Robust Assistive Navigation with the Intelligent Mobility Platform (IMP)

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Introduction

IMP (**I**ntelligent **M**obility **P**latform)
- Quality of Life project headed by Geoff Gordon
- Assistive walker for the elderly and disabled
- Text-to-speech and touch-screen interface
- Aids user in sensing and cognition

Problems Addressed

- Make navigation more robust and reactive using policies
- Infer human execution of robot's "recommended" policy (human motion model)
- Replace heavy and expensive sensors (encoders, SICK laser) with lighter and ubiquitous ones (cameras and wireless cards)

Attempted Methods

Augmented MDP (steps illustrated below)

1) Generate occupancy map (using VASCO software for SLAM) and wireless signal strength map (using Kismet software). "Ground truth" position provided by Carmen software via SICK laser: P
2) Using particle filter, derive reduced space belief features based on mean and variance: $\{q\} \rightarrow b^*$
3) Sample motion & sensor models to learn transition model in reduced space : $b^* \rightarrow b^{*\prime}$.
4) Solve the learned MDP via value iteration: $\pi(b^*) \rightarrow a$.
5) Execute policy by calculating features and 1-NN: $\{q\} \rightarrow b \rightarrow b^*, \pi(b^*) \rightarrow a$.

E-PCA Approximate POMDP

1) Same as above.
2) Using particle filter, drive robot to achieve a set of reachable beliefs: B*.
<) Find (locally) optimal compression for beliefs via E-PCA: $B \rightarrow b$.
3) Sample motion and sensor models to learn transition model in reduced space (discretized by 1-NN w.r.t. b*): $b^* \rightarrow b^{*\prime}$.
4) Same as above.
5) Execute policy by projecting belief into reduced space: $\{q\} \rightarrow B \rightarrow b \rightarrow b^*, \pi(b^*) \rightarrow a$.

Insights

Foes	Weapons
State uncertainty	POMDP methods
Limited computation	Reduced beliefs and factoring
Noisy sensors	Sensor fusion
Unpredictable human behavior	Human-robot interaction model

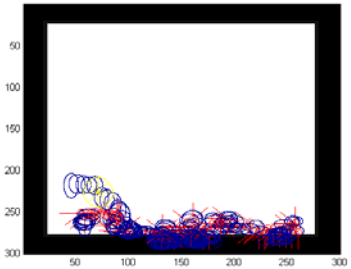
Conclusions

Both Augmented MDPs and E-PCA POMDPs are potentially useful tools for robust human/robot navigation with an assistive robot. However, Augmented MDP with mean and variance belief features was much more computationally tractable than E-PCA and regular POMDPs.

Results

So far, Augmented MDP has proven successful in being tractable for large state spaces and generating plausible navigational policies. The policies generated exhibit a coastal navigation property of minimizing localization error.

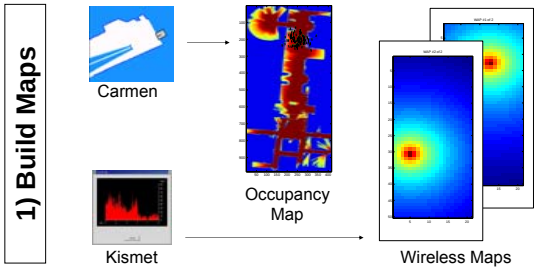
E-PCA POMDP has shown very good compression, but is still a work in progress. The drawback is the computation required for building an MDP instance from the POMDP model and E-PCA basis.

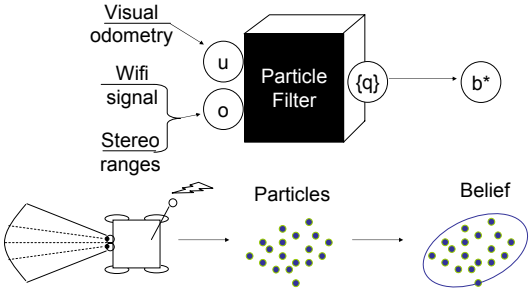


Using Augmented MDP generated policies to navigate to a goal point

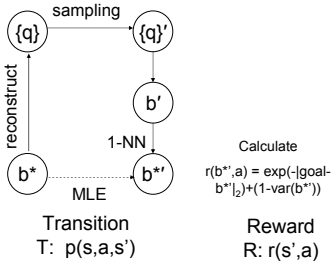
Future Work

In the future, we will continue working towards application of navigational policy guidance on the IMP and will also look into online policy updating. We will also finish our comparison between A-MDP and E-PCA POMDP and other comparable methods. In particular, we will test these methods in the real world with the IMP.

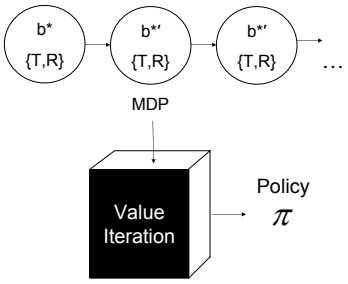




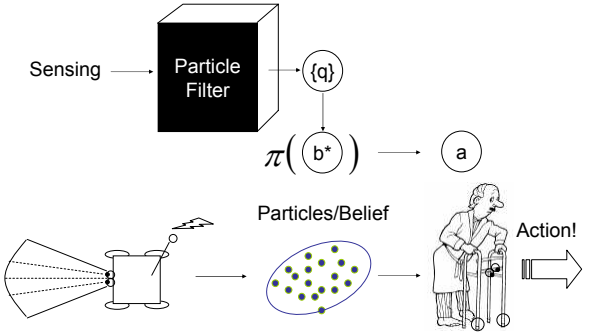
2) Collect "Reachable" Beliefs



3) Learn Reduced Models



4) Solve MDP



5) Execute Policy Online