Summary of Estimation and Mapping

Herman Bruyninckx

Scene understanding is a major prerequisite for intelligent and adaptive robotic systems, and the Bayesian paradigm has become the de facto computational framework to link sensor information to scene models. Progress in this paradigm goes in various complementary directions:

- more realistic Bayesian Networks to improve the accuracy with which the robot system can represent (i) the aspects of the scene that it is interested in, and (ii) the mathematical relationships between these relevant real-world properties and the raw data that its sensors can capture about its environment.
- improved computational algorithms to bring Bayesian information processing closer to realtime.
- increased world model complexity to add a richer semantic context to the interpretation of the estimates that result from the Bayesian algorithms.

The papers in this session each describe progress in one of these three directions.

Baba and Chatila report progress in the use of a more realistic network that allows the robot to distinguish between static and dynamic objects in its environment, using 2D laser scan histories. The static part of the world (the “map”) is represented and built via the traditional occupancy grid approach, and fast and local changes between subsequent map updates are interpreted as potentially moving objects. Each of these moving object hypotheses is then tracked by a particle filter, and these tracked trails are prevented from “polluting” the static map, as long as the motion hypothesis remains consistent with the particle filter motion model.

Grocholsky, Stump and Kumar report about an improved computational algorithm to do range only SLAM. The measurement equations are quite nonlinear in this case, and the authors provide their results with two algorithmic ideas: (i) the transformation of the sensor processing mathematics to a higher-dimensional parameter space in which the estimation problem is linear, and (ii) the use of elliptical feasibility sets to reduce the computational complexity of uncertainty tracking.

Fox et al. present increased world models that add activity and environment semantics to the lower level motion tracking (done with GPS and . The activities
considered in the paper are motion based: walking, running, driving a vehicle, etc.; the environment can be indoors, outdoors or in a vehicle. The interpretation results come from adding another layer of hidden environment and activity parameters on top of the motion and location nodes in the dynamic Bayesian network.

These papers are a perfect illustration of the rapid progress in the completion of the Bayesian sensor processing paradigm, in all above-mentioned directions.