Chapter 10
Advanced SLAM Techniques

ABSTRACT
This chapter is the conclusion of the book. It is devoted to providing an overview of emerging paradigms that are appearing as outstanding the traditional approaches in scalability or efficiency, such as hierarchical sub-mapping, or hybrid metric-topological map models. Other techniques not based on Bayesian filtering, such as iterative sparse least-squares optimization (Graph-SLAM and Bundle adjustment), are also introduced due to their efficiency and increasing popularity.

CHAPTER GUIDELINE
• You will learn:
  ◦ Why SLAM in 6D represents especial complications from a mathematical point of view.
  ◦ How to modify classic parametric filters, like the EKF, to correctly deal with 6D robot poses.
  ◦ A unifying view of graph SLAM and Bundle Adjustment under the perspective of graphical models.
  ◦ What we mean with the sparse structure of the SLAM problem.
  ◦ The close relation between abstract sparse algebra algorithms (mostly sparse Cholesky) and recent approaches to SLAM.
  ◦ Least squares optimization algorithms: the Gauss-Newton and Levenberg-Marquardt methods.
  ◦ What is the Schür complement of a matrix and why it is key to solve SLAM efficiently.
  ◦ A broad discussion on approaches to SLAM alternative to the Bayesian recursive formulation, and potential future directions.
• Provided tools:
  ◦ Detailed formulas for implementing (and understanding) the newest 6D SLAM algorithms.
  ◦ Pseudo-code descriptions of most recent SLAM algorithms, including how to exploit the sparseness of the problem structure.

DOI: 10.4018/978-1-4666-2104-6.ch010
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- Figures representing the most important sparse matrix operations in a visual way, for easily grasping how they work.
- A table summarizing robust kernels for least-squares optimizers.
- Relation to other chapters:
  - This final chapter presents alternative methods for situations that are especially complex, which should be put in contrast by the reader to the Bayesian recursive solutions of chapter 9.
  - Many of the detailed formulas required for 6D SLAM have been put separately in Appendix D, which the interested implementer should read.

1. INTRODUCTION

This book has explored in detail the most widely used approaches to Bayesian localization and SLAM in small to moderately sized scenarios, with the intention of revealing their mathematical foundations. But as the reader should have realized at this point, there exists no such thing as a perfect or “magic” approach to localization or SLAM that works in all cases for any kind of sensor and operation conditions. That limitation is more patent in SLAM than in localization, due to the more complex nature of the former estimation problem. While exposing each of the SLAM algorithms described in chapter 9, we stated the advantages of each method in contrast to the rest, but also insisted in their unique drawbacks. In this chapter we will reason further about those problems and will introduce different alternatives, out of the recursive Bayesian framework, that have been proposed in the literature to mitigate them in cases where the environment of the robot or the state-space of the problems are large or particularly complex. The objective is to offer the reader a wide perspective of the most relevant ideas present in the newest research, and also to serve as a complement to the rest of the book

In order to better realize the problems with all the methods for metric SLAM exposed so far when we augment the dimension or complexity of the mathematical setting, we could imagine what would be an “ideal,” “perfect” solution for enabling SLAM in mid or large-sized complex environments over extended periods of time. We certainly believe that this goal should comprise:

- **Objective 1:** Allowing any arbitrary mix of sensors, with the intention that they complement each other. Notice that this includes handling different kinds of maps simultaneously.
- **Objective 2:** Robustly detecting loop closures, paying special attention to avoiding false positives.
- **Objective 3:** Being scalable for building large-scale maps.
- **Objective 4:** Being able to process arbitrary three-dimensional trajectories for the robot and its sensors, e.g. a hand-held camera, a laser range finder attached to a robotic arm, etc.

Next follows a discussion of the first three of these ambitious goals, stressing how they have been pursued in the research community in diverse ways. The fourth objective is the only one which can be considered as solved thanks to an increasingly popular approach which, due to its need for some extra mathematical background, will be discussed in section 2. Afterwards, a set of other selected ideas and especially advanced solutions aimed to overcome the difficulties of recursive Bayesian SLAM techniques in particularly difficult scenarios will be studied in sections 3 and on.