# Autonomous refuelling mission in subarctic conditions

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## Abstract

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## 1 Introduction

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<sup>\*</sup>Use footnote for providing further information about author (webpage, alternative address). Acknowledgments to funding agencies should go in the **Acknowledgments** section at the end of the paper.

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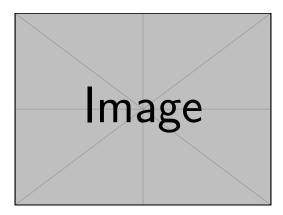


Figure 1: Warthog driving / Aerial shot of the different paths

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## 2 Related work

### 2.1 Robotic deployments in snow

To our knowledge, few robots have been deployed in harsh winter environments. Dante II is a 900 kg tethered legged robot, which conducted a 5-day, 165 m descent into the Mount Spurr Volcano, in Alaska (Bares & Wettergreen, 1999). During this deployment, Dante II reached speeds upwards to 0.011 m/s during the descent. A two-axis lidar was used to create a local elevation map around the robot in order to conduct autonomous navigation.

Nomad is a gasoline-powered 725 kg unmanned ground vehicle (UGV), was deployed at Elephant Moraine, Antarctica for a duration of 4 weeks (Apostolopoulos et al., 2000). The robot reached speeds upwards of  $0.5\,\mathrm{m/s}$  while using differential-Global Positioning System (GPS) as the primary method of localization. The platform also used stereo cameras and a lidar sensor for obstacle detection, although stereo vision was found to be ineffective on blue ice and snow in Antarctica due to extreme lack of texture (Moorehead, Simmons, Apostolopoulos, & Whittaker, 1999). Roll/pitch/yaw sensors were also added to the robot to make it cognizant to hazardous terrain. Nomad achieved its initial goal to identify meteorites autonomously in Antarctica at a search rate of  $160\,\mathrm{m}^2/\mathrm{h}$ .

MARVIN I and MARVIN II are two diesel-powered Skid-steering mobile robots (SSMRs) weighing 720 kg were deployed in Greenland (Stansbury, Akers, Harmon, & Agah, 2004) and Antarctica (Gifford, Akers, Stansbury, & Agah, 2009) respectively. The goal of these robots was to increase survey safety in remote polar regions and large sensor payloads led to the selection of large vehicles. Both vehicles used Real-time Kinematics (RTK) GPS as primary method, achieving a centimeter-level accuracy. They also used a lidar sensor for obstacle detection and a a gyroscope and inclinometer were used to provide the robot's pitch and roll angles. Skid-steer turns often caused MARVIN I to get immobilized in snow and its transmission eventually broke down during operation. MARVIN II thus incorporated design improvements to the hydrostatic drive and track systems to increase its durability.

Sno-mote Mk1 and Mk2 are dual-drive 1:10 scale snowmobiles equipped with a single camera and GPS antenna were deployed on Alaskan glaciers and Wapekoneta, Ohio (Williams & Howard, 2009). These robots were used to conduct manually-driven traverses of about 100 m at a speed of 1 m/s. The data gathered with the Sno-motes was then used to improve visual Simultaneous Localization and Mapping (SLAM) feature extraction methods in snow. Despite improving feature detection methods on snow, it was shown that snow is still feature-sparse (Williams & Howard, 2009). Through this work, improvements were also done on slope estimation (Williams & Howard, 2010) and horizon line estimation (Williams & Howard, 2011).

Yeti is a battery-powered  $81\,\mathrm{kg}$  UGV in Antarctica and Greenland (Lever et al., 2013). Yeti was used to conduct ground penetrating radar (GPR) surveys in order to detect subsurface crevasses or other voids to increase vehicle travel safety in remote polar environments. Since polar terrain is largely obstacle-free and the effort required to provide reliable obstacle detection on low-contrast snowfields is considerable, Yeti drove "blind", relying only on GPS waypoint following. During surveys, Yeti reached a top speed of  $2.2\,\mathrm{m/s}$  and managed to acquire data on hundreds of crevasse encounters and even locate a previously undetected buried building in the South Pole.

A Clearpath Robotics Grizzly, a battery- and gasoline-powered SSMR was deployed during winter on the University of Toronto Institute for Aerospace Studies (UTIAS) campus, in Ontario, Canada (Paton, Pomerleau, MacTavish, Ostafew, & Barfoot, 2017). Only stereo cameras were used through a visual SLAM algorithm to localize the robot during autonomous teach-and-repeat runs. Path tracking was accomplished using a Model Predictive Control (MPC) algorithm. A 250 m path was successfully repeated on an light snow cover 3 hours after it was first manually driven. However, deep snow path-following provided unsatisfactory results due to features almost only being observed on the horizon, leading to inaccurate pose estimates, which caused

issues for the path tracker. Furthermore, vehicle tracks that constantly change when driven over lead to an increased pose estimation error.

A full-scale battery-powered Toyota Prius was deployed during winter on roads in Massachusetts, USA (Ort, Gilitschenski, & Rus, 2020). Localization was accomplished using a custom-designed localizing GPR. A prior mapping must be conducted during which the driven is driven by a human operator and the vehicle's sensor data is recorded, the saved map can then allow the vehicle to localize within this area. The GPR location information is then probabilistically fused with wheel odometry and inertial measurement unit (IMU) measurements to provide accurate vehicle localization. Path tracking is accomplished through the use of a Pure Pursuit controller, specifically designed for Ackermann steered autonomous vehicles. The system showed similar performance in localization accuracy (0.34 m to 0.39 m) and cross-track error (0.26 m to 0.29 m) between clear weather and snow-covered road. The localizing GPR sensor's measurement range depends on the width of the array, meaning the system cannot be easily miniaturized, which means it was mounted on the rear of the vehicle, at 32 cm above the ground. This sensor size and mounting requirement could lead to decreased performance in deep snow or in off-road environments.

In this work, we demonstrate that lidar-based localization and navigation allows a robot to localize in Global Navigation Satellite System (GNSS)-deprived areas as well in snow-covered terrain. Our system has been deployed in complex meteorological scenarios, relying on lidar, IMU and wheel encoders measurements to localize and track the desired path through a week-long deployment in a subarctic forest.

### 2.2 Teach-and-Repeat

In Visual Teach and Repeat (VT&R), a robot is first driven manually along a given path as a training example in order to build a manifold map of overlapping submaps. Then, a visual path-tracking system is able to achieve high autonomy rates over many kilometres of steep terrain, relying on a single stereo camera (Furgale & Barfoot, 2010). Experience-based navigation (EBN) has then been introduced to increase the robustness of VT&R to scene appearance change, caused by illumination variation or dynamic environment changes (Churchill & Newman, 2013). This feature was added in VT&R through Multi-experience Localization (MEL), with the added ability to use landmarks from previous experiences in the same localization problem (Paton, MacTavish, Warren, & Barfoot, 2016). Recall of relevant landmarks for a specific scenario was then improved in computation speed through a bag-of-word approach (MacTavish, Paton, & Barfoot, 2017). To mitigate the impact of illumination variations, colour-constant image transformations have been added to VT&R (Paton, MacTavish, Ostafew, & Barfoot, 2015). The VT&R framework has also been shown to work with various sensors, such as intensity-based lidar (McManus, Furgale, Stenning, & Barfoot, 2013) and monocular cameras (Clement, Kelly, & Barfoot, 2017). Convolutional Neural Networks (CNNs) and particle filters have also been used for visual place recognition in VT&R frameworks in order to localize the robot in the teached trajectory (Camara et al., 2020). In this work, the horizontal offset of the reference image with the current image is used to correct the steering during the teach phase. Recently, Congram and Barfoot (2021) expanded VT&R's localization ability to environments where the ability to visually localize is compromised by using GNSS measurements. While VT&R has proven to be an efficient method for repeating trajectories in outdoor environments, the literature does not show the system to be deployed in snow. Our work aims to demonstrate that Lidar Teach and Repeat (LT&R) approaches allow to repeat trajectories that were recorded multiple days prior and under vastly different lighting conditions. We also demonstrate that LT&R offers good performance on snow-covered terrain, which is known to be complex for visual localization.

While all these works rely using cameras, LT&R is a similar framework relying on lidar sensors. Marshall, Barfoot, and Larsson (2008) were the first to suggest a similar framework using encoders and 2D lidars. In this work, a sequence of overlapping metric maps are recorded along the path using 2D lidar measurements to allow the robot to localize within during the repeat phase. Sprunk, Tipaldi, Cherubini, and Burgard (2013) used a similar approach to LT&R, however the teach phase directly logs 2D lidar data at an interval based on the distance from the last recorded scan. Mazuran, Sprunk, Burgard, and Tipaldi (2015) have improved

this framework by introducing an optimization step between the teach and the repeat phase, allowing the constraints to be defined by user preferences. While more focused on localization, Landry and Giguère (2016) have worked to improve topometric maps used to localize the robot during the repeat phase in order to minimize the number of nodes in the topometric map. In this work, the localization was done using a 3D lidar. Following a similar idea, Boniardi, Caselitz, Kummerle, and Burgard (2017) have extended this work to allow using architectural floor plans of buildings to localize within using 2D lidar scans. Our work differs from previous work on LT&R mainly because the system is deployed in an unstructured, outdoor environment and subject to harsh winter conditions. We also demonstrate the performance of our LT&R system on 22 km of autonomous path repeating.

## 3 System description

Our LT&R framework was designed to allow to repeat previously driven paths over large distances. Localization is done mainly using lidar scans registration through the iterative closest point (ICP) algorithm. During the teach phase, every ICP pose is logged in order to record the path that was driven by the operator. All registered scans are also logged into a map, with a limit of density of points. During the repeat phase, the corresponding map and trajectory are loaded and the robot follows the reference path using a simple controller. Registered scans are not added to the map during the repeat phase, we have found empirically that not updating the map during repeat runs increases the localization robustness.

## 3.1 Hardware description

Our system was deployed on a Clearpath Robotics Warthog UGV. The Warthog is a SSMR using two drive units located on each side of it's chassis. The drive For SSMRs, steering is done by sending rotating the wheels on each side of the vehicle at different velocities to creating a skidding effect, effectively turning the vehicle. The Warthog can be equipped with wheels or tracks, for this work, we selected the latter in order to maximize mobility. The Warthog is also equipped with a differential suspension, maximizing track or wheel traction when navigating steep terrain. The warthog is also equipped with a standard sensor suite for autonomous navigation. In order to enable the LT&R framework, a Robosense RS-32 3D lidar is mounted in front of the robot, for this work, it is the only lidar used for localization. 3 Hall effect sensors are added to each motor to provide wheel odometry for the robot. Finally, an XSens MTi-10 IMU provides angular velocity, body linear acceleration and gravitational acceleration measurements. Additional sensors used for recording in this work include a Dalsa C1920 camera and two Emlid Reach RS GPS receivers. Two Robosense RS-16 lidars were added to the rear of the platform to collect measurements on tree canopy but no data was recorded through those sensors. All technical specifications for the platform are given in Table 1.

Table 1: Warthog specifications

Physical		Power		Sensors	
Mass	$590\mathrm{kg}$	Chemistry	Lead Acid 2	LT&R	
Footprint	$2.13 \times 1.52 \ \mathrm{m}$	Voltage	$48\mathrm{V}$	Front lidar	Robosense RS-32
Top speed	$18\mathrm{km/h}$	Capacity	$105\mathrm{Ah}$	IMU	XSens MTi-10
Steering geometry	Skid-steering	Drive	Sevcon	Wheel encoders	$3 \times \text{hall effect}$
Locomotion	Tracks			Recording	
				Camera	Dalsa C1920
				GPS	Emlid Reach-RS



Figure 2: Warthog figure, pointing to every sensor.

### 3.2 Lidar teach-and-repeat

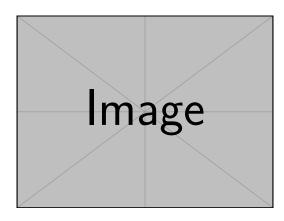


Figure 3: Flowchart for LTR

#### 3.2.1 Iterative closest point

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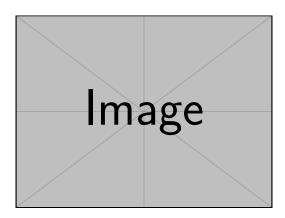


Figure 4: Figure explaining Simon-Pierre's tiled mapping framework

	$k_g$	$k_o$	$c_3$	$c_4$	$c_5$
Careful/Sparse	0.334	0.597	1.101	9.621	8.170
Careful/Dense	3.124	3.195	1.094	5.899	7.318
Aggressive/Sparse	0.840	9.153	2.853	8.274	0.187
Aggressive/Dense	4.838	2.841	0.670	7.952	0.386
Hand-Tuned	0.767	0.060	0.340	2.000	0.250

Table 2: ICP parameters

#### 3.2.2 Path following

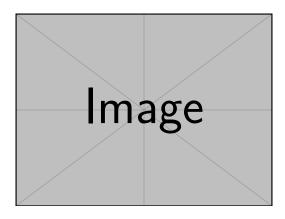


Figure 5: Figure explaining Differential orthogonal-exponential controller

## 4 Environment

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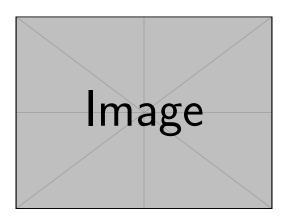


Figure 6: Johann's various runs and meteo figure

## 5 Results

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#### 5.1 Localization

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#### 5.1.1 Vision-based

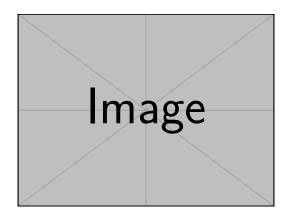


Figure 7: Olivier's over and under exposition figure for cameras

#### 5.1.2 GNSS

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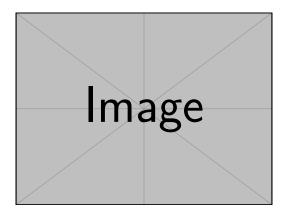


Figure 8: Maxime's GNSS error figure

#### 5.1.3 ICP

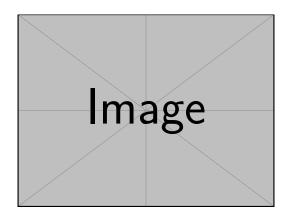


Figure 9: Figure explaining ICP error for every run (correlated with meteo).

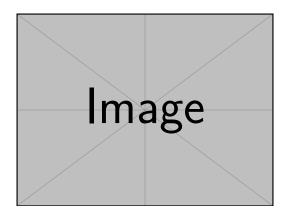


Figure 10: Figure explaining special cases when mapping needed to be enabled.

#### 5.2 Motion and control

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#### 5.2.1 Path following error

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### 5.2.2 Command error and power consumption

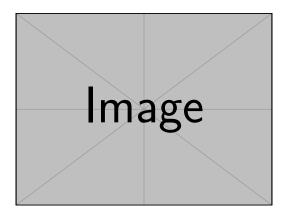


Figure 11: Dominic's path following error figure

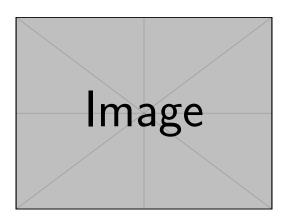


Figure 12: Power consumption / motion efficiency figure.

## 6 Lessons learned

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## 7 Conclusion

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