

Simultaneous Localization And Mapping via Extended Kalman Filter

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November 8, 2016

1 Introduction

In the context of robotics, Simultaneous Localization And Mapping (SLAM) is the problem of a robot dynamically constructing a map of an unknown environment and concurrently localizing itself within it, while exploring such environment. It may seem a chicken-or-egg problem, since a map is needed for localization and a frame of reference is needed for building a map, but the problem has been studied and solved both from a theoretical (probabilistic) and practical point of view in [TBF05].

SLAM involves a robotic agent being at least able to move within, and gather information about, the environment. Wheels and laser scanners are common choices to satisfy such requirements. Generally speaking, we will refer to them as *actuators* and *exteroceptive sensors*, respectively. Optionally, the robot may be equipped with one or more *odometric* sensors allowing it to actually measure its own movement, which should otherwise be inferred, e.g., by the speed imposed to the wheels. Generally speaking we call them *proprioceptive sensors*.

It is well understood in robotics that sensory data and inferred movement information are inherently noisy. From a probabilistic point of view this means that, if the robot is keeping track of its own position, the *uncertainty* of about such position increases as the robot moves. Conversely, supposing the robot is able to detect some objects (*landmarks*, in jargon) within its surroundings, recognize them for a number of observations, and estimate the relative position between itself and each landmark, then it can use such information to reduce the uncertainty about its own position. Such a correlation between position estimation and landmark measurement is clearly explained in [Bre14, Unit C].

The generic approach to SLAM requires the following models to be properly defined:

Motion model: describes how the robot updates the estimation of its own position and orientation according to the proprioceptive sensor data. It depends on the degrees of freedom of the robot and the nature of the available data. For instance, in this report, we consider the case of a differential robot constrained to move on a plane. So the robot pose variables are x , y and θ (the *bearing*, in jargon) and the proprioceptive data consist of the last velocity values v_l and v_r imposed to the wheels motors.

Inverse Observation model: describes how exteroceptive sensor data is used to deduce the landmarks positions, taking into account the current estimation of the robot position and orientation too. It depends on the nature of the data and the number of dimensions required to localize a landmark on the map. For example, in this report, we consider the case of a laser sensor providing, for each landmark, both its distance and angle w.r.t. the laser sensor. So the exteroceptive data consist of (ρ, α) pairs, which are used to deduce the landmark position (x_m, y_m) on the map.

Direct Observation model: describes how to predict the expected exteroceptive sensor data for a known landmark. From a conceptual point of view, it's the inverse function of the Inverse Observation model. E.g., for our concerns, the Direct Observation Model takes into account the current estimation of the robot position and orientation (x, y, θ) and some known landmark position (x_m, y_m) and computes the expected sensor data (ρ, α) .

References

- [Bre14] Claus Brenner. Slam lectures. https://www.youtube.com/playlist?list=PLpUPoM7Rgzi_7YWn14Va2F0Dh7LzADBSm, 2014.
- [TBF05] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*. The MIT Press, 2005.