Robotics and Autonomous Systems 104 (2018) 40–55

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

An efficient approach for undelayed range-only SLAM based on Gaussian mixtures expectation☆

Felipe R.Fabresse *, Fernando Caballero, Iván Maza, Aníbal Ollero

University of Seville, Escuela Técnica Superior de Ingeniería, Camino de los Descubrimientos s/n, 41092 Sevilla, Spain

HIGHLIGHTS

- Improved bearing Gaussian Mixture weights update scheme when receiving a new range-only measure.
- Novel single-equation range-only observation model to update all landmark hypotheses.
- Integration of inter-node range.only observations even for non-converged Gaussian Mixtures.
- Extended validation and comparisons with simulated and real experiments with aerial robots.

ARTICLE INFO

Article history:
Received 19 April 2017
Received in revised form 11 January 2018
Accepted 21 February 2018
Available online 7 March 2018

Keywords:
Range-only simultaneous localization and mapping
Robot localization
Kalman filtering
Gaussian mixture models

ABSTRACT

This paper deals with range-only simultaneous localization and mapping (RO-SLAM), which is of particular interest in aerial robotics where low-weight range-only devices can provide a complementary continuous estimation between robot and landmarks when using radio-based sensors. Range-only sensors work at greater distances when compared to other commonly used sensors in aerial robotics and they are low-cost. However, the spherical shell uniform distribution inherent to range-only observations poses significant technological challenges, restricting the approaches that can be used to solve this problem. This paper presents an undelayed multi-hypothesis Extended Kalman Filter (EKF) approach based on Gaussian Mixture Models (GMM) and a reduced parameterization of the state vector to improve its efficiency. The paper also proposes a new robot-to-landmark and landmark-to-landmark range-only observation model for EKF-SLAM which takes advantage of the reduced parameterization. Finally, a new scheme is proposed for updating hypothesis weights based on an independence of beacon parameters. The method is firstly validated with simulations comparing the results with other state-of-the-art methods and later validated with real experiments for 3D RO-SLAM using several radio-based range-only sensors and an aerial robot.

1. Introduction

Range-only simultaneous localization and mapping (RO-SLAM) aims to map the position of a set of elements (landmarks) while at the same time localizing a mobile robot with respect to that map using range-only observations. In contrast to other SLAM approaches, the main challenge of RO-SLAM is the rank-deficiency of the range-only observation model. These observations consist of a single value which represents the distance between a pair of elements (robot or landmarks). Thus, given a single range-only observation, the lack of bearing information between these two elements makes the relative position between them follow a uniform spherical shell probability distribution as is shown in Fig. 1 for a single range-only observation between an aerial robot and a landmark. Furthermore, in contrast to other schemes like bearing-only SLAM [1], RO-SLAM presents an increased complexity for higher dimensionality (e.g. 3D SLAM in aerial robotics) due to the 1-rank observation model associated with range-only observations (azimuth and elevation angle not observed) compared to other bearing-only models in which the only unobserved parameter is the distance between the robot and one landmark, or other fully observable approaches like RFID SLAM [2,3]. Hence, when applying multi-hypothesis approaches, this rank-deficiency implies a higher number of hypotheses/parameters in the state vector.

Range-only methods have gained research interest in the last decade particularly for robot/people/object indoor localization and ubiquitous applications among others and more recently in aerial robotics for radio frequency source localization in military, rescue, aerial manipulation or inspection scenarios. RO-SLAM becomes

☆ This work is partially supported by the ARCAS project (FP7-ICT-2011-7-287617) funded by the European Commission of the Seventh Framework Programme and two national projects, RANCOM (P11-TIC-7066) and CLEAR (DPI2011-28937-C02-01).

* Corresponding author.
E-mail addresses: fabresse@us.es (F.R.Fabresse), fcaballero@us.es (F. Caballero), imaza@us.es (I. Maza), aollero@us.es (A. Ollero).

https://doi.org/10.1016/j.robot.2018.02.014
0921-8890/

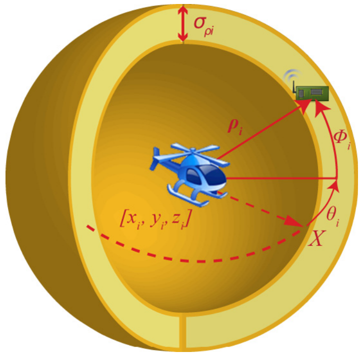

Fig. 1. Spherical parameterization of a landmark position in 3D RO-SLAM. The yellow area represents the uniform spherical shell distribution where the landmark might be located with a single range-only observation ρ_i between an aerial robot and this landmark. The green object represents the real position of the landmark, whereas the center of the sphere is composed by the position of the aerial robot at the time the range-only observation is received. The thickness of the 3D shell represents the standard deviation of the range measurement σ_{ρ_i}. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

especially interesting in aerial robotics due to the small size and low weight associated to these kind of sensors. Additionally, most range-only sensors include a unique identifier in their signal that simplifies the common data association problem present in other SLAM schemes. RO-SLAM algorithms becomes a good complement to other SLAM approaches where a direct line of sight between robot and landmark is not always possible due to high altitudes or static/dynamic obstacles as is the case for cameras or LIDAR sensors [4].

Depending on the kind of technology employed to measure the distance between a pair of sensors (e.g. radio-based or ultrasound range-only sensors), different ranging methodologies are proposed in the literature: the most common is based on the radio signal strength of ranging messages [5,6] (also known as Radio Signal Strength Indicator or RSSI range-only sensors), or the time of arrival (TOA) or Time Differential of Arrival (TDOA) of the signal [7–9] for radio and/or ultrasound range-only sensors.

The main research interest of range-only methods resides in how to cope with the spherical shell uniform distribution of the position as shown in Fig. 1. Thus, in the case of range-only localization several methods [10–12] are based on numerical optimization approaches which trilaterates the position of the mobile robot employing 3 or more static ranging nodes (also known as anchors) at different positions. On the other hand, [13] proposes a fingerprinting method using a neural network which is particularly useful when RSSI-based devices are used. Fuzzy logic has also been used for range-only localization [12] employing a Voronoi diagram to cope with common flip ambiguities in the probability distribution associated to range-only estimations. Other range-only localization approaches are based on Bayesian filters [10,14,15] or batch-processing techniques [16].

In the case of mapping problems, the estimated variables are the position of a set of static elements or landmarks (also known as self-localization or network localization). Three common approaches are used for mapping: one based on the use of inter-node range-only observations to estimate the relative position of static nodes, another based on the use of mobile robots with known position to trilaterate the position of each individual landmark using non-linear optimization methods and finally, a hybrid approach which combines the advantages of both methods. Some early works use batch-processing techniques like Multidimensional Scaling (MDS) [17] or Least square methods [18] to map the relative position of each node. However MDS methods require a high connectivity between static nodes to localize each of them, which is why other authors proposed different approaches based on sub-map estimation [19] or the use of artificial nodes created from a set of range measurements taken from different robot positions [20]. Other authors have used decentralized inference to solve the mapping problem by means of multilateration from a mobile robot using probabilistic frameworks like particle filters [21,22]. Particle filters model the inherent spherical shell uniform distribution of range-only landmarks position by using Monte Carlo sampling methods.

In the case of Gaussian filters, authors tend to use two common approaches: the first and most common consists on a delayed initialization of the Gaussian filter based on a pre-estimated position of landmarks [23,21,24] and the second approach uses undelayed initialization based on multi-hypotheses frameworks to cope with the non-Gaussian distribution of landmark positions. However, in delayed initialization approaches, single estimation convergence will always depend on the robot's trilateration with respect the landmark so that important delays might be produced until these landmarks converge and can be integrated in the Gaussian filter used to refine the robot position. On the other hand, undelayed approaches have the advantage of integrating range-only observations into the Gaussian filter since the very beginning without loss of information and, more importantly, they are able to improve the robot's position estimation without requiring single solution convergence of landmarks. One of these undelayed approaches [25] is based on a polar parameterization which allows the Gaussian filter to be initialized using a predefined variance around the $\rho\theta$-space. The main drawback of this approach is the use of heuristics based on the robot trajectory to split the initial unimodal distribution into two Gaussians which, in the case of 3D RO-SLAM, becomes more complex. In [26] a method is proposed which integrates a Gaussian Mixture in an Extended Kalman Filter (EKF) to represent the non-Gaussian distribution of the sensor's bearing information. This approach has the additional advantage of making the integration of inter-node range-only observations without losing cross correlation information between landmarks possible as is the case of the decentralized approach presented in [25]. The main drawback of multi-hypothesis methods is the computational burden of keeping all possible hypotheses in the system. To cope with this drawback, [26] uses a pruning strategy which allows the computational burden of the multi-hypothesis approach to be reduced as landmarks converge to a single solution. In a previous work, the authors of this article proposed an extended version of [26] which deals with higher dimensionalities by using a reduced parameterization approach. The method proposed in this paper extends the 3D approach presented in [27] by introducing a new observation model for range-only measurements which only requires a single update equation as opposed to the Federated Information Sharing approach [1] inherited from [26]. The paper compares the computational burden and accuracy obtained with the new correction model with respect to previous observation models based on Federated Information Sharing. Also, this paper shows a scheme for updating Gaussian Mixture weights based on the same independence assumption between beacon parameters proposed in [27]. This paper will show both how the reduced parameterization and how the new range-only observation model might be used with other approaches (i.e. for example, how new observation model might be used with a Cartesian parameterization, or how the reduced parameterization might be used with other classical range-only observation models). The use of the reduced parameterization proposed in [27] does not imply an independence between beacon parameters, so other classical approaches might be used to update the weights of the Gaussian Mixtures.