Accuracy evaluation of SLAM algorithms

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Abstract. The paper is devoted to methods for solving the problem of simultaneous localization and mapping (SLAM) for an autonomous vehicle. Accuracy evaluation of the three-dimensional SLAM approach as compared to classical two-dimensional SLAM is obtained through the simulation study.

Introduction
The problem of simultaneous localization and mapping (SLAM) can be defined as an estimation both landmark’s coordinates in a surrounding area and coordinates of a vehicle that observes the area at the same time [1-5]. The landmarks are extracted form the map of the area and the vehicle-observer defines location with respect to them. For example, solving of such problem is needed for autonomous vehicle indoor navigation or underwater navigation where global navigation satellite system (GNSS) signals are not available. Methods for solving SLAM problem are broadly described in literature [1-5]. In context of different applications SLAM problem has its own specificities. Range and bearing measurements between the vehicle-observer and the landmarks are usually used to solve the problem. These measurements can be directly done by laser rangefinder [1-2], multibeam sonar [6] or extracted form camera images [7] or even gradiometer data [8-11]. In most indoor applications the vehicle motion and map are considered to be planar, which is quite natural if laser rangefinder scans are used as measurements. This approach is referred to as two-dimensional (2D) SLAM. On the other hand, modern SLAM application with the use of camera images [1-2, 5] or gradiometer and gravity map data [8-10] assumes landmark and map in three-dimensional (3D) space. This approach is referred to as 3D SLAM.

The paper provides the accuracy evaluation of the 3D SLAM approach as compared to classical 2D SLAM. The paper is organized as follows. The second part provides problem statements for 2D and 3D SLAM approaches, discuss their differences, and describes the solution methods. The third part provides the simulation results. The main contribution and future work are in conclusion.

1. The problem statement and solution methods
Despite the variety of existing SLAM methods, they are based on two typical stages [1-3]. Front-end and back-end. Front-end algorithms provide landmark extraction from sensor data, map building, and new landmark association with those which have been already placed in the map. Back-end algorithms provide landmark and vehicle position estimates basing on a full set of data obtained both from vehicle motion model and direct landmark observations obtained in front-end. Nonlinear Bayesian filtering algorithms like extended and unscented Kalman filters or particle filters with Rao-Blackwellized procedure are used to solve the estimation problem at back-end stage [1-3]. The landmark and vehicle
position accuracy estimates obtained in the algorithms are fed back in front-end to solve landmark association problem.

The classical 2D SLAM approach [2] supposes that vehicle move on a plane and the landmarks are extracted from a plane laser beam scans of the surrounding area. The distances between the vehicle and the landmarks and the directions to the landmarks (bearings) form the measurements model for the back-end stage, which can be described by equations (1)

\[
\rho_i = \sqrt{(x-x_i)^2 + (y-y_i)^2} + v_{\rho},
\]

\[
b_i = \arctan \frac{y-y_i}{x-x_i} - K + v_b,
\]

where \(\rho_i\) is the measured distances between vehicle and \(i^{th}\) landmark, \(b_i\) is measured direction angle in horizontal plane (relative bearing) to \(i^{th}\) landmark, \(x, y\) are vehicle coordinates, \(K\) is the vehicle heading, \(x_i, y_i\) are \(i^{th}\) landmarks plane coordinates in local coordinate frame, \(i=1...N\), \(N\) is number of landmarks, \(v_{\rho}, v_b\) are white noise measurement errors.

The following model is often used to describe the vehicle motion [2-3]

\[
\dot{x} = (\bar{V} - \Delta V) \sin K,
\]

\[
\dot{y} = (\bar{V} - \Delta V) \cos K,
\]

\[
\dot{K} = (\bar{V} - \Delta V) \tan(\bar{y} + \Delta y),
\]

where \(\bar{V}\) is measured vehicle velocity, \(\bar{y}\) is set steering angle, \(\Delta V, \Delta y\) are errors in velocity measurements and steering respectively. Thus, vehicle state is defined by true coordinates \((x, y)\) and heading angle \(K\).

Coordinates of landmarks are added in special database as they are found. Considering that vehicle finds new landmarks all the operation time the database should be dynamically expanding. As landmark coordinates are supposed to be estimated they dynamically expand the estimated state with two new estimated values

\[
\dot{x}_i = 0,
\]

\[
\dot{y}_i = 0,
\]

for each landmark.

Thus, the classical 2D SLAM back-end problem can be formulated as the estimation problem of state vector (2), (3) by the measurements (1).

Unlike common 2D SLAM problem, the 3D SLAM problem assumes landmarks, which coordinates belong to three-dimensional space [5, 7]. Measurements in this case can be represented as

\[
\rho_i = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} + v_{\rho},
\]

\[
b_i = \arctan \frac{y-y_i}{x-x_i} - K + v_b,
\]

\[
\theta_i = \arccos \frac{-z_i}{\sqrt{(x-x_i)^2 + (y-y_i)^2}} + v_{\theta},
\]

where \(\theta_i\) is the elevation angle to \(i^{th}\) landmark, \((x_i, y_i, z_i)\) are cartesian landmark coordinates in predefined local coordinate frame. Vehicle motion model for this problem can be taken the same as in 2D case, considering constant altitude above or under the seabed [8]. Thus, three new landmarks states
\[ x_i = 0, \]
\[ y_i = 0, \]
\[ z_i = 0, \]

are added to the state vector as new landmark \( i \) is extracted.

Thus, the classical 3D SLAM back-end problem can be formulated as the estimation problem of state vector (2), (5) by the measurements (4). This problem can take place in several approaches such as SLAM problems with the use of video images and so on.

The solution of the SLAM problem can be divided into three steps. First is the time update of the current state estimate of state vector using the velocity and steering angle data. Second is measurement update of the estimated state (2), (3) by using the measurements to re-observing landmarks. Re-observed landmarks are those, that were associated with previously observed in front-end algorithm. Third is adding new landmarks to the current state. This is done using the range end bearing measurements to the landmark, that were not associated with previously observed in front-end algorithm.

Note that landmark data association plays significant role in the algorithm because it is not always possible to re-observe landmarks every time step, it is not always possible to observe something as being a landmark but fail to ever see it again, landmarks might be wrongly associated to a previously observed landmark. Also, amount of re-observed landmarks has significant influence for algorithm accuracy.

It is important to note that gravity SLAM measurements do not have any angle limits unlike indoor SLAM. It means that all landmarks in sensor range can be detected. Therefore, we consider 3 cases with different observation angles in following simulation.

2. The simulation results

To evaluate the accuracy of 3D SLAM, as compared to 2D SLAM we consider three cases.

First case is the planar 2D SLAM which is the estimation problem of state vector (2), (3) by the measurements (1). For this case the vehicle is supposed to be equipped with laser rangefinder with maximal range of 30 m. and observation angle of 180\(^\circ\), which means that only landmarks in front semicircle of vehicle can be observed. The range measurement error root mean square (RMS) is 0.2 m and bearing angle measurement RMS is 1\(^\circ\). Steering error RMS is 3\(^\circ\) and velocity error RMS is 0.3 m/s. Array of waypoints which vehicle goes through set to form a square with side of 140 m. Totally 35 landmarks are randomly set in the observable area.

Second case is the 3D SLAM (180 deg) which is the estimation problem of state vector (2), (5) by the measurements (4) in the same conditions as in the first case. The elevation angle errors and limits set the same as for the relative bearing angle in the first case. Thus, only landmarks in front hemisphere of vehicle can be observed. The height of the landmark set randomly in range ±20 m. This case is much like 3D SLAM for the vehicle which is equipped with camera.

Third case is the 3D SLAM (360 deg) which is the estimation problem of state vector (2), (5) by the measurements (4) but without observation angle limits. Thus, all landmarks in radius of 30 m. can be observed in this case. This case is much like 3D SLAM for the vehicle equipped with a gravity sensor that does not have any angle observation limits [8].

To solve 2D SLAM problem (for first case), we used the extended Kalman Filter originally implemented in [12]. For second and third case we improved it to solve 3D SLAM problem. For data association we used the nearest-neighbour approach based on calculating the Mahalanobis distance between new and already recorded in the base landmarks [12]. Each new extracted landmark is associated to the closest landmark in the base. All landmark couples with distances lower than predefined threshold are considered as the same landmark. In other case the extracted landmark is added as a new to the database. Figure 1 shows an example of MATLAB simulation setup and SLAM solution.
The figures 2-3 provide the RMS of vehicle coordinate estimation errors for all three cases. The blue line shows the RMS of coordinates for the first simulation case, the red line – for the second simulation case, the green line – for the third simulation case.

Simulation results show that the 3D SLAM with the same parameters have significantly lower accuracy as compared to 2D case. This is also result of lower observability of landmarks, which become farther with adding third coordinate as compared to 2D case. Increasing observability in third case makes the accuracy of 3D SLAM pretty the same that in the first case. In other words, the estimation accuracy mainly depends on number of landmarks which vehicle can observe. The number of observable landmarks concerns SLAM front-end algorithms as well. The paper [8] reviews the problem of interconnection between gravity-based SLAM problem and 3D SLAM. In view of the questions discussed here the main interest are the problem of landmark extraction and observability by using the modern gravity measuring equipment and the problem of accuracy estimation. Estimation accuracy in SLAM problem greatly depends on nonlinear transform which is done in front-end algorithms to obtain range-bearing or range-elevation-bearing measurements. Studying these transformations of gravimeter or gradiometer measurements for gravity-based SLAM [8] along with taking into account other possibilities to use such measurements [10] are subjects of future research.
Conclusions

2D SLAM algorithm have been modified to evaluate the accuracy of 3D SLAM. The simulation results have shown that 3D SLAM estimation accuracy of vehicle coordinates is much less than in 2D SLAM in the same conditions. Nevertheless, it has been shown that increasing the observability of landmarks, for example increasing the observation angles, can compensate the lost in accuracy. Authors can emphasize the connection of the issues discussed in paper with the gravity-based SLAM problem [8-10]. The study of the gravity-based SLAM from the presented point of view is the matter of future research.

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