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Sensor-based globally exponentially stable range-only simultaneous localization and mapping

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HIGHLIGHTS

- A novel filter for range-only SLAM is proposed.
- Sensor-based formulation of SLAM and state augmentation allow LTV Kalman filtering.
- The error dynamics of the filter are globally exponentially stable.
- Global convergence of undelayed initial guesses is guaranteed.

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ABSTRACT

This paper proposes the design, analysis, and validation of a globally exponentially stable (GES) filter for tridimensional (3-D) range-only simultaneous localization and mapping. For observability analysis purposes, a nonlinear sensor-based dynamical system is formulated resorting only to exact linear and angular kinematics and a state augmentation is exploited that allows the proposed formulation to be considered as linear time-varying without linearizing the original nonlinear system. Constructive observability results can then be established, leading naturally to the design of a Kalman Filter with GES error dynamics. These results also provide valuable insight on the motion planning of the vehicle. Experimental results demonstrate the good performance of the algorithm and help validate the theoretical results presented. For completeness and to illustrate the necessity of a proper trajectory, simulation data are included as well.

1. Introduction

Simultaneous Localization and Mapping (SLAM) is the problem of navigating a vehicle in an unknown environment, by building a map of the area and using this map to deduce its location, without the need for a priori knowledge of location. The solution to this problem is of great importance to the field of autonomous robots operating in GPS-denied environments, and therefore SLAM has been a subject of intensive research by the community since first proposed in the 1980s, when a series of seminal works such as [1–3] were published. From that initial discussion, a myriad of approaches have arisen. The better known include EKF-SLAM [4], graph-based solutions [5], and particle filters (see [6,7] for a two-part survey on all these algorithms). Apart from varying in concept, SLAM approaches also depend on different mapping sensors: SONAR [8], LIDAR [9], monocular and stereo cameras [10] are within the most common. These sensors involve obtaining range and bearing information of the environment, and usually demand the existence of a data association algorithm, due to the unknown correspondence between the reality and the created map.

Although localization using distances to beacons is a very well known subject, the number of SLAM algorithms using only ranges is relatively small, especially when compared with the widespread use of algorithms working on range and bearing, or on bearings-only. On one hand, the Range Only SLAM (RO-SLAM) problem is not prone to association errors, as are other SLAM formulations. In fact, this is a very relevant topic in this area, as can be seen by the variety of strategies proposed by the scientific community to min-

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imize spurious associations, from general purpose algorithms such as the joint compatibility branch and bound [11] or more evolved strategies that make use of the unique characteristics of the detected features as the one proposed in [12]. RO-SLAM bypasses this error source due to the nature of the ranging signals that are usually tagged. Another of the issues in SLAM with both bearing and range information available that is avoided by RO-SLAM is the loop closing [13]. This is the problem of recognizing that a previously visited area is once again within the field-of-view of the vehicle. It is closely related to the association problem and with the inconsistency that some SLAM approaches suffer from, see [14]. In RO-SLAM, this is also not an issue, as the information carried by the ranging signals allows the unambiguous association of the measurement and the corresponding state at all times. On the other hand, one of the main problems in RO-SLAM is the initialization of the algorithm, either due to the absence of global convergence results in EKF solutions such as [15], or the computational burden of having a sufficiently representative prior belief, in particle filter solutions [16]. Most of the RO-SLAM solutions include some form of initializing procedure before inserting a new landmark in the state. These include trilateration with ranges from different instants to obtain a first estimate, usually through least squares, such as what was proposed in [17]. Also, due to the sparse information extracted from ranging, RO-SLAM algorithms are commonly designed for 2-D environments, e.g., a ground robot and landmarks at the same height, see [18].

The common RO-SLAM formulation has similarities with the problem of Sensor Networks (SN), in the sense that there is an agent receiving signals from a network of sensors, and, therefore, the two ideas have been used in conjunction in works such as [19,20], where, along with agent-to-sensor ranges, sensor-to-sensor ranges are also used.

This paper introduces a novel RO-SLAM algorithm that eliminates the landmark initialization problem through the establishment of global convergence results with a tridimensional (3-D) sensor-based formulation that avoids the representation of the pose of the vehicle in the state, as it becomes deterministic and available by construction. Furthermore, the sensor-based approach allows the direct use of odometry-like information that is usually expressed in body-fixed coordinates. This is related with previous results in the SLAM literature, such as the robocentric map joining [21] in which the filtering process is centered on the vehicle, while using an EKF to maintain estimates of both the map and the inertial vehicle pose. Another related work is Linear SLAM [22], in which the map joining procedure is followed, while the state is transformed and augmented in order to achieve a linear least squares formulation. The algorithm proposed in this paper relates to these works in the sense that the filter is designed in a body-fixed frame, while disposing of the vehicle pose. This solution is influenced by the source-localization algorithm proposed in [23], as the global convergence results are achieved through a similar state augmentation.

The main contributions of this paper are the design, analysis, and experimental validation of a 3-D RO-SLAM algorithm that (i) has globally exponentially stable (GES) error dynamics; (ii) resorts to the exact linear and angular motion kinematics; (iii) uses as odometry-like measurements the linear and angular velocities; (iv) solves a nonlinear problem with no linearizations whatsoever; and (v) builds on the well-established linear time-varying Kalman filtering theory. Note that, although the maps provided by this filter are body-fixed, it is possible to obtain an inertial estimate of both the map and the vehicle pose using, for example, the algorithm proposed in [24], in which a methodology was presented to obtain inertial estimates of the pose of the vehicle and of the landmark map using only the sensor-based map. This algorithm was successfully used with other purely sensor-based SLAM filters such as [25,26].

The constructive observability and convergence results achieved provide physical insight on what kind of trajectories the vehicle must take in order for the RO-SLAM algorithm to be able to perform accurately. These results were validated in real conditions, using a Cricket [27] sensor network as landmarks and an optical flow procedure to determine the linear velocity. Furthermore, simulation results are also presented to illustrate the good vertical performance when the trajectory is sufficiently rich, which was not possible to perform in the experiments carried out.

This problem was previously addressed by the authors in a preliminary version in [28]. This paper introduces new results on the observability of the designed nonlinear system, with the establishment of necessary conditions for observability, stability, and convergence that are important for trajectory planning. Furthermore, expanded and revised proofs for the theoretical results are presented, and more and better documented experiments are now reported.

The paper is organized as follows: in Section 2, the problem addressed in this paper is stated and the dynamics of the system to be filtered are presented; the observability analysis of the system is performed in Section 3 and filter implementation issues are detailed in Section 4. The results of simulation and real experiments are presented in Sections 5 and 6, respectively, and, finally, Section 7 addresses some concluding remarks.

Notation. The superscript ^{I} indicates a vector or matrix expressed in the inertial frame $\{I\}$. For the sake of clarity, when no superscript is present, the vector is expressed in the body-fixed frame $\{B\}$. $\mathbf{I}_n$ is the identity matrix of dimension n, and $\mathbf{0}_{n\times m}$ is a n by m matrix filled with zeros. If m is omitted, the matrix is square. $\mathbf{S}[\mathbf{a}]$ is a special skew-symmetric matrix, henceforth called the cross-product matrix, as $\mathbf{S}[\mathbf{a}]\mathbf{b} = \mathbf{a} \times \mathbf{b}$ with $\mathbf{a}, \mathbf{b} \in \mathbb{R}^3$.

2. Problem statement and system dynamics

Consider a vehicle moving in a static world where acoustic beacons are installed at unknown locations. The vehicle is equipped with a sensor suite capable of measuring the linear and angular velocities as well as radio and acoustic signals from the static beacons. The distances to the emitting beacons can then be computed from the time differences of arrival. This section details the design of a dynamical system as part of a simultaneous localization and mapping filter using only, apart from vehicle motion information, the distance to the beacons placed in the environment.

2.1. Problem statement

Assume the existence of two frames: a reference inertial frame $\{I\}$ and a body-fixed frame $\{B\}$. Points in the latter frame are mapped to the former through a rotation, given by the rotation matrix $\mathbf{R}(t) \in SO(3)$ and a translation, given by ${}^I\mathbf{p}(t) \in \mathbb{R}^3$ that represent, respectively, the attitude and position of the vehicle. The rotation matrix respects the relation $\dot{\mathbf{R}}(t) = \mathbf{R}(t)\mathbf{S}[\boldsymbol{\omega}(t)]$, where $\boldsymbol{\omega}(t) \in \mathbb{R}^3$ is the angular velocity of the vehicle expressed in the body-fixed frame.

Let $\mathcal{L} := \{1, \ldots, N\}$ be a set of N landmarks fixed in the environment, to be mapped, containing, in each instant, N_O observed, or visible, landmarks in the set $\mathcal{L}_O$, and N_U unobserved, or invisible, landmarks in the set $\mathcal{L}_U$, such that $\mathcal{L} = \mathcal{L}_O \cup \mathcal{L}_U$. Furthermore, suppose that $\mathbf{p}_i(t) \in \mathbb{R}^3$ corresponds to a sensor-based landmark in the set $\mathcal{L}$, i.e., the position of the ith landmark relative to the vehicle expressed in $\{B\}$, given by $\mathbf{p}_i(t) = \mathbf{R}^T(t)\left({}^I\mathbf{p}_i(t) - {}^I\mathbf{p}(t)\right)$, where ${}^I\mathbf{p}_i(t) \in \mathbb{R}^3$ corresponds to the inertial position of the landmark. Hence, the dynamics of any landmark expressed in the robotic vehicle coordinate system $\{B\}$ are given by

$$\dot{\mathbf{p}}_i(t) = -\mathbf{S}[\boldsymbol{\omega}(t)]\,\mathbf{p}_i(t) - \mathbf{v}(t),$$