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

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Georgia Tech / Mobile Intelligence
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Adaptation and Learning Methods

- Case-based Reasoning for:
  - deliberative guidance ("wizardry")
  - reactive situational-dependent behavioral configuration

- Reinforcement learning for:
  - run-time behavioral adjustment
  - behavioral assemblage selection

- Probabilistic behavioral transitions
  - gentler context switching
  - experience-based planning guidance

Available Robots and MissionLab Console

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1. Learning Momentum

- Reactive learning via dynamic gain alteration (parametric adjustment)
- Continuous adaptation based on recent experience
- Situational analyses required
- In a nutshell: If it works, keep doing it a bit harder; if it doesn’t, try something different
Learning Momentum - Design

- Integrated into MissionLab in CNL Library
- Works with MOVE_TO_GOAL, COOP, and AVOID_OBSTACLES
- Has not yet been extended to all behaviors
Simple Example
Learning Momentum - Future Work

- Extension to additional CNL behaviors
- Make thresholds for state determination rules accessible from cfgedit
- Integrate with CBR and RL
2. CBR for Behavioral Selection

- Another form of reactive learning
- Previous systems include: ACBARR and SINS
- Discontinuous behavioral switching
The CBR Module is designed as a stand-alone module
A hard-coded library of eight cases for MoveToGoal tasks
Case - a set of parameters for each primitive behavior in the current assemblage and index into the library
Case-Based Reasoning for Behavioral Selection - Current Results

- On the Left - MoveToGoal without CBR Module
- On the Right - MoveToGoal with CBR Module
Case-Based Reasoning for Behavioral Selection - Future Plans

- Two levels of operation: choosing and adapting parameters for selected behavior assemblages as well as choosing and adapting the whole new behavior assemblages
- Automatic learning and modification of cases through experience
- Improvement of case/index/feature selection and adaptation
- Integration with Q-learning and Momentum Learning
- Identification of relevant task domain case libraries
3. Reinforcement learning for Behavioral Assemblage Selection

- Reinforcement learning at coarse granularity (behavioral assemblage selection)
- State space tractable
- Operates at level above learning momentum (selection as opposed to adjustment)
- Have added the ability to dynamically choose which behavioral assemblage to execute
- Ability to learn which assemblage to choose using wide variety of Reinforcement Learning methods: Q-learning, Value Iteration, (Policy Iteration in near future)
Selecting Behavioral Assemblages - Specifics

- Replace 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.
- CNL function interfaces robot executable and learning algorithm
Integrated System
Architecture

Environmental States

Behavioral States

Cfgedit

CDL code

MissionLab

CNL function

Learning Algorithm
(QLearning)
RL - Next Steps

• Change implementation of Behavioral Assemblages in Missionlab from simply being statically compiled into the CDL code to a more dynamic representation.

• Create relevant scenarios and test Missionlab’s ability to learn good solutions

• Look at new learning algorithms to exploit the advantages of Behavioral Assemblages selection

• Conduct extensive simulation studies then implement on robot platforms
4. CBR “Wizardry”

- Experience-driven assistance in mission specification
- At deliberative level above existing plan representation (FSA)
- Provides mission planning support in context
Current Methods: Using GUI to construct FSA - may be difficult for inexperienced users.

Goal: Automate plan creation as much as possible while providing unobtrusive support to user.
Some FSA elements very often occur together.
Statistical data on this can be gathered.
When user places a state, a trigger and state that follow this state often enough can be tentatively inserted into the FSA.
Comparable to URL completion features in web browsers.
Pinpointing where user has trouble during plan creation is an important prerequisite to improving software usability.

There was no way to record plan creation process in MissionLab. A module has now been created that records user’s actions as (s)he creates the plan. This recording can later be played back and points where the user stumbled can thus be identified.

The Creation of a Plan
Wizardry - Future Work

- Use of plan creation recordings during usability studies to identify stumbling blocks in process.
- Creation of plan templates (frameworks of some commonly used plan types e.g. reconnaissance missions)
- Collection of library of plans which can be placed at different points in “plan creation tree”. This can then be used in a plan creation wizard.

Plan Creation Tree
5. Probabilistic Planning and Execution

- “Softer, kinder” method for matching situations and their perceptual triggers

- Expectations generated based on situational probabilities regarding behavioral performance (e.g., obstacle densities and traversability), using them at planning stages for behavioral selection

- Markov Decision Process, Dempster-Shafer, and Bayesian methods to be investigated
Probabilistic Planning and Execution - Concept

- Find the optimal plan despite sensor uncertainty about the current environment
Probabilistic Methods: Current Status

POMDP

MissionLab (current work)
Varying Costs  Different
Plans

-5
P(detect mine|mine) = 0.8

-5000
move

-100
clear mine

100
move

-5
scan

-5
P(detect mine|no mine) = 0

mission

no mine

clear mine

-50

POMDP

MissionLab
(current work)

FSA

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MIC’s Role

- Develop conceptual plan for integrating learning algorithms into *MissionLab*
- Guide students performing integration
- Assist in designing usability studies to evaluate integrated system
- Guide performance and evaluation of usability studies
- Identify key technologies in *MissionLab* which could be commercialized
- Support technology transfer to a designated company for commercialization
## Schedule

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<tr>
<th>Milestone</th>
<th>GFY01</th>
<th>GFY02</th>
<th>GFY03</th>
<th>GFY04</th>
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<tr>
<td>Demonstration of all learning algorithms in simulation</td>
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<td>Initial integration within MissionLab on lab robots</td>
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<td>Learning algorithms demonstrated in relevant scenarios</td>
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<td>MissionLab demonstration on government platforms</td>
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<td>Enhanced learning algorithms on government platforms</td>
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<td>Final demonstrations of relevant scenarios with govt. platforms</td>
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