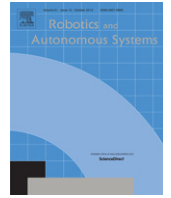




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Contents lists available at ScienceDirect

Robotics and Autonomous Systems

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

A novel method for computation of importance weights in Monte Carlo localization on line segment-based maps

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HIGHLIGHTS

- Monte Carlo localization has rarely been studied on line segment-based maps.
- Importance weights play a key role in the performance of Monte Carlo localization.
- A heuristic-driven method for weight computation on segment-based maps is proposed.
- The proposed method is compared with three other weight computation methods.
- Results corroborate that the proposed method is more accurate, robust and efficient.

ARTICLE INFO

Article history:

Received 22 August 2014

Received in revised form

22 June 2015

Accepted 3 July 2015

Available online xxx

Keywords:

Importance weight

Line-segment map

Localization

Monte Carlo

Particle filter

Pose tracking

ABSTRACT

Monte Carlo localization is a powerful and popular approach in mobile robot localization. Line segment-based maps provide a compact and scalable representation of indoor environments for mobile robot navigation. But Monte Carlo localization has seldom been studied in the context of line segment-based maps. A key step of the approach – and one that can endow it with or rob it of the attributes of accuracy, robustness and efficiency – is the computation of the so called importance weight associated with each particle. In this paper, we propose a new method for the computation of importance weights on maps represented with line segments, and extensively study its performance in pose tracking. We also compare our method with three other methods reported in the literature and present the results and insights thus gathered. The comparative study, conducted using both simulated and real data, on maps built from real data available in the public domain clearly establish that the proposed method is more accurate, robust and efficient than the other methods.

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1. Introduction

The capability of localization, which enables a mobile robot to continually estimate its position and heading direction (collectively referred to as *pose*), is a key requirement for autonomous navigation. While odometers do provide incremental estimates of pose, such estimates cannot be trusted upon for long periods of time because of integration of measurement errors over the length of travel. Modern mobile robots are equipped with Laser Range Finders (LRFs), which provide the robot with an accurate range estimate of the nearby objects. Thus, if a spatial model of the environment is available in the form of a map, it is possible to estimate the pose of the robot.

Maps are commonly represented as occupancy grids [1]. A major drawback of the occupancy grid representation is that a large amount of memory is necessary to store the map. The requirement of memory increases as the size of the environment to be mapped increases. The recent trend of deploying mobile robots in larger and larger working environments has made the issue of scalable map representations a significant one. Maps based on line segments [2–4] are compact, provide floating-point resolution, consume significantly less memory and scale well with the environment size. Moreover, line segments are an obvious choice in the representation of indoor environments that predominantly comprise objects like walls, corridors and cupboards. These objects have planar external surfaces and thus naturally lend themselves to representation by line segments in the 2D-plane.

Monte Carlo Localization (MCL) [5] is a popular approach for mobile robot localization. It employs a Bayes' filter to recursively estimate the posterior probability density function of the robot

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<http://dx.doi.org/10.1016/j.robot.2015.07.001>

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pose, over the state space, given (noisy) measurements that arrive sequentially in time and probabilistic models of robot motion and perception. It uses a finite set of random samples (a.k.a *particles*) with associated *importance weights* (or simply, *weights*) to represent, in approximation, the posterior density. Each particle, representing a robot pose, is a hypothesis as to the true, but unknown pose, while its associated weight provides a relative measure of the “importance” of the sample towards approximation of the target density function. Hereinafter, we shall use the terms sample, particle and hypothesis synonymously.

MCL makes no restrictive assumption about the state space dynamics or the shape of the density function. It is able to track multiple hypotheses about the robot pose and can also trade-off the computational resources available with the accuracy of localization. It has a modular structure and is simple to implement. The benefits associated with the use of line segment-based maps (as detailed above) and the effectiveness of MCL as evident, for instance, from [6], are sufficient motivations for implementing MCL on such maps. Unfortunately, studies on the performance of MCL on line segment-based maps have not been extensively reported in the literature. To the best of our knowledge, only [7] has reported it in some detail. A few other authors [8,9] do talk about MCL on such maps, but they are mentioned in different contexts.

The particle filtering framework on which MCL is based only lays down the broad sequence of steps to be followed. The choice of the motion model and the measurement model is left to the programmer. The importance weights, derived from the measurement model, play a key role in the pose estimation process and thus it is imperative to compute the weights in a judicious and efficient manner.

In this paper, we present the results and insights gathered from our investigation into different methods of weight computation in the context of line segment-based maps. The main theme of this paper, however, relates to a proposal on a new, heuristic-driven approach for weight computation on such maps. Apart from being simple to implement and efficient to compute, the novelty in our approach lies in the fact that it just takes into account how closely the actual perception of the robot fits in or is consistent with the environment map when referred to a hypothesized pose. We extensively study the performance of a Monte Carlo-based method for pose tracking that incorporates the proposed approach of weight computation, both using simulated data and real data. Detailed comparative study reveals that our method is more efficient, robust and accurate than three other methods [7,10,11]. The studies were conducted in three different environments whose maps were built from real data using the method described in [2].

The remainder of the paper is organized as follows: In Section 2, we make a brief review of related work. In Section 3, we describe the proposed method, while in Section 4, we overview three competing methods for weight computation. In Section 5, results obtained from simulated and from real data are presented while in Section 6, we discuss on issues germane to the results obtained in Section 5. We summarize the concluding remarks in Section 7.

2. Related work

Mobile robot localization has been an area of active research for around three decades. A myriad of localization methods, differing in approach as well as in the intended domain of application, has been proposed during these years. When formulated as a probability density estimation problem, localization is commonly solved using the Bayes’ filter [12,13]. The Kalman filter-based methods postulate the robot pose as a unimodal Gaussian distribution and assume the state-transition model and the measurement model to be linear in its arguments with added Gaussian noise. However,

in real-life applications, the Extended Kalman filter (EKF) is often used to address deviation from linearity [14,15].

Methods based on Markov Localization (ML) maintain a discrete approximation of the probability density function of the robot’s pose. If the state space is represented as a grid array, as in [16–18], each cell of the grid holds the probability that the robot is currently located in it. Experimental evidence suggests that while grid-based ML is more robust, Kalman filter-based methods are more efficient and accurate [19]. To inherit the virtues of both, a hybrid method named Markov–Kalman localization (ML-EKF) was proposed in [20].

MCL utilizes a particle filter-based framework [21] to overcome the computational overhead and memory demands inherent in grid-based ML methods by using a sample-based representation of the probability density [5,22]. By using two different ways of generating samples, a more robust method that goes by the name of Mixture-MCL was proposed in [23]. A method that improves upon the efficiency of MCL by constraining the robot’s path such that it suffices to sample the pose space only in the vicinity of the path was proposed in [24]. A method for Monte Carlo-based pose tracking was proposed in [25]. To make the method robust against unmodelled objects in the map, an approach called *sampling from a noncorrupted window* was proposed. A hybridization of ML with MCL, wherein the former is used to zero in on a probable region of the state space before the latter is used to precisely estimate the robot pose in that region, was reported in [26]. In [27], the accuracy of MCL-estimated pose at pre-decided locations was improved upon by matching scans with previously stored reference scans taken at those locations.

The efficacies of the Bayesian methods have often been augmented by combining them with evolution-based methods [8,28–30]. The evolutionary methods are formulated as an optimization problem that progressively reduces the initial uncertainty of the robot pose by generating new solutions in the promising regions of the state space by using feedback information available during the evaluation of the solutions. Localization methods based solely on evolution-based metaheuristics have also been proposed. For instance, Differential Evolution-based algorithms for localization are reported in [31–34].

The method due to Espinace et al. [7] deals with MCL on line segment-based maps. It extracts line segments from the current range scan of the robot. This set of segments is called *Observed Segments Group* or OSG. Next, the portions of the line segments of the map, as visible from a given sample pose (visible in full or in part) are brought together to form a set of line segments, called the *Map Segments Group* or MSG. The method then computes a modified form of the Hausdorff distance [35] between OSG and MSG, followed by a nonlinear transformation of the distance to determine the importance weight associated with the sample pose. In [10] a method is presented for assigning weight to a particle by assessing the Euclidean distance between the laser range scan actually acquired by the robot and the predicted scan obtained from the particle. In the context of presenting an improved resampling technique of a particle filter for tackling the global localization problem, Gasparri et al. [11] proposed a method of weight computation that is similar in concept to the method of [10] but it uses an additional nonlinear transformation to map the computed Euclidean distance values to the corresponding weight values. The method in [7] was improved upon in a recent work [36] by using a different distance measure [37] and using the same nonlinear transformation as used in [11].

Ref. [38] presents a Monte Carlo localization algorithm that works with 3D laser range scans and a line segment-based map. The 3D point cloud is first reduced to a virtual 2D scan, which is then used to compute the weights of the particles by comparing the predicted scans with the virtual scan. Reference to MCL on line

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