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Laser and Radar Based Robotic Perception

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Abstract

Perceptive laser and radar sensors provide information from the surrounding environment and are a critical aspect of many robotics applications. These sensors are generally subject to many sources of uncertainty, namely detection and data association uncertainty, spurious measurements, biases as well as measurement noise. To deal with such uncertainty, probabilistic methods are most widely adopted. These probabilistic environmental representations, for autonomous navigation frameworks with uncertain measurements, can generally be subdivided into two main categories — grid based (GB) and feature based (FB). GB approaches are popular for robotic exploration, obstacle avoidance and path planning, whereas FB maps, with their reduced dimensionality, are primarily used for large scale robotic navigation and simultaneous localization and map building (SLAM). While researchers commonly distinguish both approaches based on their environmental representations, this paper examines the fundamental, theoretical

aspects of the estimation theoretic algorithms for both approaches. Emphasis on the measurement likelihoods is used to incorporate measurement uncertainty, and their impact on the resulting stochastic formulations is examined.

This paper also explores the front-ends of commonly used laser and radar sensors to develop an in-depth understanding of inherent measurement uncertainty. In this monograph, perceptive uncertainty is largely categorized into that related to signal detection and range measuring. While range noise is commonly addressed in the robotics literature, there is less emphasis placed on detection uncertainty and its subsequent impact on stochastic robotic perception algorithms. As such, following a signal level analysis of both laser and radar range finders, this paper addresses stochastic measurement modeling and map representations. In particular, occupancy grid methods based on spatial statistics are reviewed as well as those more recently based on detection statistics. Recent work, which proposes that the occupancy state space is more appropriately propagated by applying the discrete Bayes recursion using estimates of the detection and false alarm probabilities, as opposed to the commonly used range measurement likelihoods, is discussed.

A review of FB perception methods is presented, with particular attention to the important fields of robotic mapping and SLAM. In particular, comparisons of state-of-the-art Gaussian, Gaussian mixture, and nonparametric map representations are given, demonstrating the assumptions and advantages of each technique. Finally, recent FB frameworks using random finite sets are reviewed in which the measurement model is generalized to include detection uncertainty and the feature map representation is generalized to incorporate uncertainty in the number of features present. These recent developments add a new direction to the well-studied problem of robotic perception and the estimation of any given environment.

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1

Introduction

1.1 Perception

According to the Oxford English dictionary, perception can be defined as: "To be perceivable, the object must be able to be understood by the mind through the interplay of sight, sound, taste, touch and smell. To be perceived, a sensation must pass through the body through one of the sensory organs, that is, the eye, ear, nose, mouth, or skin. To interpret that sensation is what is known as perception." A crucial component then of perception, is the understanding of information which has passed through a sensor's detection process. In the world of autonomous robotics this takes the form of sensor understanding and modeling, feature detection, predicting measurements/observations, feature matching, and sensor data representation. This monograph presents a review of autonomous robotic perception, exploring recent work from the autonomous robotics and tracking communities in general as well as from the authors' own experiences. Throughout the monograph, experiments and results are derived from the authors' experiences with laser- and radar-based sensors. The concepts used in the experiments, and conclusions drawn from them, are compared with state-of-the-art perception methods in a review type fashion.

The foundation for any form of intelligent mobile robot navigation is based upon the perception of the environment by the robot. A sensor, or combination of sensors, accompanied by algorithms capable of automatically extracting useful information from it/them to make estimates about the current state of the robot's environment are required. To date, arguably the most impressive results in the application of robot perception have been based on probabilistic algorithms which take into consideration uncertainty in sensor data as well as prior information. This monograph therefore also reviews and presents methods which cope probabilistically with *missed detections* (the possibility of a sensor not detecting an object of interest), object *spatial uncertainty* (in which detected objects are given uncertain range and/or bearing values due to sensor noise) and *false alarms* (the possibility of a sensor reporting a detection, due to noise, when in fact nothing (or nothing of interest) is present). Environment measurement models based on these phenomena are therefore analyzed. A further concept, often over-looked in the robotic, but apparent in the tracking literature, is that of estimating the *correct number of features* in an environment. Recent work which advocates the joint estimation of map features with respect to their number as well as location will be reviewed.

1.2 Range Estimation with Laser and Radar

Based on the above uncertainties, illustrations, taken from the authors' work and the robotics literature in general, with laser range finders and short range (millimetre wave) radars, are given. Laser range finders transmit well focussed light beams into the environment, which reflect from the objects they impinge. The detected reflections often yield reliable range and bearing measurements, which can be recorded at high speed. Such devices are now affordable within the robotics community and indoor and, to a more limited extent, outdoor applications are evident. In the presence of unpredictable atmospheric (rain, fog, dust, etc.) and lighting conditions, laser range finders soon become inadequate for reliable range perception. In such situations, short range radar provides a good solution, due to the ability of the transmitted radio waves to penetrate such media, and its insensitivity to ambient light. With common, short range radar technologies, the Fast Fourier Transform can be used to return a power value at discrete range increments. This allows for the analysis of detection methods as well as their effect on subsequent perception algorithms. This comes at the expense of a lower angular resolution than laser range finders and more complicated processing to detect objects. Laser and radar based technologies between them therefore encompass a large application domain both indoors and outdoors. It should be mentioned that a great deal of robotic perception work has taken place in the field of machine vision however, since this is a research field in its own right, this is not covered in detail here, and robotic range sensing based on laser and radar techniques is the focus of this monograph.

The monograph advocates an understanding of the sources of noise in any such sensor as well as principled methods for its incorporation into subsequent stochastic map representations. A review of methods for modeling the uncertainty of sensor data is thus initially provided. A vast array of literature on sensor measurement models exists, in which the measurement process is modeled as a conditional probability density to reflect the nondeterministic aspects of the sensing process. Laser and radar sensors with contrasting measurement techniques are examined in Section 2. These adopt the commonly used Time-Of-Flight (TOF), Amplitude Modulated Continuous Wave (AMCW) and, in the case of radar, the Frequency Modulated Continuous Wave (FMCW) range measurement methods, respectively. In-depth analysis of the front-end processing units is provided to develop useful models of the signal noise present and how it effects the measurements of interest in mobile robotics applications. For many laser range sensors, users do not have access to the signal detection parameters, however the analyses given in these sections still gives informative methods for quantifying various noise sources of interest.

1.3 Map Representations with Occupancy Grids

To date, two fundamentally different approaches, namely the occupancy grid (OG) [72] and the feature-based (FB) map [105], have emerged as the most popular means of probabilistic mapping. Numerous examples of impressive localization, mapping and navigation algorithms which adopt these environment models can be seen both in indoor [33, 38, 52, 64, 111] and outdoor [17, 36, 71, 76, 126] environments. The OG approach propagates estimates of landmark existence on a grid with a fixed, predetermined number of cells. In environmental representations of this type, the number of map states is therefore predefined, and constant and therefore, only the cells' "contents," which typically correspond to the likelihood of objects' existences at those cells' coordinates, need to be updated. Hence, the grid, which fully represents the environment, can be represented mathematically by either a vector or matrix of predefined, *fixed* dimensions. For most OG maps, the occupancy is distributed in a Gaussian manner as a function of the returned range. The intensity of the returned signal is rarely considered however, resulting in *discrete* observations of occupancy in each cell. The discrete Bayes filter is then used as a solution, which is possible as it subtly assumes a completely known occupancy measurement model to update the posterior occupancy probability.

A review of these techniques will be given in Section 3. Probabilistic models, based on laser range finders, will be derived which yield range and bearing uncertainty. It will be demonstrated that such models provide a useful characterization of spatial uncertainty based on various parameters, but typically assume an ideal detector. This means that every detection is treated as a valid reflection from an environmental landmark and added to the map after passing some heuristic landmark initialization requirements. Using this assumption, the distribution of the landmark's spatial coordinates can be conveniently modeled with probability density functions (typically Gaussian), where the probabilistic sum under the distribution is unity. That is, complete certainty is assumed that a landmark exists *somewhere* within that area, thus readily allowing for numerous stochastic filtering techniques to be applied.

The *reliability* of data from active sensors such as laser range finders, radar and also sonar, often depends on the magnitude of the received signal strength resulting from the sensor's transmitted signal reflecting from an object/objects. A review of the literature, and the work of the authors, which demonstrates that such sensors exhibit object *existence* uncertainty, as well as estimated spatial uncertainty, will be given in Section 4. The work reviewed in this section demonstrates that, contrary to the theories reviewed in Section 3, noise in such range/bearing measuring sensors is in fact 3 dimensional. This is because, as well as spatial range/bearing noise, an added uncertainty exists in the detection process itself. Hence this section begins with an overview of detection uncertainty and introduces the concepts of missed detections and false alarms for realistic sensor models and sensor processing algorithms.

1.4 Feature-Based Map Representations

The paper then address the FB map representation and modeling of measurements used to propagate estimates of such maps. FB mapping approaches offer the advantage that the sensor data is compressed into features (such as point clusters, circles, lines, corners, etc.). The origins of the feature map can be traced back to the seminal work of Smith et al. [105], in which the environment is assumed to consist of these simplified representations of the physical landmarks — the features. The feature map representation has since gained wide spread popularity, particularly in the outdoor robotics domain due to its ability to estimate large scale maps and provide correction information for simultaneous vehicle pose estimation. The work also first established the "*vector of all the spatial variables, which we call the system state vector*."

In this section, a review of state-of-the-art FB map representations, cast into the popular SLAM framework, will be given. In particular, popular feature and vehicle descriptions based on Gaussian, Gaussian mixture, and nonparametric methods will be reviewed and compared. Finally, recent methods which have reformulated the well known FB robotic mapping (FBRM) and simultaneous localisation and mapping (SLAM) problems, by casting them under a random finite set (RFS) representation, will then be reviewed. This representation will be shown to exhibit several fundamental advantages over the former vector-based techniques. In particular the issues of estimating the correct *number* of features which have passed through the field(s) of view (FoV) of the sensor(s) as a robot moves, will be shown to be of extreme importance in mapping. Further, the RFS formulation directly incorporates a sensor's, or the corresponding feature detection algorithm's, probability of false alarm and missed detection values into the estimation process. Finally, the concept of a useful error metric, which assesses the true quality of an estimated map in its entirety, again in terms of the number of features estimated as well as their spatial locations, will be demonstrated.

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