uSLAM Implementation for Autonomous Underground Robot

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***Abstract*—This paper presents an Underground Simultaneous Localization and Mapping (uSLAM) method to localize an autonomous underground robotic system and map its surroundings. A Rao-Blackwellized Particle Filter (RBPF) with the information provided by a Ground Penetrating Radar (GPR) system installed in the robot and odometry data is described. RBPF generates possible trajectories, where each one of them has its 3D occupancy grid map. A scan matching method based on groups of GPR measurements to improve the proposed trajectories is also described.**

***Index Terms*—Underground robot, SLAM, Particle filters, Scan-matching**

I. Introduction

Nowadays, society would not be able to live without underground utilities (pipes, cables, conduits, etc.). On a global scale, urban population is growing, e.g. cities are expected to grow at the rate of 1.5% per year between 2025 and 2030. As a consequence of this, there will be more demand for utility services.

Traditionally, open-cut excavation is the most common approach for accessing the subsurface. This technique requires the excavation large surface trenches, which generate noise, traffic congestion, destruction of surface civilian infrastructure, danger for the workers and citizens, and environmental impacts. Trenchless technology methods offer a viable solution to install, replace, or repair underground utilities or conduits between two defined points without continuous open-cut excavations. Despite the reduction of the disturbances compared to the trench excavation, trenchless methods are still underused, currently representing only 5% of street works.

Currently, commercially available trenchless systems have limited perception of the surrounding environment. Trenchless excavation methods require obstacle free space and previous good knowledge of the surface. Additionally, the maneuverability of existing trenchless technologies is very limited. Paths are restricted either to straight or really low curvature lines over long distances. Trenchless operations are normally executed by an operator with limited feedback.

BADGER is a research project funded by the European Commission under Horizon 2020 with the aim of designing an autonomous underground robotic system. This robot can drill, manoeuvre, localize it self, map and navigate in the underground space (Fig. 1). Therefore, the robot must be equipped with a Ground Penetrating Radar(GPR) system to perceive its surroundings and provide information to the Simultaneous Localization and Mapping (SLAM) system. The SLAM problem is the problem of determining the pose of an autonomous robotic system moving through an unknown environment, and simultaneously, mapping its environment. The main contribution of this work is the implementation of a Rao-Blackwellized Particle Filter (RBPF) SLAM solution with the GPR system installed in the underground robot to map the subsurface. In addition, a scan matching approach using the GPR's data is also described.

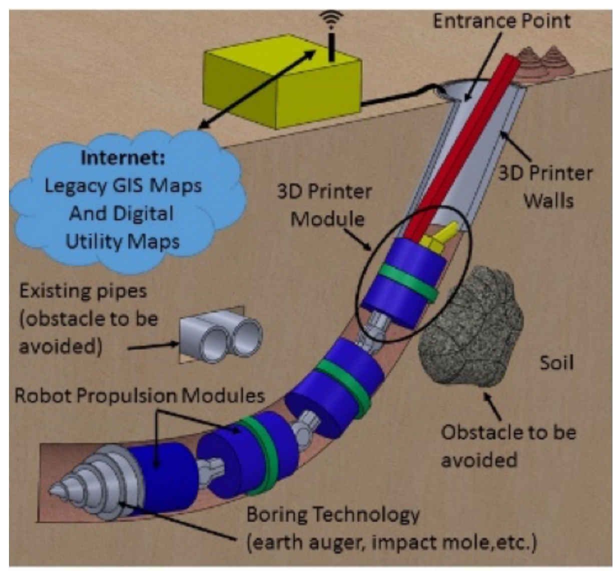

Fig. 1. Badger concept

II. Related work

The SLAM problem has been studied with different type of sensors and environments. Ground robots employ the information provided by Laser sensors [1], monocular and stereo cameras [2] to map their environment. The accuracy and density of their measurements makes them more appealing for SLAM approaches. Regarding underwater robotics, sonars are extensively used [3]. Sonars lack the resolution, update rate, and density of a lasers. Our robotic system has can not rely on visual, laser or sonar sensors, since they do not work in the soil. Instead, a ground penetrating radar (GPR) system is installed in the robot to be used in the SLAM method.

There are three main SLAM approaches Extended Kalman Filter (EKF), Graph Optimization (Graph-SLAM) and Particle Filter (PF). Graph-SLAM methods create a graph where the nodes are the robot poses or features, and the edges represent the constraints between poses obtained from the sensor measurements. These approaches have been extensively used in the last years [4]. Although, Rao-Blackwellized particle filter (RBPF) SLAM is still the most popular solution [5].

Scan-matching is a useful method for any kind of SLAM approach. It basically computes the displacement between two sets of laser readings based on an initial guess of this relative displacement [6]–[8].

SLAM method also vary by the way they represent the map. Octomap [9] is a framework for 3D mapping based on octrees and uses probabilistic occupancy estimation. Using probabilistic occupancy estimation represents not only the occupied areas, but also the free and unknown.

III. Badger robotic system

The BADGER underground robot is composed of four different modules: Drill head module, service modules, joint modules and wall support module (Fig. 2). The drill head module integrates a drilling mechanism based on rotatory drilling technologies to construct the bore hole. In addition, a cutting transportation mechanism to transport the soil cuttings to the surface is installed in this first module.

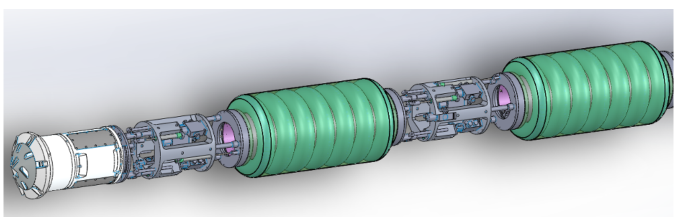

Fig. 2. Badger robotic system general design

The joint modules consist of the hollow steel-made cylinder with the six actuators. The synchronized actuation of three of the actuators provides the propulsion movement. The other three actuators compose a Stewart-like actuated joint to steer the robot at the desired pitch and yaw angles.

Both service modules include a clamping mechanism, which consists of airbags that inflate and deflate to provide anchor points for the joint modules to push against. The combined operation of the clamping mechanisms and the joint modules generates a worm-like motion. These clamping mechanisms also react the torque produced during drilling, and avoid roll motion.

The last module is the tunnel wall support. This module sprays the walls of the drilled bore with additive material (resin or other) to construct pipe wall support.

In order to detect the surrounding environment of the underground robotic system, Ground Penetrating Radar (GPR) units are installed in the drill head module. The GPR system of the underground robot includes three GPR antenna modules with a 120° field of view. Fig. 3 depicts the uniform disposition of the housings where these antennas are installed. Fig. 4 shows how these GPR units cover with a 360° field of view their surrounding environment. A single measurement from the GPR (A-Scan) can provide data about the distance of the antenna to the closest object that falls within the field of view of the sensor. However, this data is not enough for the estimation of the position of the underground objects. This problem has been solved by concatenating A-scans while surface GPRs move on straight lines to build a B-scan [10]. In our approach, we do not employ this B-scan method. Instead, we used the distance provided by each GPR to localize the robot and map the environment using 3D occupancy grid.

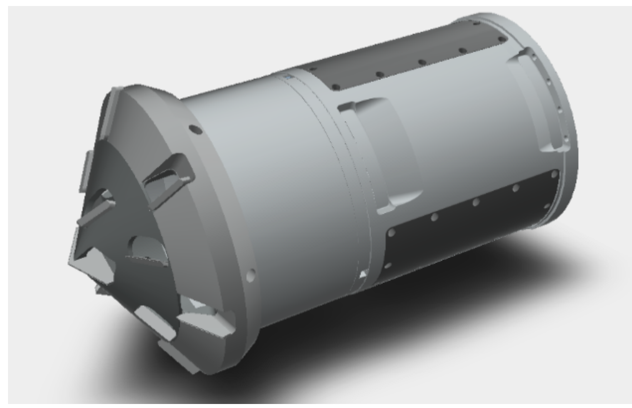

Fig. 3. Three GPR units are installed in the drill head.

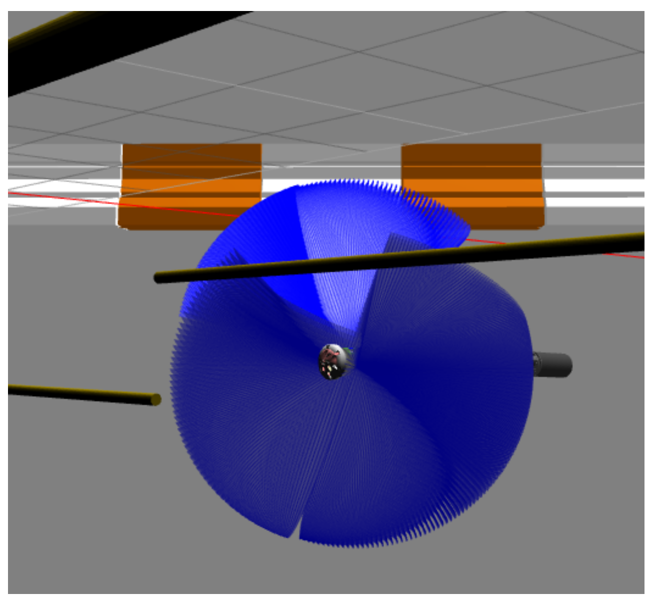

Fig. 4. Each GPR cover a field of view of 120°x 120°.

IV. GPR BASED SCAN MATCHING

A. Grouping GPR scans

The essential requirement of any scan maching method is two sets of readings to establish the correspondence. Each single measurement from a GPR unit (A-scan) provides the distance between the antenna and the closest obstacle that falls within the field of view of the sensor. GPRs processed information provides range measurements, like ultrasonic range sensors, but with a bigger field of view. Each range measurement can be drawn as a spherical sector centered in the GPR. These GPR units does not provide a dense set of readings, so a process where sets of GPR range readings are grouped is needed. In addition, the grouping process provides redundancy to discard the incorrect readings.

The grouping GPR scans process consist in gathering the range measurements of the GPR ring and the odometry while the robot is moving [11]. A range measurement $r_{i,k}$ taken by the GPR i at time k is expressed with respect to the drill head reference frame $s_{r_{i,k}}$. The relative pose of GPR i with respect to the drill head reference frame is fixed and it is perfectly known.

As the robot moves, the odometry is used to estimate the displacements between the successive poses where the GPR measurements are taken. The current pose k of the drill head with respect to the reference frame, located at the pose of the drill head when the previous GPR measurement k-1 was performed, is stored x_k^{k-1}.

The set of the odometric estimations X_{scan} and the correspondent group of GPR measurements S_{scan} are stored.

$$X_{scan} = \{x_2^1, x_3^2, ..., x_k^{k-1}\} \tag{1}$$

$$S_{scan} = \{s_1, s_2, ..., s_k\} \tag{2}$$

Where each item of the S_{scan} consists of a set of the three GPRs range measurements $s_{r_{i,k}}$ with respect to the drill head reference frame at instant k. These range measurement can be transformed to the drill head reference frame at the first instant.

B. Scan Matching

The scan matching method utilize two successive group of scans to estimate the relative displacement between the current group of scans S_{cur} and the reference group of scans S_{ref}.

Given a reference scan S_{ref}, a new scan S_{cur} and an initial guess of the displacement estimation between them, the objective of scan matching methods is to obtain a better estimate of the real displacement $q = (x, y, z, \phi, \theta, \psi)$. The motion of the underground robot does not allow roll (ψ) rotation.

Our method combines two perpendicular 2d grid maps to estimate the motion of the drill head between two groups of scans. These maps coordinates are with respect to the drill head reference frame when the first range measurement was performed. The XZ grid map is employed to estimate the displacement in x and z, and the tilt angle (ϕ). Regarding the XY grid map, it is used for the estimation of the motion in x, y and the yaw angle (θ).

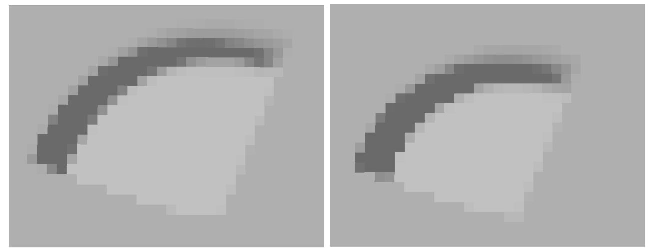

Fig. 5. Occupancy grids generated with the two successives groups of scans to compute the motion in the plane XZ.

Let $M_{ref,xz}$ be a 2D occupancy grid. Each grid cell has a probability of occupancy $p(m_{xz})$. Given S_{scan} we seek to estimate the posterior probability over the grid cel xy $p(m_{xz}|S_{scan})$. Usually, the posterior is represented using log-odds ratios (l_{xz}), which is computed recursively:

$$l_{xz}^t = log\frac{p(m_{xz}|s_t)}{1 - p(m_{xz}|s_t)} + log\frac{1 - p(m_{xz})}{p(m_{xz})} + l_{xz}^{t-1} \tag{3}$$

where $p(m_{xz})$ is the prior occupancy probability of cell xz, the prior for occupancy and $p(m_{xyz}|s_t)$ is given by the inverse sensor model [12] . A simple inverse sensor model is used in our approach. For the cells inside the field of view of each GPR at distances between 0 and the neighbourhood of the range, $p(m_{xz}|s_t)$ has a value smaller than the prior. In the neighbourhood it has a value bigger than the prior.

Another map $M_{cur,xz}$ is created in a similar way for the current group of scans to estimate the relative displacement (x, y, ϕ). Fig. 5 shows an example of the 2D maps created with the reference group of scans and the current group of scans. This relative displacement is calculated using a Ceres based scan-matcher [1]. It computes the displacement that maximizes the probabilities at the cells $M_{cur,xz}$ when inserted on $M_{ref,xz}$.

$$argmin \sum (1 - M_{ref,xz}(T_\chi M_{cur,xz}))^2 \tag{4}$$

where T_χ transforms $M_{cur,xz}$ cells from its current frame to the frame of the reference map. Fig. 6 depicts in a darker color the aligned maps after the scan matching process.

V. BADGER MOTION MODEL

The motion of Badger underground robot is constrained by the bore hole that it is drilling. This robotic system cannot move sideways and must always move forwards in order to steer. The drill head pose $\mathbf{X_t} = (x, y, z, \phi, \theta, \psi)$ at instant t is summarized by the following equation:

$$\mathbf{X_t} = \mathbf{X_{t-1}} + \begin{bmatrix} \mathbf{R_{t-1}} & \mathbf{0} \\ \mathbf{0} & \mathbf{T_{t-1}} \end{bmatrix} (\mathbf{u} + \mathbf{w_u})\delta t \tag{5}$$

Where $\mathbf{R_{t-1}}$ is the is the 3D rotation matrix and $\mathbf{T_{t-1}}$ is the kinematic transformation matrix.$\mathbf{u}$ represents the linear

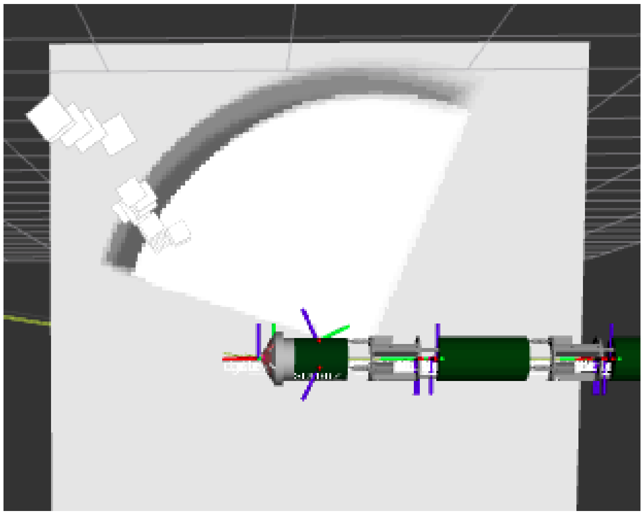

Fig. 6. Final matched 2D occupancy grid of the maps from Fig. 5.

and angular velocities in the body frame. Since the joints of the underground robot are under-actuated, the only velocities inputs are the linear velocity in x-axis and the angular velocity about axis x and y. The motion of the underground robot does not allow roll (ψ) rotation. Further, $\mathbf{w_u}$ represent random noise.

VI. Rao-Blackwelized SLAM using Ground Penetrating Radars

The key idea of this paper is the introduction of the GPR data into a Rao-blackwellized particle filter to estimate the pose of the drill head and mapping the environment. In Rao-Blackwellized SLAM, each particle has a trajectory and a map. Initially, the number of particles and the size of each group of scans need to be set. For each particle the following procedure is executed:

1) The pose of each particle x_t^i is predicted from the previous pose of the particle x_{t-1}^i and the odometry u_{t-1} since the last update using the motion model.
2) The particles keep being updated by the odometry until two group of scans are available to perform the scan matching (S_{ref} and S_{cur}). The scan matching is performed based on an initial guess provided by the odometry transformation between the reference frame of both group of scans.
3) If the scan matcher does not report any failure, a set of poses are chosen from a Gaussian distribution around the particle pose $x_{1:J}$.
4) Each of this poses gets assign a weight ω_j that depends on the probability of the pose given the odometry and the pose of the particle $p(x_j|x_{t-1}^i, u_{t-1})$, and the group of scans and the current Octomap m_{t-1}^i of this particle $p(S_{cur}|m_{t-1}^i, x_j)$. (6) is used to compute the weights:
$$\omega_j = p(x_j|x_{t-1}^i, u_{t-1})p(S_{cur}|m_{t-1}^i, x_j) \tag{6}$$
5) A Gaussian distribution computed with the weighted mean η_t and covariance $\sum_t$ is used to get the new pose of the particle (7). In addition, the particle weight is updated (8).
$$x_t^i \to \mathcal{N}(\eta_t, \sum\nolimits_t) \tag{7}$$
$$\omega_t^i = \omega_{t-1}^i \sum w_j \tag{8}$$
6) The OctoMap of the particle is updated with the current group of scans using log-odds formulation. Also, this current group of scans is stored as reference for the next scan matching process.
7) Depending on the number of effective particles, a re-sampling process is necessary.

This algorithm is explained in detailed in [5].

VII. Simulations

For performing the simulations, we select Robot Operating System (ROS) [13] and Gazebo Simulator. Fig. 7 shows the underground robot model created for performing the simulations and the underground scenario with several utilities to be mapped. For sensing, the underground robot is equipped with three sonars to simulate the three GPR units (Fig. 4). These sonars provides the range distance to the closest obstacle within the field of view.

An example of the resulting 3D Octomap from mapping the simulated subsurface from Fig. 7 is depicted in Fig. 8. This map was created using the described method in this work while the robot drills in a straight line. Cells with a probability of occupancy higher than 0.7 are considered obstacles. The resulting map shows that the utilities perpendicular to the motion of the robot are represented with low error. Although, the green pipe, which is tilted in the simulated environment, is represented as a wider surface in the Octomap. It is similar as if the obstacle is inflated in the plane of the pipe. This ”inflated” Octomap can be used for collision avoidance.

The resulting map tend to be misaligned when the robot moved large distances since we only used the previous group of scans to correct the pose of the particles using scan-matching. In addition, the underground environment where the robotic system is tested is not cluttered and, it is possible that the robot travel distances of approximately one meter without the detection of any obstacles.

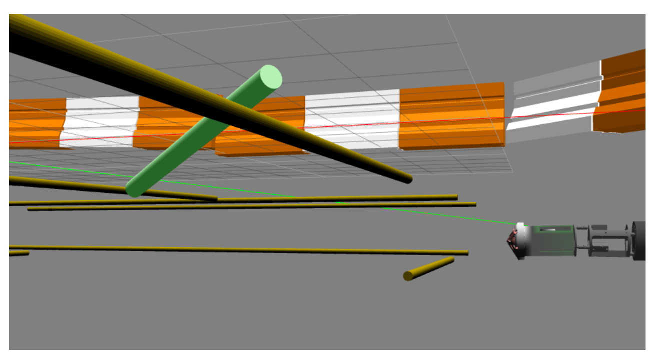

Fig. 7. Badger underground robot is simulated in Gazebo.

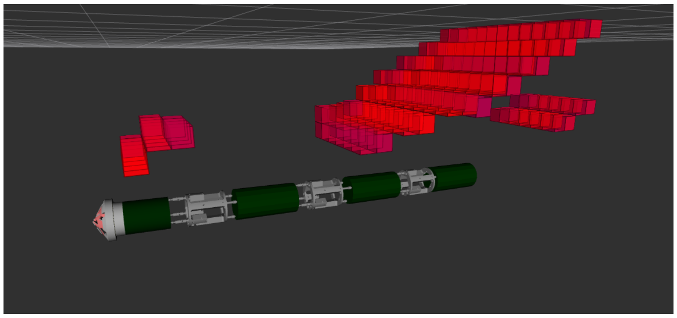

Fig. 8. 3D Octomap of the underground environment represented in the previous figure.

VIII. Conclusions and Future Work

In this paper, we presented a SLAM method applied to the new underground robotics field, called uSLAM. This approach is based on the Rao-Blackwellized Particle Filter using the distance information provided by the Ground penetrating radar (GPR) system installed in the underground drilling robot. In our method, a scan matching technique that matches two successive groups of GPR scans is also applied to correct the predicted pose from the motion model. Simulations have shown that the proposed method creates a map of the underground environment that can be used for navigation and obstacle avoidance tasks. In our future work, we plan to use a previously constructed subsurface map from the surface. The combination of this prior map and the detection of obstacles from the underground robot would be use to localize the robot, as well as to relocate the known obstacles and map new ones.

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