M5 TOWARDS REALTIME AUV SLAM WITH OCCUPANCY GRIDS

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Abstract
This paper describes a Realtime Terrain Based Navigation algorithm designed for the Girona500 AUV and tested in a water tank. This paper seeks to establish the foundations for a future online SLAM and planning. Realtime TBN is achieved by means of a parallelized Particle Filter and a fast query and insertion map 3D Occupancy Grid representation using Octomap library. Particle Filter is implemented as a single ROS node in the vehicle's software architecture with a motion model based on AHRS-DVL and measurement model based on a multibeam sonar profiler sensor. Several parameters of the particle filter are studied as well as its realtime performance.

Keywords – Terrain Based Navigation, Autonomous Underwater Vehicle, Octomap, Particle Filter, multibeam.

I. INTRODUCTION

Terrain Based Navigation (TBN), is the name used by the marine robotics community to refer to the more general problem of mobile robot localization with a known map. In particular, TBN solves for the robot pose given an a priori known map, fusing information from dead reckoning navigation with map referenced observations. The principle is the same as has been used for centuries: Localize the vehicle based on observations of known characteristics of the map.
TBN has been mainly applied to aerial and underwater vehicles. During the last years the accuracy and extension of the maps has been increased considerably, and TBN has been adopted as a method to complement inertial navigation system (INS), as an alternative when GPS is not available. Underwater, TBN is still at a research stage, not having evolved into a commercial product. During the last two decades, the scientific community working with mobile robots, has pushed forward the boundaries of the knowledge facing an even more challenging problem: the Simultaneous Localization and Mapping. Both SLAM and TBN have a great potential to improve the autonomy of the underwater vehicles, allowing AUVs to freely move abroad the areas of coverage of the acoustic transponder networks.
Using navigation sensors it is possible to measure the robot velocity, acceleration and attitude, to be used as the input for the dead reckoning equations needed to compute the robot pose. Due to the noisy measurements, the position estimate will rapidly grow without bounds. TBN takes advantage of existing digital terrain maps of target area, where the vehicle shall navigate. Conventional dead reckoning navigation methods provide a prior estimate of the robot pose within the map. Then, using exteropceptive sensors, terrain observations are obtained to be correlated to the a priori known map in order to compute the robot pose.

$$p(\overline{x}_t) = \int p(x_t|x_{t-1}, u_t)p(x_{t-1})dx_t \quad (1)$$

$$p(x_t) = \eta p(z_t|x_t)p(\overline{x_t}) \quad (2)$$

TBN problem can be solved with the Bayes Filter (BF). In the most general case, the BF cannot be implemented because it relies on the close form solution of the integral shown in Equation 1. Under some conditions, the BF can be implemented using parametric filters like the Kalman Filter (KF), the Information Filter (IF) or their non-linear counter parts like the Extended Kalman Filter (EKF), the Extended Information Filter (EIF) or the Unscented Kalman Filter (UKF); or non parametric filters like the Particle Filter (PF) or the Rao-blackwellised Particle Filter (RBPF).

II. IMPLEMENTATION

TBN is implemented using a Particle Filter [1] on the Girona500 AUV [2]. PF is a non-parametric solution to the Bayes Filter, that discretizes the pdf by a set of samples or particles. It is a three-step filter: prediction, weighting and resample. Prediction, uses navigation sensors such as Doppler Velocity Logger (DVL) and Attitude Heading Reference System (AHRS) to predict the vehicle position. Weighting assigns a weight to the particles according to how similar the measurements obtained by an exteroceptive sensor, such as a multibeam sonar profiler, are to the measurements that will get each particle in their current position in the known map. Finally, resampling step, discards the particles with smaller weight and duplicates most weighted ones.

PF is integrated in the Girona500 AUV software architecture (COLA2) as a ROS node implemented as a single C++ class. Multibeam online driver had to be developed for this work. Navigation sensors (AHRS, DVL) are saved as state variables and multibeam data triggers the whole PF (prediction, weighting and resample). Since the most important information for prediction is the DVL (4 Hz), no data is lost with this approach because multibeam works at 6.25 Hz.

Known map is represented by means of octree occupancy grid thanks to Octomap [3] library available in ROS. Octrees are a memory efficient representation for 3D environments. Testing water tank is modeled following the blueprints and then exported to octree representation. Octomap library allows for easy map querying through ray casting. Since this operations are time consuming, the PF is parallelized in both prediction and weighting steps with OpenMP library. This parallelization allows for realtime implementation with 1000 particles in 86.6 ms when the available time regarding multibeam frequency is 160 ms on a Intel Core i7-2600 CPU @ 3.40 GHz x 8, 64 bit OS and 8 GB of RAM.

III. RESULTS & DISCUSSION

Girona500 AUV was teleoperated through a network connection in the CIRS water tank. All messages were recorded into a ROS bagfile, which keeps all the messages with their corresponding timestamps. Using ROS provided tools, data was played back for each experiment as if the robot was running.

Imagenex DeltaT multibeam sonar profiler, was mounted on the payload volume of the Girona500 AUV, along with the Bumblebee stereo camera. AHRS and DVL were used for the prediction step of the Particle filter, while the multibeam was used on the weighting step. The bumblebee stereo camera was mounted in order to compute the ground truth based on the photomosaic located at the bottom of the water tank (Figure 1). The method relies on the identification of point correspondences using feature-based robust matching [4]. The outcome of the matching are two lists of correspondences of points in the camera image and the photomosaic image respectively. These lists are related by an observation function that takes into account the pose, the camera calibration and the scale of the mosaic poster.

To evaluate the results of the TBN PF, different parameters were tweaked. Number of particles, beam spacing and measurement uncertainty σz . The number of particles implies how the pdf is subsampled. With too few particles, the representation of the pdf may not be accurate enough and the filter can fall easier to local maximums and lose the correct position of the vehicle. On the other hand, too much particles lead to excessive computation time impossibiliting realtime execution. Observing the results (Figure 2), different number of particles doesn't affect significantly the result. Beam spacing does not affect either, but making use of less beam can improve the runtime of the filter and leave more free time for more complex implementations such as SLAM. Finally, measurement uncertainty gives worse results when it is smaller than the map resolution (0.07 m).

IV. CONCLUSIONS

In this paper we have proposed a realtime TBN navigation method as a first step towards realtime AUV SLAM with occupancy grids. Realtime implementation is achieved by parallelization of a PF for TBN, leaving almost half the available time free (73.4 of 160 ms) for future SLAM implementation. Motion model based on DVL-AHRS navigation and a measurement model for the sonar multibeam were developed. Known occupancy map is represented by means of memory efficient Octomap library that can also be used for memory efficient SLAM implementation.

The system was implemented over the COLA2 software architecture and tested with the Girona500 AUV doing experiments in the CIRS water tank. Several filter configurations (number of particles, beam uncertainties and number of beams) were tested. The results of the particle filter were compared against a ground truth estimated by means of an accurate vision based localization method. The vehicle altitude was very accurately estimated (around 20 cm error) and half meter accuracy for the horizontal (XY) position was also easily achieved.

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