TORO: Tracking and Observing Robot

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Abstract

A humanoid robot like ASIMO is required to accomplish tasks requiring interaction with people such as object delivery tasks. These tasks require keeping track of past observations of people and objects in the environment. Previous work has used ad-hoc methods to manually encode regions to explore to accomplish these tasks. In this paper, we describe how Region based Particle Filters can be used to maintain and update belief about objects and people location over extended time periods.

We have implemented and demonstrated this work on a Pioneer mobile robot. We first detect people and objects in the scene using depth and vision sensors. We create a map of the environment and use off the shelf techniques for localization and path planning using SICK laser. We describe use of Dynamic Bayesian Network to maintain and update belief about each people and object location. We run separate particle filters for each person and object and for robots' own location. We update these particle filters with information from observations using sampling and re-sampling to incorporate observations over time during the day.

1 Introduction

In this work, we introduce a region-based belief representation of peoples' locations. The idea is to model the person's location by a hierarchical process that first selects a *region* and then conditioned on that a position (X-Y coordinate) for the person. The regions are chosen to be resting places where people people typically stop and stay for long periods of time. For example office desks, the area in front of a TV, water cooler, printer etc. Typically the region is a discrete variable, and position is a linear gaussian conditional on region. This representation allows us to separate transitions that occur at different time scales into the different layers of the model (e.g. deliberate movement from conference room to office desk vs. fidgeting in an office chair). We propose using a Dynamic Bayesian Network (DBN) to track the state of our model over time. Even if the person goes out of view of the robot, it knows that individuals tend to move at a certain maximum speed, that the individuals (for example, someone sitting in their office) is more likely to stay there for a while before moving to a different location.

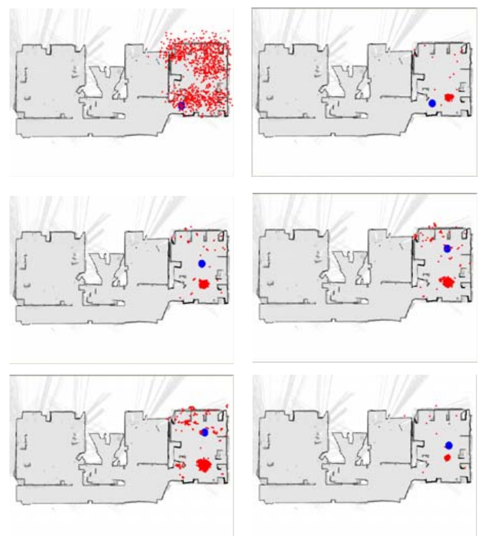
We demonstrate the use of our belief tracker to carry out simple delivery tasks: Pick up objects from a fixed location and deliver them to the corresponding individual. As a result of using multiple sensors, we have a more complicated observation model which updates measurement weights based on the current robot view and walls in the environment that limit the observation regions. Integrating these various sensors together(depth sensor, vision camera, laser scans, plus robot odometry) presented a significant engineering challenge.

2 Related Work

Past work concentrates on tracking movement of people in the immediate neighborhood of the mobile robot over short time periods. Montemerlo et. al. [2] used a probabilistic algorithm for simultaneously estimating the pose of the mobile robot and positions of people in a previously mapped environment. They used a laser sensor and tracked two people in the vicinity. Schulz et. al. [3] also used a laser sensor to keep track of people in vicinity and handle cases where people are obstructed over short time periods. Bennewitz et. al. [1] track people over long time periods but need to first learn the transitions in the environment.

3 Results

(a) Pioneer Robot in the room



(b) Particle filter with belief for robot and person position

Figure 1: (i) prior belief at starting (ii) belief after person is detected (iii) belief after person is no longer seen (iv) belief before turning around (v) belief after turning around (vi) belief after person is seen again

References

[1] M. Bennewitz, W. Burgard, G. Cielniak, and S. Thrun. Learning motion patterns of people for compliant robot motion. *The International Journal of Robotics Research*, 24(1):31–48, 2005.

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[3] D. Schulz, W. Burgard, D. Fox, and A. B. Cremers. People tracking with mobile robots using sample-based joint probabilistic data association filters. *The International Journal of Robotics Research*, 22(2):99–226, 2003.