Sensible Agents: Demonstration of Dynamic Adaptive Autonomy

K. S. Barber, A. Goel, D. C. Han, J. Kim, D. N. Lam, T. H. Liu, C. E. Martin, R. McKay

The Laboratory for Intelligent Processes and Systems
Electrical and Computer Engineering
The University of Texas
Austin, TX 78712
barber@mail.utexas.edu

Research Overview

Multi-agent Systems (MAS) meld the research fields of Distributed Computing and Artificial Intelligence into a field called Distributed Artificial Intelligence (DAI). MAS fit nicely into domains that are naturally distributed and require automated reasoning to solve problems. Sensible Agents are one MAS designed for domains with a high level of dynamism and uncertainty. A central problem in MAS is finding the correct organizational structure for the agents (e.g. hierarchical, peer group, etc.) in which responsibilities to plan for and execute goals are allocated. In dynamic situations, it is unreasonable to expect a single organizational structure to be appropriate at all times. For proof of this, one needs only look at human management theory and practice. Human corporations often reorganize to face new environmental conditions. Sensible Agents attack this problem with Dynamic Adaptive Autonomy (DAA), which allows them to reorganize themselves during runtime to solve different problems in the face of a changing environment.

Some specific research that has contributed to flexible, adaptive multi-agent coordination includes partial global planning (Durfee and Lesser, 1987), organizational self-design (Ishida et al., 1992), STEAM flexible teamwork (Tambe, 1997), and RETSINA matchmaking (Sycara and Pannu, 1998). However, these techniques do not specifically adapt agent planning-interaction styles.

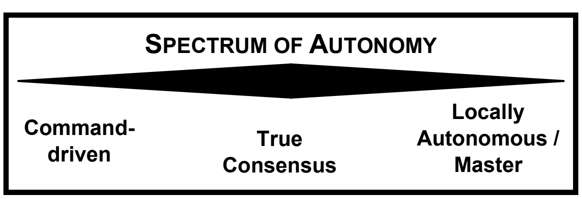

Figure 1: Spectrum of Autonomy

DAA allows agents to dynamically form, modify, and dissolve goal-oriented problem-solving agreements with other agents in a robust and flexible manner. As a member of a problem-solving organization, Sensible Agents establish their role in interacting with others by selecting an autonomy level for each goal they intend to pursue: (1) **Command driven**—agent does not plan but obeys orders given by another agent, (2) **Consensus**—agent works as a team member to devise plans, (3) **Locally Autonomous / Master**—the agent plans alone, unconstrained by other agents, and may or may not give orders to command-driven followers.

Each Sensible Agent (Barber et al., 2000) is composed of the following components: (1) the *Action Planner*; (2) the *Perspective Modeler*; (3) the *Conflict Resolution Advisor*; and (4) the *Autonomy Reasoner*. Domain-specific information, processing rules, and state are restricted to the Action Planner module, while remaining modules are domain-independent.

Sensible Agents are capable of performing: (1) trade-off assessment regarding the impact of local decision-making and goal satisfaction on system objectives, (2) their own behaviors by planning for a goal (local or system) and/or executing actions to achieve the goal, (3) group behaviors by forming binding autonomy agreements (e.g. consensus groups, master agent planning for group of command-driven agents) (4) self-organization by determining the best problem-solving organization, autonomy level, to optimally satisfy a goal, and (5) preferential learning for associating autonomy levels to situations.

Demonstration

The Sensible Agent Testbed provides an infrastructure of well-defined, publicly available interfaces where distributed agents operate and communicate. The end-user can interact with the testbed from the viewpoint of (1) the environment, by defining scenarios and injecting contingencies, or (2) the decision maker, by participating in planning and execution and receiving assistance from other Sensible Agents.

Sensible Agent capabilities will be demonstrated in the naval radar frequency management (NRFM) domain. This domain requires maintaining a set of position and frequency relationships among geographically distributed radars such that radar interference is minimized. Radar interference occurs primarily when two or more radars are operating in close proximity at similar frequencies. For a typical group of naval ships, it may take hours or days for a human assisted by a rule-based system to determine an optimal position and frequency. Unfortunately, the environment typically changes much faster than the human can respond. Local decisions impact the entire system, requiring tradeoffs between local goal (e.g. keep my radars interference free) and system goals (e.g. keep radars in my group of ships interference free).

The NRFM Sensible Agent demonstration is used to determine the performance of Sensible Agents under different problem solving organizations. Agents monitor a naval radar for interference from external sources, and, if interference is detected, attempt to eliminate it by working alone or with others (Goel et al., 1998). Several different operating scenarios are demonstrated. Each Sensible Agent has the following capabilities:

Communication: the ability to send messages to another agent and to asynchronously respond to sent messages. Communication takes the form of (1) requesting/supplying information, (2) forming Autonomy Level Agreements, (3) reporting a conflict, (4) reporting a solution to a conflict.

Sensing: the ability to sense the position of other ships. Agents can also sense their level of interference, but cannot sense the source. If an agent detects interference it initiates problem solving to minimize the interference.

Environmental modeling: the ability to maintain an internal, local, model of the agent's world, separate from the simulation model of the world. Each agent is aware of the initial state of the system (ship positions and frequencies), however as the simulation progresses, an agent's local model may deviate from the world model. The agents use communication and sensing to update their local models.

Planning: the ability to plan at each of the autonomy levels described above. Successful planning for this problem hinges on an agent's ability to determine interference-free frequency assignments. Agents do this by modeling the spectrum of available frequencies and the necessary frequency differences (delta frequencies) for each known pair of radars. Agents then attempt to make assignments that meet all delta-frequency constraints within the restricted frequency space. Three algorithms are available to each agent's planner and are associated with the appropriate autonomy level classification.

An agent attempting to resolve interference in a locally autonomous fashion will plan alone. The agent will use its internal world model to find a frequency that is likely to be interference-free. The frequencies of other radars in the system are modeled as constraints on the search process. If no frequencies are found, searching continues at regular time intervals until one is found or a random "deadlock" time limit is reached. If the agent determines that the system is in deadlock (with respect to its interference state), it will choose a random frequency to pull the system out of deadlock.

Only the master plans in a master/command-driven relationship. If the master or its command-driven agents are experiencing interference, the master attempts to eliminate the interference through iterative assignments. First, it chooses its own frequency in the manner described above, but without considering the frequencies of its command-driven agents as constraints. It then determines an interference-free frequency for each command-driven agent, adding these frequencies as constraints, until all assignments have been made. If no set of satisfying assignments is found, the planning process is restarted. Once a solution has been found, the assignments are passed to the command-driven agents. Command-driven agents may report back to the master if they are still experiencing interference after the assignment. This may occur when the master's internal model does not match the world state.

Each agent involved in consensus interaction plays an equal part in determining frequency assignments. First, each agent independently carries out the master/command-driven planning algorithm with the other members of the consensus group treated as command-driven agents. At the conclusion of this phase, each agent proposes its solution to the rest of the consensus group during a synchronization phase. Each agent includes an estimate (based on its internal model) of the expected interference for each radar. Each consensus member deterministically selects the proposal with the least amount of estimated interference, and the agents assign frequencies accordingly.

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