teamwork-based integration architecture (Pynadath et al. 1999). TEAMCORE uses STEAM, a general-purpose teamwork model (Tambe 1997) and provides core teamwork capabilities to agents by wrapping them with TEAMCORE proxies (separate from the FRIDAY agents that are user proxies). By interfacing with TEAMCORE proxies, existing agents can rapidly assemble themselves into a team to solve a given problem. The TEAMCORE proxies form a distributed team-readiness layer that provides the following social capabilities: (1) coherent commitment and termination of joint goals, (2) team reorganization in response to member failure, (3) selective communication, (4) incorporation of heterogeneous agents, and (5) automatic generation of tasking and monitoring requests. Although other agent-integration architectures such as OAA (Martin, Cheyer, and Moran 1999) and RETSINA (Sycara et al. 1996) provide capability 4, TEAMCORE's use of an explicit, domain-independent teamwork model allows it to support all five required social capabilities.

Every agent in the ELECTRIC ELVES organization (FRIDAYs, matchers, wrappers) has an associated TEAMCORE proxy that records its membership in various teams and active commitments made to these teams. Given an abstract specification of the organization and its plans, the TEAMCORE proxies automatically execute the necessary coordination tasks. They form joint commitments to team plans such as holding meetings, hosting and meeting with visitors, and arranging lunches. TEAMCORE proxies also communicate among themselves to ensure coherent and robust plan execution. The TEAMCORE proxies automatically substitute for missing roles (for example, if the presenter is absent from the meeting) and inform each other of critical factors affecting a team plan. Finally, they communicate with their corresponding agents to monitor the agents' ability to fulfill commitments (for example, asking FRIDAY to monitor its user's attendance of a meeting) and inform the agents of changes to these commitments (for example, notifying FRIDAY of a meeting rescheduling).

ELECTRIC ELVES Architecture

ELECTRIC ELVES is a complex and heterogeneous system spanning a wide variety of component technologies and languages, communication protocols, and operating system platforms. Figure 5 shows the components of the current version of ELECTRIC ELVES. TEAMCORE agents are written in PYTHON and SOAR (which is written in C); ARIADNE wrappers are written in C++; the PHOSPHORUS capability matcher is written in Common Lisp; and the POWERLOOM INTEREST MATCHER is written in STELLA (Chalupsky and MacGregor 1999), which translates into JAVA. The agents are distributed across SUNOS 5.7, WINDOWS NT, WINDOWS 2000, and LINUX platforms and use TCP/IP, HTTP, and the Lockheed KQMLAPI to handle specialized communication needs.

Tying all these different pieces together in a robust and coherent manner constitutes a significant engineering challenge. Initially, we looked for an implementation of KQML, but there was none available that supported all the languages and platforms we required. To solve this integration problem, we are using the Defense Advanced Research Projects Agency supported CoABS GRID technology developed by Global InfoTek, Inc., and ISX Corporation. The CoABS GRID is a JAVA-based communication infrastructure built on top of Sun's JINI networking technology. It provides message- and service-based communication mechanisms; agent registration; lookup and discovery services; and message logging, security, and visualization facilities. Because it is written in JAVA, it runs on many operating system platforms, and it is relatively easy to connect with non-JAVA technology. Grid proxy components connect non-JAVA technology to the GRID.

We primarily use the CoABS GRID as a uniform transport mechanism. The content of GRID messages are in KQML format and could potentially be communicated using alternative means. Not all ELECTRIC ELVES message traffic goes across the GRID. For example, the TEAM-

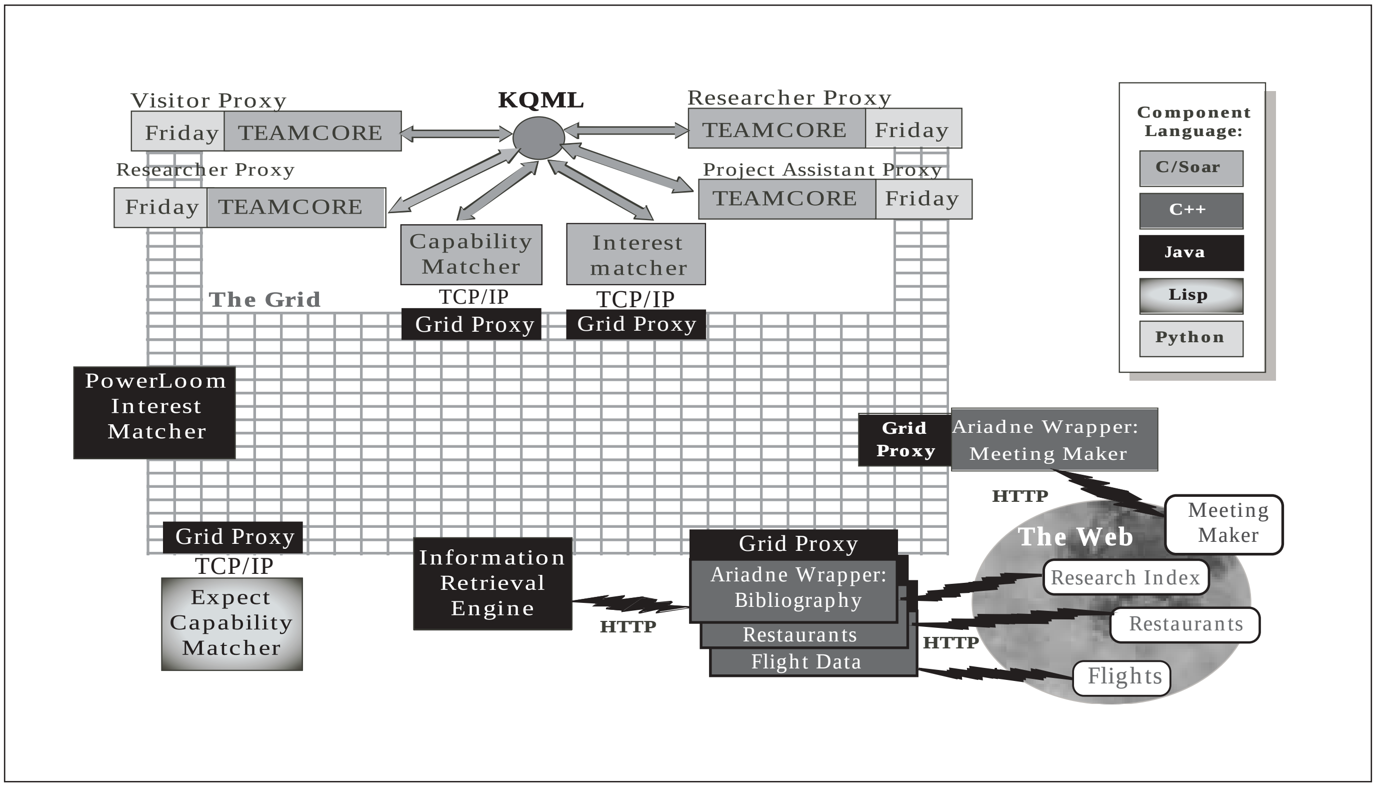

Figure 5. ELECTRIC ELVES *System Architecture.*

CORE agents communicate by their own protocol (the Lockheed KQML API) and only use the GRID to communicate with non-TEAMCORE agents such as the capability and interest matchers. Similarly, the information-retrieval engine communicates with ARIADNE wrappers directly by HTTP instead of going through the GRID.

In general, our experience with the CoABS GRID has been positive. It is reasonably robust and up to the task of 24-hour, 7-day-a-week operation (since June 2000, we have logged over 40,000 GRID messages). The GRID has provided us with basic interoperability that would have been difficult to achieve otherwise. Initially, we looked for an alternative communication solution such as using some implementation of KQML, but none satisfied all the different language, operating system platform, and protocol requirements. The synergies that resulted in part from this basic interoperability provided by the CoABS GRID are (1) simple access to ARIADNE web wrappers motivated the connection of information retrieval with knowledge representation techniques for the purpose of the INTEREST MATCHER; (2) access to the PHOSPHORUS capability matchmaker provides TEAMCORE agents with sophisticated capability reasoning that allows assembly of more efficient teams for particular tasks; and (3) similarly, by using ARIADNE wrappers for MEETING MAKER scheduling software, flight tracking, restaurant selection, and so on, TEAMCORE agents can access a much richer information sphere and support more complex and interesting tasks than otherwise possible.

Related Work

Several agent-based systems have been developed that support specific tasks within an organization, such as meeting scheduling (Dent et al. 1992) and visitor hosting (Kautz et al. 1994; Sycara and Zeng 1994). In contrast to these systems, we believe that our approach integrates a range of technologies that can support a variety of tasks within the organization. Agent architectures have been applied to organizational tasks (Lesser et al. 1999; Martin, Cheyer, and Moran 1999; Sycara et al. 1996), but none of them include technology for teamwork, adjustable autonomy, and dynamic collection of information from external sources.

To our knowledge, ELECTRIC ELVES represents the first agent-based system that is used for routine tasks within a human organization. Several other areas of research have looked at complementary aspects of the problems that

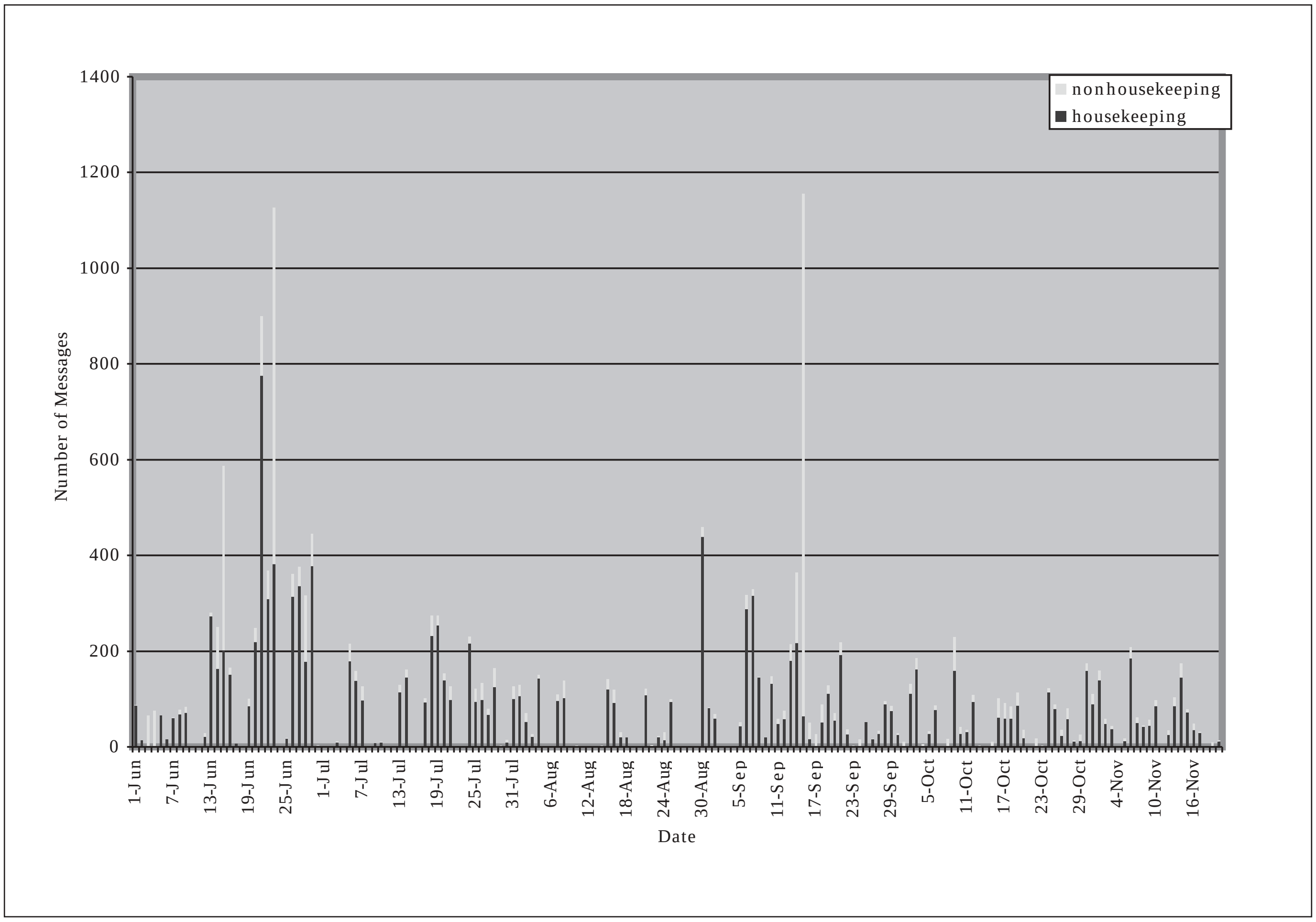

Figure 6. Number of Daily Coordination Messages Exchanged by Proxies over a Seven-Month Period.

we aim to address. Research on architectures and systems for computer-supported cooperative work include a variety of information management and communication technologies that facilitate collaboration within human organizations (Greenberg 1991; Malone et al. 1997). In contrast with our work, they do not have agents associated with people that have some degree of autonomy and can make decisions on a human's behalf. Our work is also complementary and can be extended with ongoing research on ubiquitous computing and intelligent buildings (Lesser et al. 1999). These projects are embedding sensor networks and agents to control and improve our everyday physical environments. This kind of infrastructure would make it easier for ELECTRIC ELVES to locate and contact people as well as to direct the environmental control agents in support of organizational tasks.

Current Status

The ELECTRIC ELVES system has been in use within our research group at ISI since 1 June 2000 and operating continuously 24 hours a day, 7 days a week (with interruptions for bug fixes and enhancements). Usually, nine agent proxies are working for nine users, with one proxy each for a CAPABILITY MATCHER and an INTEREST MATCHER. The proxies communicate with their users using a variety of devices: workstation display, voice, mobile phones, and palm pilots. They also communicate with restaurants by sending faxes.

Figure 6 plots the number of daily messages exchanged by the proxies for seven months (1 June 2000 to 31 December 2000). The size of the daily counts demonstrates the large amount of coordination actions necessary in managing all the activities such as meeting rescheduling. The high variability reflects the

Date	No. of bids	Winner<bid>	Autonomous?
July 6	7	Scerri<1,1>	No
July 20	9	Scerri<1,1>	Yes
July 27	7	Kulkarni<0,1>	Yes
Aug. 3	8	Nair<1,1>	Yes
Aug. 31	4	Tambe<1,1>	Yes
Sept. 19	6	Visitor<-,->	No
Oct. 31	7	Tambe<1,1>	Yes
Nov. 21	7	Nair<1,1>	Yes

Table 1. Results for Auctioning Research Presentation Slot.

fluctuation in the number of daily activities; for example, weekends and long breaks such as the Christmas break usually have very little activity. Furthermore, with continually increasing system stability, the amount of housekeeping activity necessary has reduced automatically.

Several observations show the effectiveness of ELECTRIC ELVES. First, over the past several months, few e-mails have been exchanged among our group members, indicating to each other that they might get delayed getting to meetings. Instead, FRIDAY agents automatically address such delays. In addition, the overhead of waiting for delayed members in meeting rooms has been reduced. Overall, 1128 meetings have been monitored, 285 of which have been rescheduled, 230 automatically and 55 by hand. Both autonomous rescheduling and human intervention were useful in ELVES.

Furthermore, in the past, one of our group members would need to circulate e-mails trying to recruit a presenter for research meetings and making announcements; this overhead has almost completely vanished—weekly auctions automatically select the presenters at our research meetings. These auctions are automatically opened when the system receives notification of any meeting requiring a presentation. A summary of the results is in table 1. Column 1 shows the dates of the research presentations. Although the auctions are held weekly, several weekly meetings over this summer were canceled because of conference travel and vacations. Column 2 shows the total number of bids received before a decision. The key here is that auction decisions can be made with fewer than nine bids; in fact, in one case, only four bids were received. The rest of the group simply did not bid before the winner was announced. Column 3 shows the winning bid. A winner typically bid <1,1>, indicating that the user it represents is both capable and willing to do the presentation. Interestingly, the winner of 27 July had a bid of <0,1>: not capable but willing. The proxy team was able to settle on a winner despite the bid not being the highest possible, illustrating its flexibility. Note that the capability bids for these auctions are obtained by querying the PHOSPHORUS matchmaker. Finally, column 4 shows the results. In six of the eight times, a winner was automatically selected. However, on two occasions (6 July and 19 September), exceptional circumstances (for example, a visitor) required human intervention, which our proxy team easily accommodates.

Other benefits of ELECTRIC ELVES include a web page, where different FRIDAY agents post their user's location, enabling us to track our group members quickly, again avoiding the overhead of trying to track them down manually.

Discussion

As described in this article, we successfully deployed the ELECTRIC ELVES in our own real-world organization. These agents interact directly with humans both within the organization and outside the organization, communicating by e-mail, wireless messaging, and faxes. Our agents go beyond simply automating tasks that were previously performed by humans. Because hardware and processing power is cheap, our agents can perform a level of monitoring that would be impractical for human assistants, ensuring that activities within an organization run smoothly and that events are planned and coordinated to maximize the productivity of the individuals of an organization.

In the process of building the applications described in this article, we addressed a number of key technology problems that arise in any agent-based system applied to human organizations. In particular, we described how to use MDPs to determine the appropriate degree of autonomy for the agents, how to use knowledge-based matchmaking to assign tasks within an organization, how to apply machine learning techniques to ensure robust access to the data sources, how to combine knowledge-based and statistical matchmaking techniques to derive knowledge about the participants both within and outside an organization, and how to apply multiagent teamwork coordination to dynamically assemble teams.

There are a huge number of possible applications of this work. We plan to continue to extend both the range of applications and the underlying technologies for building the agents. One of the advantages of deploying the research in our own organization is that there is no shortage of ideas for future tasks for the ELECTRIC ELVES to perform.

Acknowledgments

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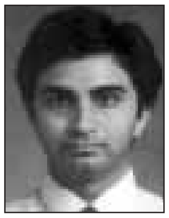

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