Multi-Level Learning in Hybrid Deliberative/Reactive Mobile Robot Architectural Software Systems

Georgia Tech College of Computing
Georgia Tech Research Institute
Mobile Intelligence Corporation
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DARPA

Summary of Approach

- Investigate robot shaping at five distinct levels in a hybrid robot software architecture
- Implement algorithms within *MissionLab* mission specification system
- Conduct experiments to evaluate performance of each technique
- Combine techniques where possible
- Integrate on a platform more suitable for realistic missions and continue development

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Overview of techniques

- CBR Wizardry
  - Guide the operator
- Probabilistic Planning
  - Manage complexity for the operator
- RL for Behavioral Assemblage Selection
  - Learn what works for the robot
- CBR for Behavior Transitions
  - Adapt to situations the robot can recognize
- Learning Momentum
  - Vary robot parameters in real time

THE LEARNING CONTINUUM:

Deliberative (premission)

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Behavioral switching

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Reactive (online adaptation)

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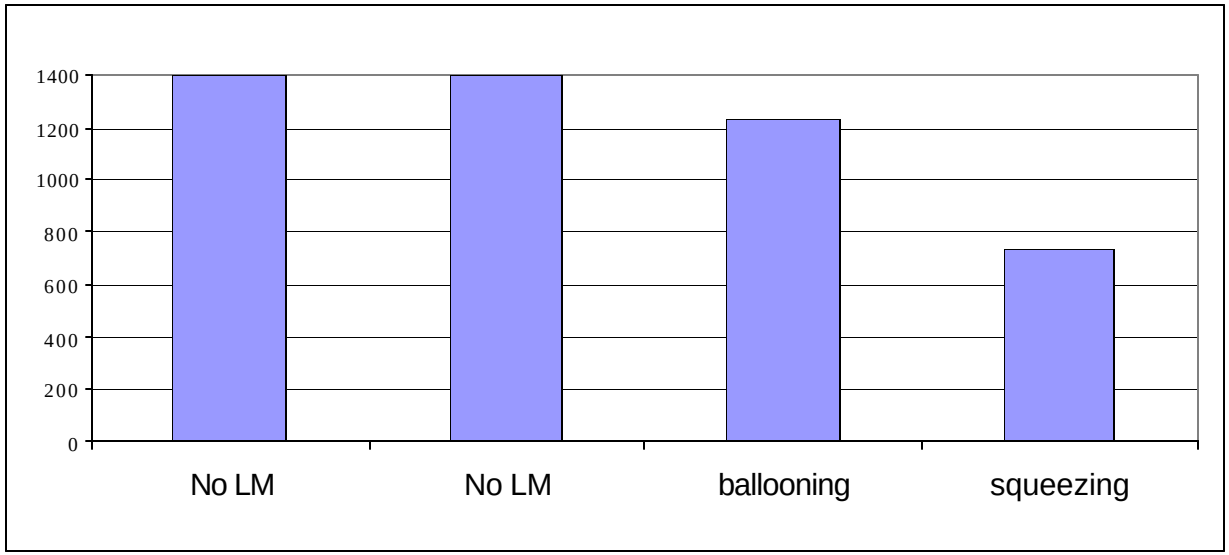
Learning Momentum

- Behavioral parameters are modified at runtime depending on a robot's prior success in navigating the environment
- Robot stores a short history of items such as the number of obstacles encountered, the distance to the goal, and other relevant data
  - uses this history to determine which one of several predefined situations the robot is in and alters its behavioral gains accordingly
  - a crude form of reinforcement learning, where if the robot is doing well, it should keep doing what it's doing and even do it more
- Two strategies were previously described: ballooning and squeezing

Learning Momentum Trials

- Augments earlier simulation trials with real robot results
- In a limited number of runs, success was achieved only with LM active
- Relied on sonar sensing of obstacles
- Future experiments will use laser scanners on indoor/outdoor robot
- Recent effort addresses integration with CBR learning



Average steps to completion for a real environment. Trials with no successful runs were given the largest value on the graph.

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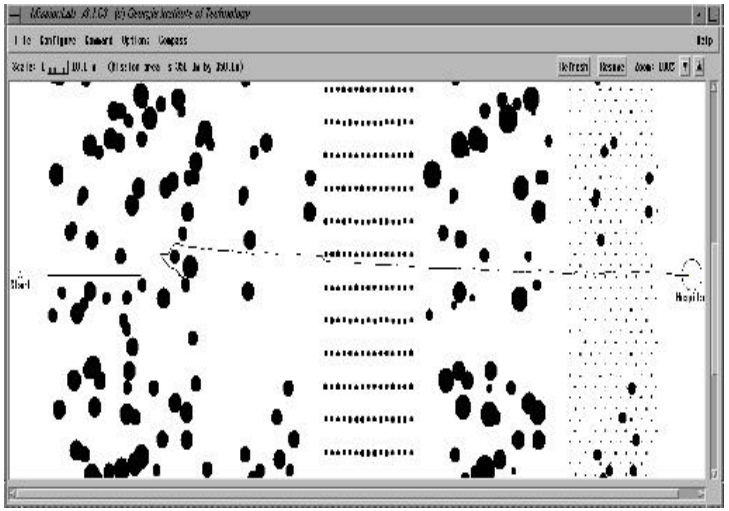
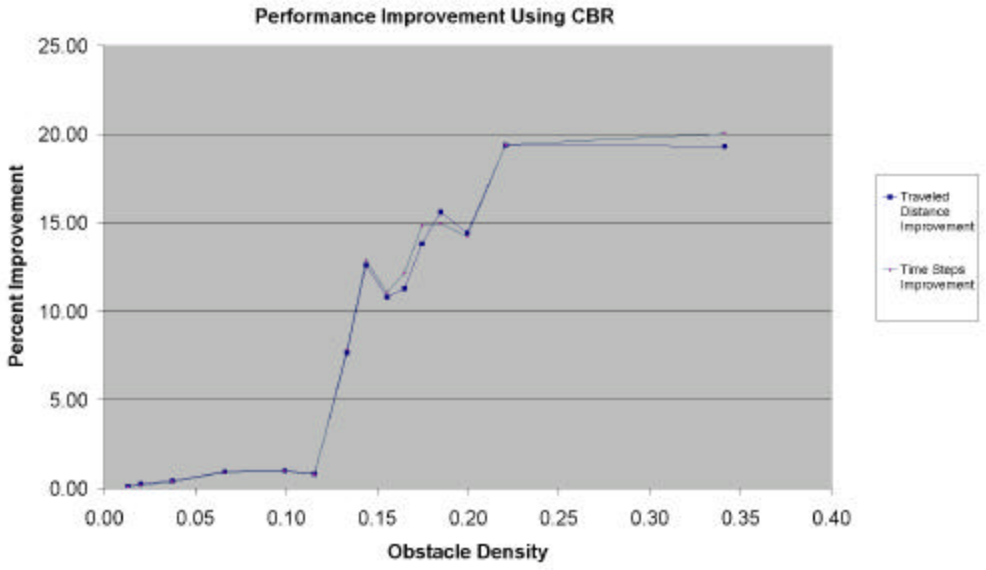
CBR for Behavioral Selection

- As the environment of a reactive robot changes, the selected behaviors should change
- Previous results showed improvements in simulation





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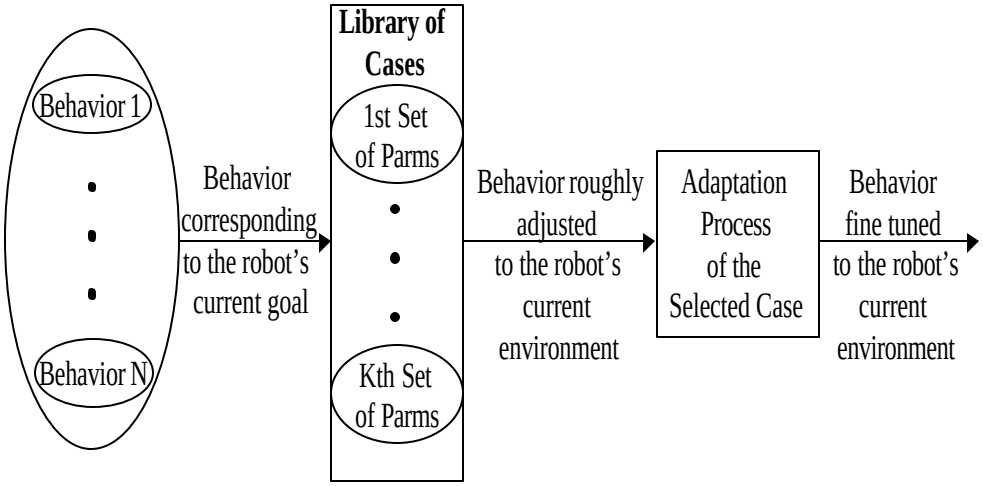
Behavioral Adaptation Approach



- Select behavioral assemblages based on robot mission specification
- Adjust parameters with CBR techniques
- Fine-tuning the behaviors allows the library of cases to remain smaller
  - Initially done only once, based on temporal "progress" measure
  - Now a continuous process, integrating with Learning Momentum method

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CBR Trials

- Ten runs were conducted with the CBR module and ten without
- Test course included box canyon and obstacle field
- Obstacle density varied from low to high
- Results correlate well with the simulation-based data
  - as the average obstacle density increases, the benefits from the CBR module also increase.

Improvement(%)		
Obstacle Density	Traveled Distance	Time Steps
Low	6.2	3.3
Medium	17.8	17.6
High	26.4	28.6

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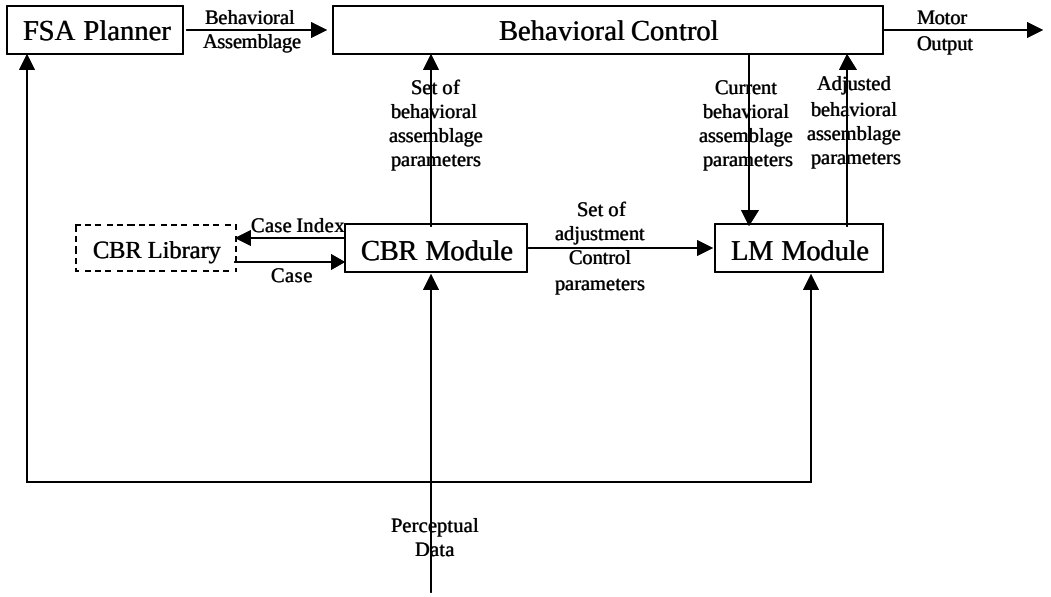
Integration of LM and CBR

- The first of several integration steps to combine the advantages of different robot shaping methods
- CBR module provides discontinuous switching of behavioral parameters based on sufficiently drastic changes in the environment
- LM module provides a continuous adaptation of behavioral parameters



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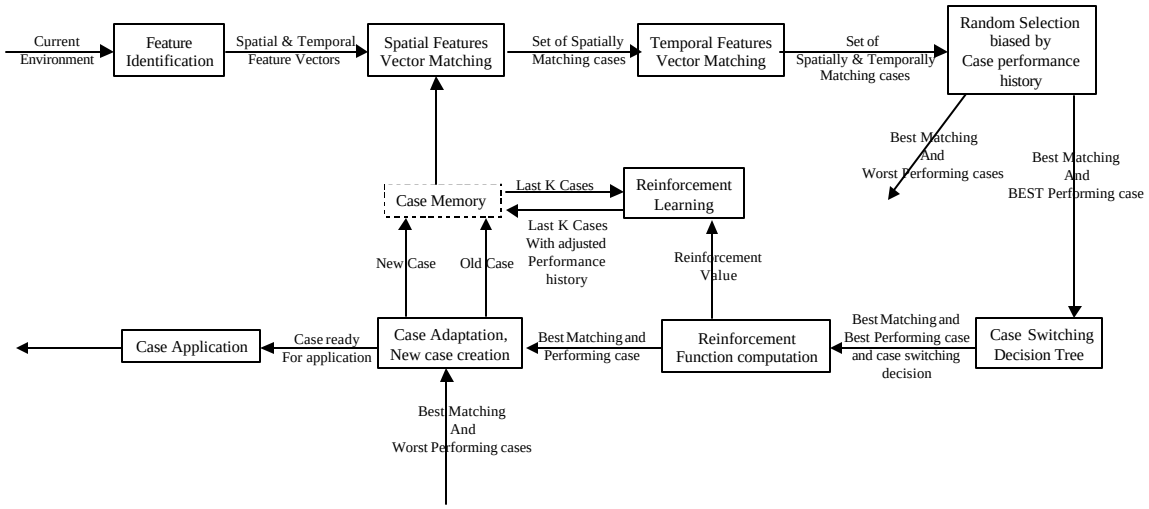
Specifics of LM/CBR Integration

- CBR module selects a new case either
  - when environment characteristics significantly change, or
  - when robot performance falls below a threshold for a specified interval
- A case is defined as before, but now includes a set of parameters that control the LM adaptation rules
- LM Module acts as before, but is “conditioned” by the CBR-provided parameters
- The previous library of cases is insufficient
  - Lacks adaptation parameters
  - Does not address outdoor environments
  - Larger parameter space will make manual case building difficult and time-consuming

Automatic Case Learning

- Addresses the rebuilding of the case library
- CBR library now contains cases with both positive and negative performance history
- Reinforcement function computation sub-module computes a reinforcement function which is used to adjust the performance history measure for the last K applied cases
- The previous random selection is now weighted by the goodness of each of the spatially and temporally matching cases



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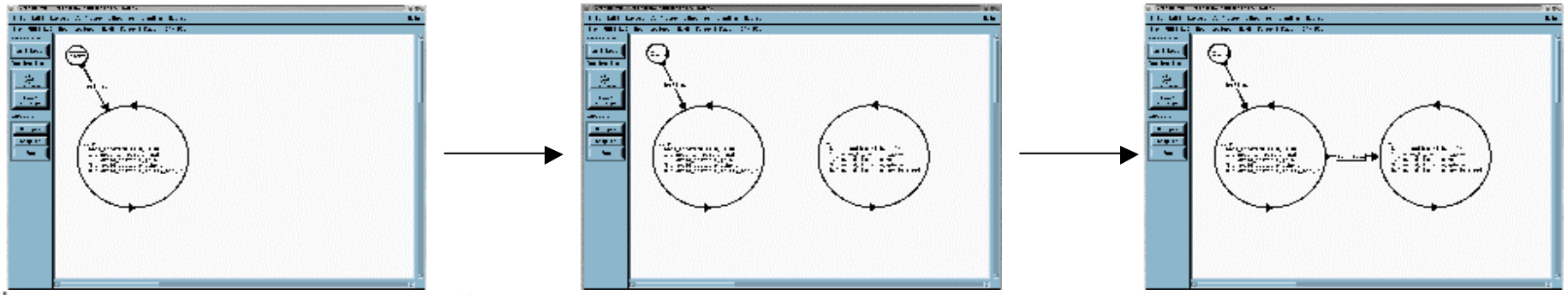
CBR “Wizardry”

- Help the user during mission specification
  - check for common mistakes
  - suggest fixes
  - automatically insert elements
- Previous highlights include the addition of a *plan creation recorder* and initial usability studies



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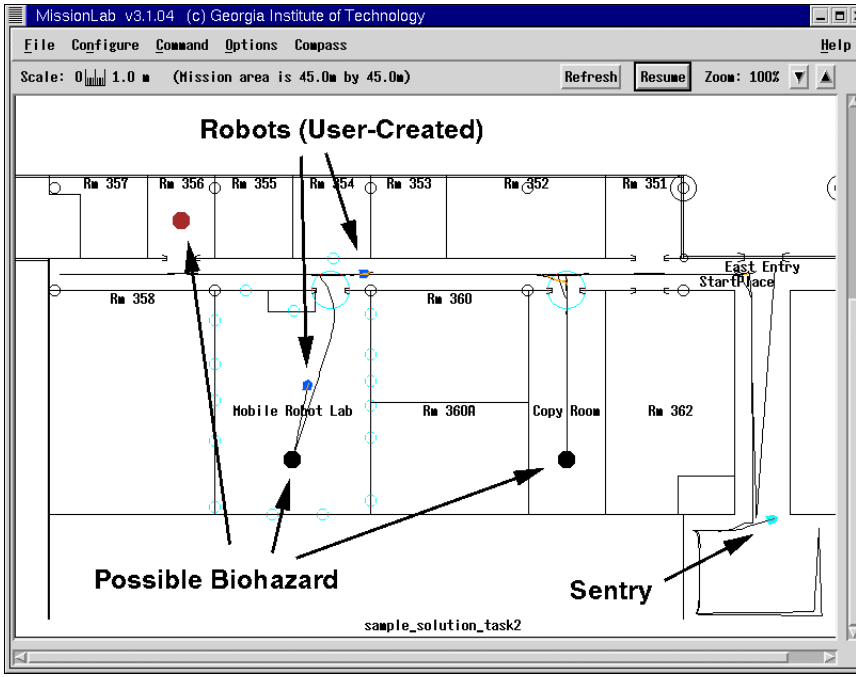
Usability studies

- Conducted a set of experiments
  - to evaluate the usability of the *MissionLab* interface
  - to determine to what extent the current interface enables novice users to design relevant missions
  - to provide a baseline against which future versions of the system will be evaluated



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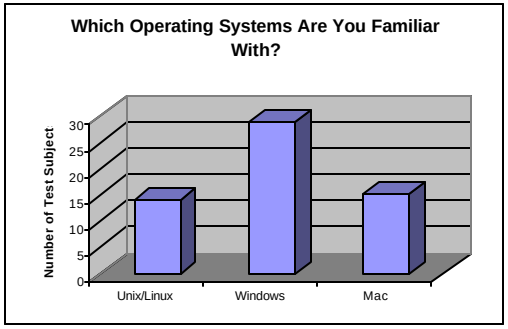
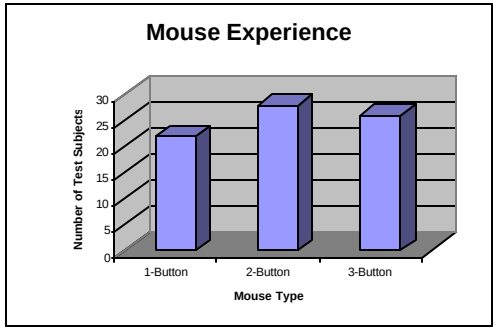
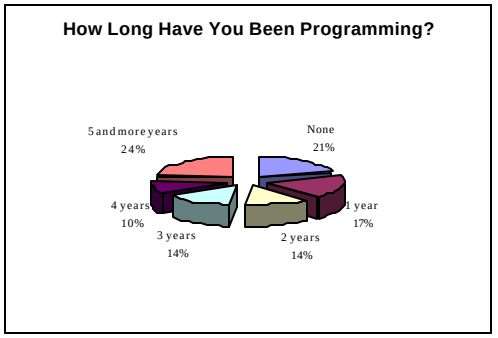
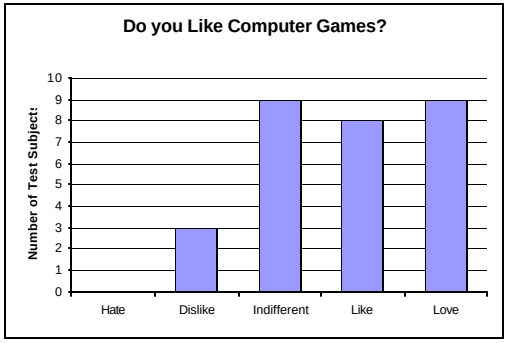
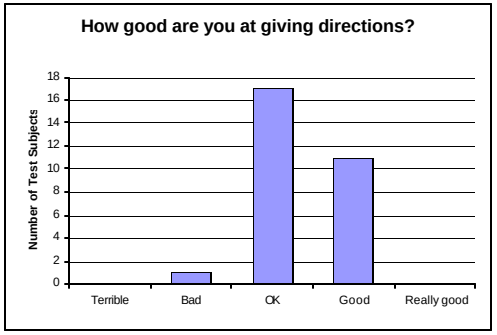
Test subject demographics

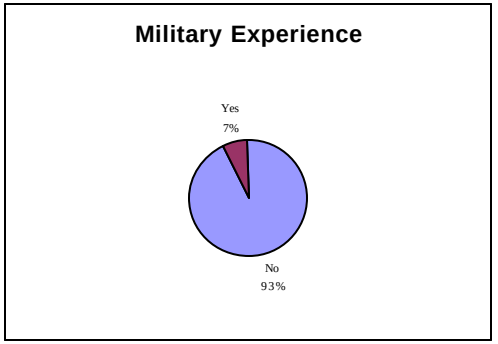












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Usability study results

- Results suggest that novices perform nearly as well as experienced users
- Two-robot scenario was considerably more difficult than single-robot scenario
- Studies have contributed to the population of a case database that will be used in the initial implementation of the wizard
- Summary data for all subjects:

	Single Robot Scenario	Two Robot Scenario
Number of Tasks	14.23	23.40 (both robots)
Number of Triggers	21.27	38.50 (both robots)
Modifications	36.32	69.00
Modification Time	6 min 10 sec	12 min 11 sec
Total Completion Time	33 min 3 sec	45 min 2 sec
Mission Restarts	0.180	0.127

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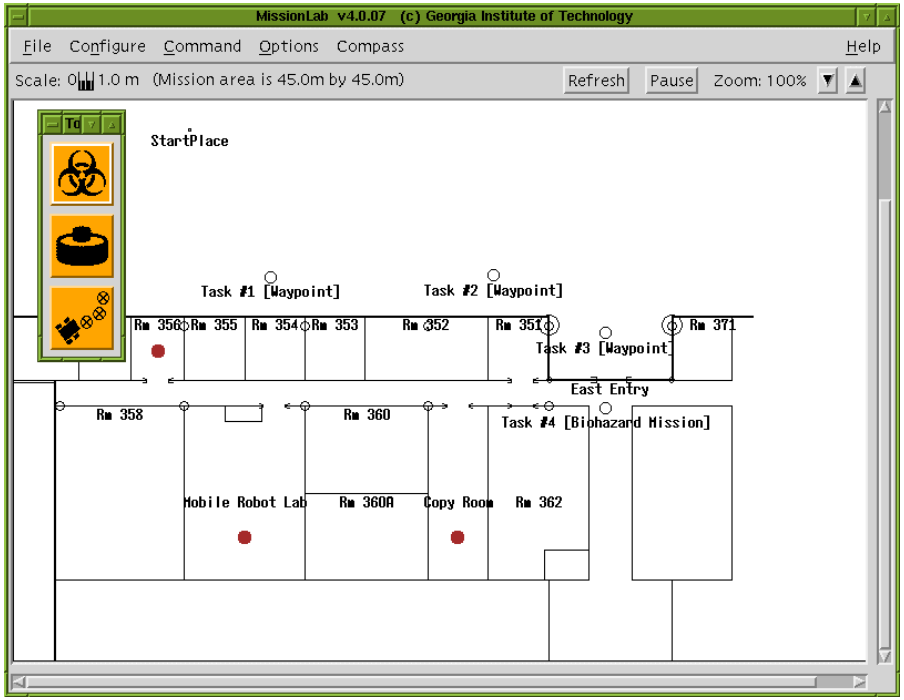
Proposed CBR Wizard

- Will utilize a map-based interface and iconic task representations
- Will empower less-skilled robot commanders to develop sophisticated missions by avoiding the complexities of directly building FSAs
- Instead, users will build a mission by marking critical aspects on a map
- Case-Based Reasoner will fill in the gaps to form a complete mission plan.



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CBR component of Wizard

- Relevant cases stored in standard relational database
- Two types of cases:
  - Task-based mission fragments (e.g., those from usability studies)
  - Location-based mission fragments (learned from experience in similar situations)
- Possible case indices:
  - type of mission (indoor, urban, wooded, etc.)
  - number of robots
  - localization requirements (accurate map, landmarks, etc.)
  - stealthiness of the mission
  - presence of enemy threats
- Case evaluation and adaptation currently being considered

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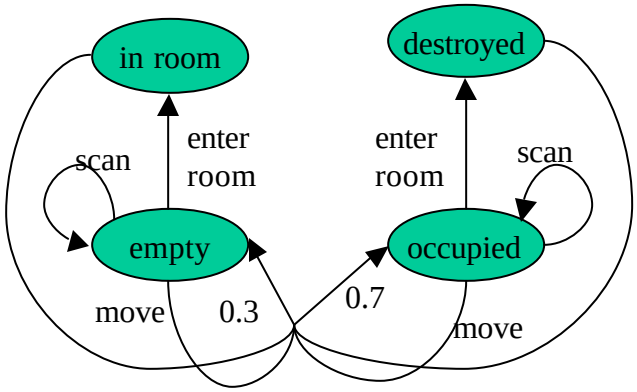
Probabilistic Planning

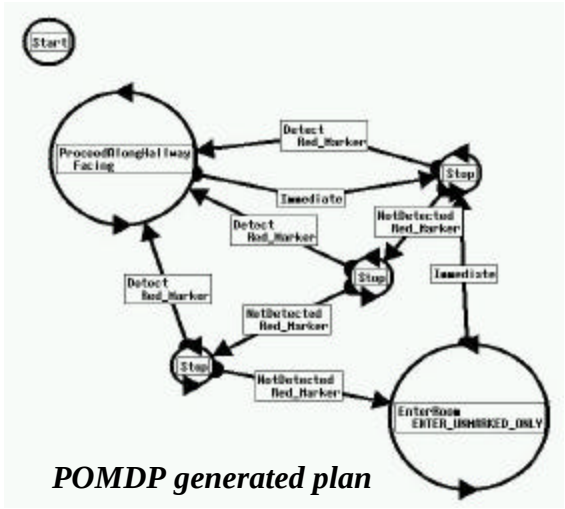
- Partially Observable Markov Decision Processes (POMDPs) can model uncertainty for mobile robots
  - uncertainty due to sensor noise
  - actuator uncertainty
  - unpredictable events in the environment
- Hypothesis is that robots can act more robustly by modeling this uncertainty explicitly with POMDPs
- Distinctions between this and previous application of POMDPs to robot control:
  - Emphasis here has been on sensor-planning in the context of behavior-based robot systems
  - Solutions of POMDPs can be expressed as policy graphs, which are similar to the finite state automata used in *MissionLab*

POMDP Planning Progress



POMDP Model

Sensor model for scan:
P(detect-occupied|occupied) = 0.8
P(detect-empty|empty = 1.0



POMDP generated plan

- Previously, we showed the creation of FSAs from policy graphs
- Recent efforts have included simulation runs and actual robot runs

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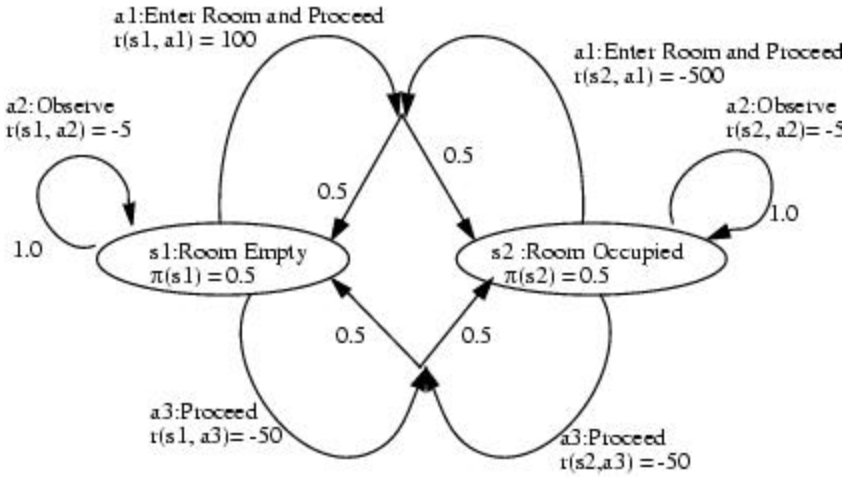
Test scenario – cautious room entry



- Penalized heavily for entering an occupied room
- Equal chance of encountering an occupied or unoccupied room
- Observing room has small penalty and imperfect result (20% false negative)

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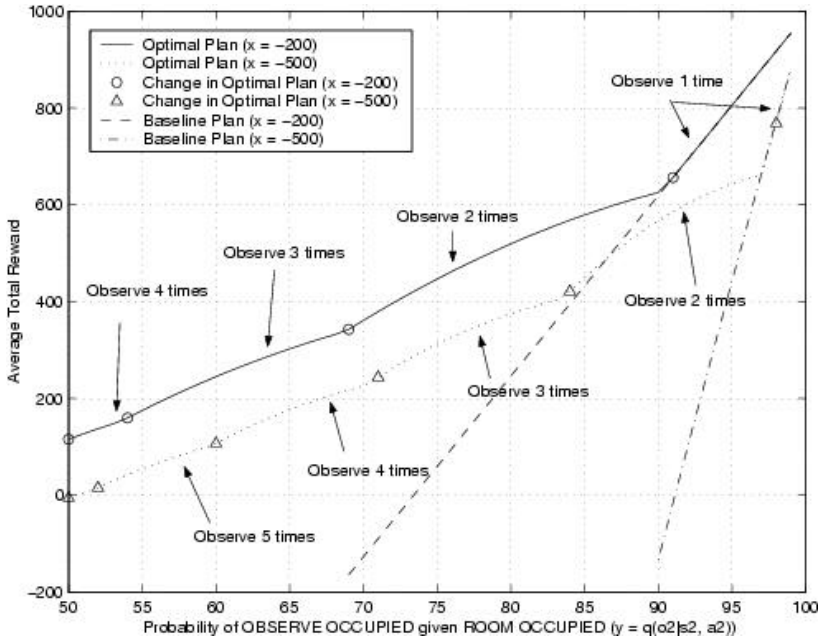
Analysis & Simulation Results

- Analysis shows that multiple observations pay off as penalty for entering occupied room increases
- Simulation study compared naïve "baseline" plan against POMDP-based "optimal" plan
- Results correlated well with analysis



	Baseline Plan	Optimal Plan
Reward for Entering Occupied Room x = -200	16.92	282.89
Reward for Entering Occupied Room x = -500	-1000.42	498.23

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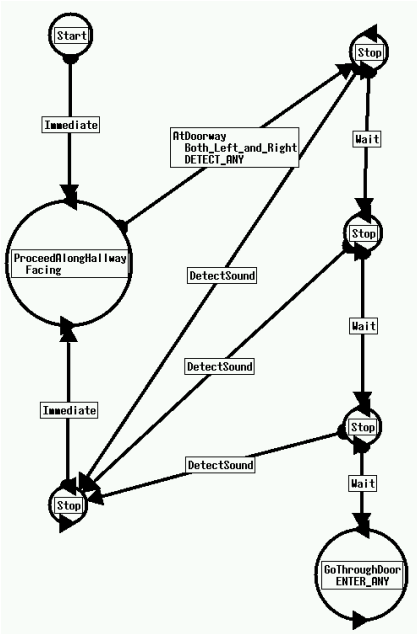
Actual Robot Results

- Used a Nomadic Technologies 150 equipped with a stereo microphone
- Robot proceeded down a hallway until it detected a door
- Robot stopped and listened for sound
  - For occupied rooms, a sound was generated every 10 seconds with 80% probability
- When executing the baseline plan, the robot would enter the room after one failure to detect noise
  - This caused the robot to incorrectly enter a room in 1 out of 5 attempts
- The POMDP-generated plan instructed the robot to sense 2-3 times
  - the robot correctly avoided occupied rooms in all trials



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RL for Behavioral Assemblage Selection

- Essentially involves trial and error to determine when to switch from one behavior to another
- Operates at coarse granularity
  - implements behavioral assemblage selection
  - as opposed to parameterization, as is done in CBR/LM methods
- As reported previously:
  - Approach replaces the FSA with an interface allowing user to specify the environmental and behavioral states
  - Agent learns transitions between behavior states
  - Learning algorithm is implemented as an abstract module and different learning algorithms can be swapped in and out as desired.

RL test scenario

- An intelligent landmine
  - designed to intercept enemy tanks as they move down a nearby road and destroy them
  - idealized sensor determines the location of enemy tanks within a certain radius
  - sensor information is used with two perceptual triggers: CAN_INTERCEPT and NEAR
- Every timestep that the NEAR observation is made, the landmine receives a reward of +2
- The landmine is not penalized for any action.
- After making an observation and receiving a reward, the mine can choose WAIT or INTERCEPT

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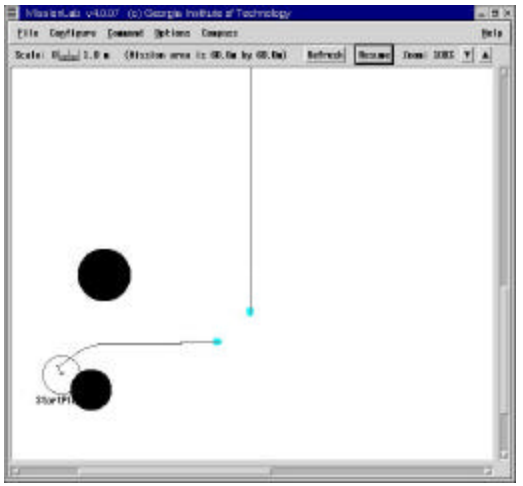
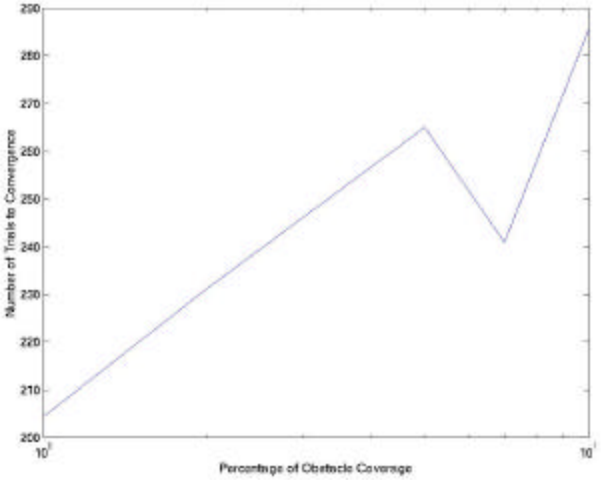
RL learning trials

- 750 learning scenarios
  - A learning scenario consists of 300 time steps in which the mine is attempting to intercept the tank
- Success of the Q-learner judged by the convergence properties of the Q-value table





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Recent MARS-related publications

- Maxim Likhachev and Ronald C. Arkin, “Spatio-Temporal Case-Based Reasoning for Behavioral Selection,” to appear at IEEE International Conference on Robotics and Automation (ICRA) 2001.
- Amin Atrash and Sven Koenig, “Probabilistic Planning for Behavior-Based Robotics,” to appear at the 14th International FLAIRS Conference.
- J. Brian Lee and Ronald C. Arkin, “Learning Momentum: Integration and Experimentation,” to appear at IEEE International Conference on Robotics and Automation (ICRA) 2001.

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