FoMo: A Proposal for a Multi-Season Dataset for Robot Navigation in Forêt Montmorency

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Abstract—In this paper, we propose the FoMo (Forêt Montmorency) dataset: a comprehensive, multi-season data collection. Located in the Montmorency Forest, Quebec, Canada, our dataset will capture a rich variety of sensory data over six distinct trajectories totaling 6 kilometers, repeated through different seasons to accumulate 42 kilometers of recorded data. The boreal forest environment increases the diversity of datasets for mobile robot navigation. This proposed dataset will feature a broad array of sensor modalities, including lidar, radar, and a navigation-grade Inertial Measurement Unit (IMU), against the backdrop of challenging boreal forest conditions. Notably, the FoMo dataset will be distinguished by its inclusion of seasonal variations, such as changes in tree canopy and snow depth up to 2 meters, presenting new challenges for robot navigation algorithms. Alongside, we will offer a centimeter-level accurate ground truth, obtained through Post Processed Kinematic (PPK) Global Navigation Satellite System (GNSS) correction, facilitating precise evaluation of odometry and localization algorithms. This work aims to spur advancements in autonomous navigation, enabling the development of robust algorithms capable of handling the dynamic, unstructured environments characteristic of boreal forests. With a public odometry and localization leaderboard and a dedicated software suite, we invite the robotics community to engage with the FoMo dataset by exploring new frontiers in robot navigation under extreme environmental variations. We seek feedback from the community based on this proposal to make the dataset as useful as possible.

I. INTRODUCTION

Recent years have seen an unprecedented growth of mobile robots venturing into unstructured environments. From caves and forests to deserts, this shift from urban centers to wild settings has been reflected in the development of new algorithms for Simultaneous Localization and Mapping (SLAM), semantic segmentation, traversability, and other tasks [1]–[3]. Due to the costs of executing demanding experiments, especially in the wild, the community relies heavily on open-source datasets that serve as an essential benchmark tool, allowing the comparison of different approaches. Moreover, as robotics research matures, new datasets provide new challenges. Indeed, the past few years have seen releases of several high-quality datasets, focusing

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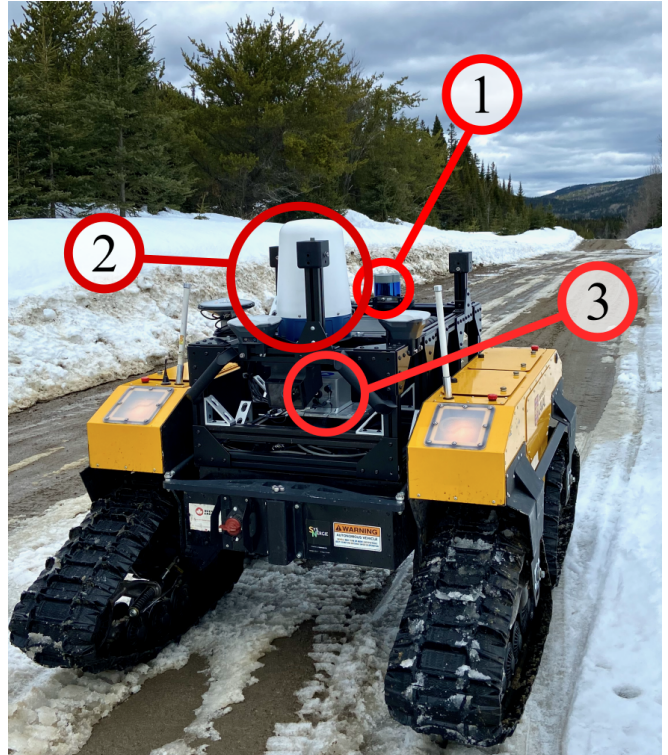
Fig. 1. The data acquisition platform in the Montmorency Forest, Quebec, where the planned data recording will take place. The platform can navigate through diverse terrain, including deep snow, supporting the multi-seasonal nature of the proposed dataset. Marked in red circles are the main sensor modalities: (1) lidar, (2) radar, (3) navigation-grade IMU.

on outdoor environments with low texture [4], poor lighting conditions [5], or seasonal changes [6].

Motivated by these recent efforts, we focus our attention on boreal forests. Despite being the largest land biome on Earth [7], boreal forests have been widely overlooked in the development of autonomous vehicles and remain, to the best of our knowledge, unexplored within the realm of a comprehensive robotics dataset. While works similar to ours exist, they do not capture the desired range of sensors [8], [6], are mainly designed for tasks other than localization [9], or do not contain multi-season data. It is worth noting that only a few works incorporate extensive online benchmarking tools and public leaderboards, both of which are essential prerequisites for the rigorous evaluation of various algorithms created by the community.

In this article, we present the Forêt Montmorency (FoMo) dataset, our future work on a mobile robot navigation dataset

recorded in a boreal forest. We see this work as a proposal to the robotics community and welcome feedback on the presented sensor modalities, calibration procedures, and suggested trajectories. The planned contributions of our work are as follows:

- A rich, natural-environment dataset with six diverse trajectories spanning a combined length of 6 km within a boreal forest. Due to regularly repeated experiments, the total length of the recorded data will reach 42 km.
- Seasonal changes, including tree canopy change and snow accumulation of up to 2 m.
- A wide range of sensing modalities, featuring a navigation-grade Inertial Measurement Unit (IMU) and a radar.
- Centimeter-accurate Ground Truth (GT) trajectories, corrected with a Post Processed Kinematic (PPK) Global Navigation Satellite System (GNSS) method.
- A public odometry and localization leaderboard, supported by a software suite to facilitate data manipulation.

II. RELATED WORK

In mobile robotics, datasets play an important role in evaluating and benchmarking trajectory and state estimation algorithms. To date, a variety of such datasets have been proposed, featuring different robot manipulators, environments as well as sensor availability. Early notable works include the MIT-DARPA [27] and KITTI [28] datasets. Both feature a variety of sensors, as well as ground truth data via differential GNSS. The environments featured in these early datasets are highly structured, mostly focusing on urban environments with static scenes while exhibiting idealistic weather and lighting conditions. Consequently, evaluating algorithms on these datasets might not reflect their behavior in more challenging, less ideal environments and circumstances.

To overcome this shortcoming, additional datasets have been proposed to highlight and illustrate specific challenges and non-ideal features of real-world environments. For instance, the KAIST Day/Night dataset [29] features urban environments at different times throughout the day, leading to vastly different lighting conditions. Both, the ComplexUrban [30] and UrbanLoco [31] datasets highlight more challenging scenarios within urban environments, e.g., unreliable and sporadic GPS data, drifting IMU measurements, complex building structures, as well as scenes with an abundance of dynamic objects. Lastly, several datasets have been proposed that feature urban environments throughout different times of the year, highlighting the impact of weather and lighting in different seasons. Prominent examples include the Oxford RobotCar [32], the 4-Seasons [33], the Canadian Adverse Conditions [34], and the BOREAS Multi-Season [35] datasets. While these efforts lead to datasets featuring more realistic scenarios, the aforementioned works are limited to highly structured, mostly urban environments. However, in field robotics, robots are usually exposed to significantly unstructured environments, which introduce additional challenges to localization due to non-static scenes and few well-defined features. Thus, existing datasets of structured environments are of limited use when evaluating field robotics algorithms and the development of specialized datasets featuring unstructured environments is warranted.

Although they have generally received much less attention, a variety of different datasets in unstructured environments have been published in the current literature. Table I shows an overview of relevant works, particularly highlighting the featured environment, the envisioned application, as well as the utilized sensors. Datasets have been proposed for a variety of unstructured environments, ranging from off-road scenes [12] to planetary surface analogues [4], mining tunnels [5], agricultural farms [20] as well as natural environments such as gardens [14] or waterways [25]. In the following, we discuss the most relevant ones with respect to the work presented here, specifically focusing on forest environments.

The BotanicGarden dataset [14], targeted at navigation, mapping, and segmentation applications, features data collected in a natural garden environment using stereo vision, lidar, and IMU data. Both the Canoe [24] and USVInland [25] datasets provide data collected along rivers and waterways in woodland and forest environments. Both datasets include stereo camera images and IMU data, while Cheng et al. [25] further provide lidar and radar data. Additional prominent forest navigation datasets are the SFU Mountain [22] and Montmorency [9] datasets, featuring camera, lidar, and IMU data. Tremblay et al. [9] additionally include stereo vision images and provide detailed tree classification labels. The FinnWoodlands [26] and Freiburg Forest [23] datasets mostly target semantic segmentation tasks. Both datasets provide stereo vision data and detailed ground-truth segmentation labels, while Lagos et al. [26] also feature lidar scans of the environment. The Oxford Offroad Radar Dataset [15] is one of the few publicly available datasets including radar data in harsh weather conditions. Similar to our proposal, the authors concentrate on repeated trajectories, in their case in the Scottish Highlands.

Typical applications of current forest datasets include autonomous navigation, mapping, and segmentation tasks. However, only a subset of the studied navigation datasets feature data to evaluate long-term estimation and localization algorithms, which are crucial in changing unstructured environments. Two such datasets are the FinnForest Dataset [8] and Wild-Places [6]. While they both feature data collected in different seasons and over the course of several months, the included sensor readings are limited. The FinnForest dataset lacks both radar and lidar readings of the environment. Wild-Places, on the other hand, mainly focuses on lidar scans of the environment and similarly lacks radar. Several cameras are recorded, but no matched stereo pairs are provided. These shortcomings motivate the collection of the FoMo dataset, which aims to collect long-term data in a boreal forest over several months, particularly focusing on capturing multi-seasonal changes and the gradual accumulation of snow. A large variety of sensors are considered, including lidar, radar, stereo vision, and IMU data. We specifically envision that the use of radar, often neglected in other datasets,

Name & References	Environment	Application	Camera	Stereo Vision	Lidar	Radar	IMU	GT
Yamaha-CMU Dataset [10]	Shrubland	Segmentation	●	○	●	○	●	Pose (GPS), Segmentation
RELLIS-3D [11]	Shrubland	Navigation, Segmentation	●	800×592	●	○	●	Pose (D-GNSS), Segmentation
Tartandrive [12]	Shrubland, Woods	Learning Dynamics	●	1024×512	●	○	●	Pose (D-GNSS)
Goose Dataset [13]	Grassland, Woods	Multi-Season Segmentation & Perception	●	○	●	○	●	Pose (D-GNSS), Segmentation
BotanicGarden [14]	Grassland, Park	Navigation, Mapping, Segmentation	●	1920×1200	●	○	●	Pose (Map-ICP), Map (Scanner), Segmentation
Oxford Offroad Radar Dataset [15]	Grassland, Lake	Navigation	○	○	○	●	●	Pose (GPS)
Devon Island Dataset [4]	Moon/Mars Analogue	Navigation	●	1280×960	○	○	○	Pose (D-GPS)
Katwijk Beach Dataset [16]	Moon/Mars Analogue	Navigation	●	1024×768 & 1280×960	●	○	●	Pose (GPS)
Mt. Etna Dataset [17]	Moon/Mars Analogue	Navigation	●	1292×964	○	○	●	Pose (D-GPS)
MADMAX Dataset [18]	Moon/Mars Analogue	Navigation	●	1032×772 & 2064×1544	○	○	●	Pose (GNSS)
Chilean Mine Dataset [5]	Mining Tunnel	Navigation	●	1280×960	●	●	○	Pose (Markers & Lidar)
SubT-Tunnel Dataset [19]	Mining Tunnel	Navigation, Mapping	●	2048×1088	●	○	●	Pose (SLAM), Map (Scanner)
Agricultural Dataset [20]	Agricultural	Navigation, Mapping, Plant Class.	●	512×424 (time-of-flight)	●	○	○	Pose (GPS), Map (Scanner), Plant Class. Data
Rosario Dataset [21]	Agricultural	Navigation	●	672×376	○	○	●	Pose (GPS)
SFU Mountain Dataset [22]	Forest	Navigation, Mapping	●	752×480	●	○	●	Pose (GPS), Location Correspondences
Freiburg Forest Dataset [23]	Forest	Segmentation	●	1024×768	○	○	○	Segmentation
Canoe Dataset [24]	River, Forest	Navigation	●	800×600	○	○	●	Pose (GPS)
Montmorency Dataset [9]	Boreal Forest	Navigation, Tree Class.	●	○	●	○	●	Pose (SLAM), Map (SLAM), Tree Class. Data
FinnForest Dataset [8]	Forest	Multi-Season Navigation	●	1920×1200	○	○	●	Pose (GNSS)
USVInland Dataset [25]	Inland Waterways	Navigation, Segmentation	●	640×400 & 1280×800	●	●	●	Pose (GPS), Segmentation
FinnWoodlands Dataset [26]	Forest	Segmentation	●	1280×720	●	○	○	Segmentation
Wild-Places [6]	Forest	Long-Term Navigation, Mapping	●	○	●	○	●	Pose (GPS), Map (SLAM)
FoMo (Ours)	**Boreal Forest**	**Multi-Season Navigation**	●	**1920×1200**	●	●	●	**Pose (GNSS)**

can be advantageous. Unlike lidars and cameras, radar's performance does not degrade in harsh weather conditions, such as heavy snowfall. Compared to lidars, it also offers a longer range of up to 1 km, whereas lidars typically operate within lower hundreds of meters.

III. THE FOMO DATASET

The data will be gathered in the Montmorency Forest located 70 km north of Quebec City, Canada at a latitude of 47°19′15″N and a longitude of 70°9′0″W. The site receives about 900 mm of rainfall and 600 cm of snowfall each year. The snow accumulation height reaches 200 cm in open areas and 100 cm under tree canopy before the onset of snowmelt, which typically occurs at the end of April [36]. The proposed dataset will capture the seasonal changes in a typical example of boreal forests with dense coniferous vegetation, as well as deciduous species, including mostly
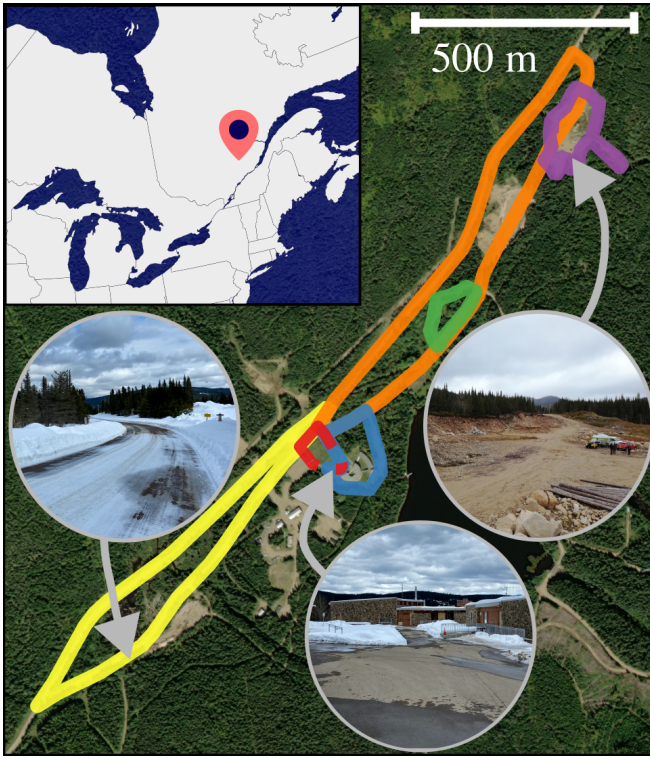
Fig. 2. Satellite image of the Montmorency Forest, our data collection area, located in Quebec, Canada. The six proposed trajectories, overlaying the satellite image, have a combined length of 6 km. In circles, we highlight images from the data collection site.

birches and beeches. We specifically target the changes in the tree canopy, as well as the accumulation of snow.

The planned data recording will start in early fall and continue once per month through winter up to spring, leading to approximately seven recording sessions. We propose six trajectories with varying length and difficulty, shown in Figure 2. The Red and Blue routes are situated in a semi-urban environment near the forest research center. While the Red route has a total length of about 290 m and serves as an entry point to get familiar with the data, the Blue route, with a total length of 540 m, passes through a nearby forest with high snow cover in winter. Similarly, the Green route (350 m long) traverses through a dense boreal forest marked by limited GNSS coverage. The Magenta route enters a stone quarry and has a total length of 730 m. Finally, the Orange and Yellow routes have a path length of around 2000 m. They follow maintained forest roads with good GNSS signal coverage and will be the primary benchmarks of the proposed dataset. In total, the described routes cover 6 km, which leads to 42 km of total length of the dataset. The weather-resistant acquisition platform and proposed sensor configuration are described in the following sections.

A. Acquisition Platform

The acquisition platform, displayed in Figure 1, is a Clearpath Robotics Warthog Uncrewed Ground Vehicle (UGV). The vehicle is equipped with four CAMSO ATV T4S tracks instead of wheels for the proposed dataset. The skid-

steered mobile platform has a differential suspension system. Sufficient power autonomy is achieved with 16 Lithium-Ion battery modules with a total capacity of 7.8 kWh. A custom-built modular sensor frame, detailed in Figure 3, is attached to the robot's chassis. Mounted sensors and their calibration are described in detail in the next sections.

B. Sensor Setup

The proposed dataset will contain data from different proprioceptive and exteroceptive sensors. A ZED X Stereo camera with 1920×1200 resolution and RoboSense RS-32 3D lidar are mounted in front of the robot. A Navtech CIR-304H radar is mounted in the rear, with the Atlans-C navigation grade Inertial Navigation System (INS) underneath it. The Atlans-C uses integrated Real Time Kinematic (RTK) data from the Septentrio global navigation satellite system (GNSS) receiver. Offering multiple types of IMU data, we also include an MTi-10 2A8G4 and a VectorNav VN100 Micro-Electromechanical Systems (MEMS) IMUs. In the rear, a Basler ace2 with a fisheye lens operating at 1920×1200 points downwards. As the robotics community shows increasing interest in multi-modal sensor data, for example as a supplementary input to neural networks, we also include an Audio-Technica ATR4650-USB microphone with a bit rate of 128 kbit s^{-1}, mounted underneath the rear camera, and two Adafruit DPS310 barometric pressure sensors. Precise GNSS position is acquired with four Emlid ReachRS+ receivers. One receiver is static and serves as a reference station while the other three are mounted on the UGV. Detailed sensor specifications can be found in Table II.

TABLE II
SENSOR SPECIFICATIONS.

Sensor Type	Model	Recording Frequency
Lidar	RoboSense RS-32	10 Hz
IMU	MTi-10 2A8G4	100 Hz
IMU	VectorNav VN100	200 Hz
INS	Atlans-C	200 Hz
GNSS	4 × Emlid ReachRS+	5 Hz
Radar	Navtech CIR-304H	5 Hz
Pressure sensor	2 × Adafruit DPS310	100 Hz
Stereo camera	ZED X	10 Hz
Camera	Basler ace2 + Fisheye Lens	10 Hz
Wheel encoders	2 × Hall effect sensors	20 Hz
Microphone	Audio-Technica ATR4650	16 kHz

C. Time Synchronization

The proposed data collection system operates in a distributed manner. For this reason, it is critical to synchronize the clocks on every device. To minimize this discrepancy, the IEEE1588 Precision Time Protocol (PTP) is enabled on the system. The computer is the PTP Grandmaster device because it is directly connected to the GNSS receiver and maintains the most accurate time using the satellites' atomic clock. PTP is capable of synchronizing clocks within a few microseconds [37]. Using PTP with the combination with an GNSS receiver is the current standard, outside of hardware triggering. Hardware triggering is infeasible for this system

due to the additional wiring and compatibility requirements. PTP may require a few minutes to synchronize every clock. As part of the operational procedure, the robot will not record any data for at least five minutes after GNSS lock to allow every device to update to the received time.
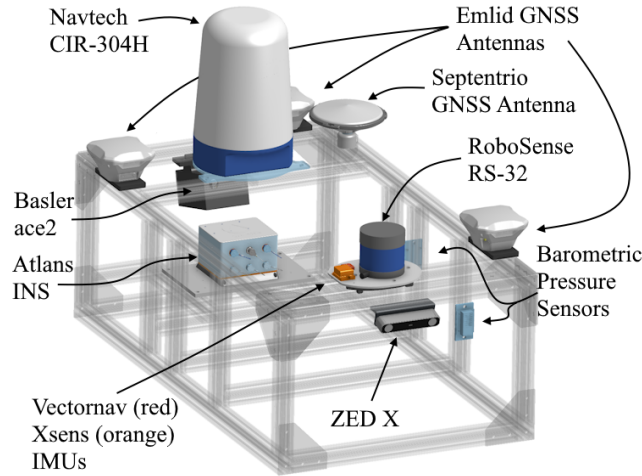

Fig. 3. Rendering of the CAD of the sensor frame, mounted on the UGV. A lidar, a radar, two cameras, two barometric pressure sensors, three IMUs and four GNSS antennas are attached to the frame.

D. Spatial Calibration

The initial calibration estimate is determined from the mounting positions of the sensors in its Computer Aided Design (CAD) model shown in Figure 3. A calibration protocol for each sensor and sensor combination will be closely followed and executed before every deployment day. The calibration data will be provided as part of every recorded sequence in a standard calibration format.

1) Cameras: The intrinsic characteristics of the ZED X are factory-calibrated through an extensive multi-step process. The certified calibration procedure includes thermal measurements. The Basler ace2 camera is calibrated with the ROS2 image_pipeline library.[1] Since the field of view of the Basler camera does not overlap with any other sensor, its position on the mounting system is taken from the CAD model alone.

2) Camera-IMU Calibration: The spatial calibration between the IMUs with respect to the ZED X camera is achieved with the Kalibr library.[2] To allow for a wide range of movements needed for the calibration, the sensor frame is lifted with a crane and manipulated manually to excite all axes of the IMUs. Our calibration target, also used for the intrinsic calibration of the Basler ace2 camera, is a chessboard 765 mm wide and 1000 mm tall.

3) Camera-Lidar Calibration: We employ the open-source calibration technique[3] described by Koide *et al.* [38]

[1]https://github.com/ros-perception/image_pipeline
[2]https://github.com/ethz-asl/kalibr
[3]https://github.com/koide3/direct_visual_lidar_calibration

to find the transformation between the ZED X stereo camera and the RoboSense RS-32 lidar. The method provides a target-less framework, relying instead on the structure of the environment. The calibration will take place in the feature-rich space near the forest research center, depicted in the bottom circle in Figure 2.

4) Lidar-Radar Calibration: The Navtech CIR-304H is a 2D spinning radar. For this reason, only the 3D position and 2D rotation will be estimated. Additionally, because the range resolution of the sensor is 4.4 cm, the CAD model will be used for the translation offset. The assembly tolerances are less than 1 cm, which is unattainable from scan matching with these sensors. To estimate the heading offset between the two sensors, the Iterative Closest Point (ICP) algorithm is used. The lidar point cloud is filtered by using the current estimate of the extrinsic calibration and the beam width to retain only points that could be measured by the radar. The radar's polar power image is converted into a point cloud using the CACFAR method [39]. To ensure that the point clouds contain distinctive geometric features during calibration, this calibration step will occur in a structured environment near the deployment site. Figure 4 visualizes a lidar and extracted radar point clouds overlaid on top of each other.

E. Data Collection

In addition to the data captured by the onboard sensors, the dataset will contain comprehensive meteorological data from a weather station in the Montmorency Forest. The data from the station include temperature and relative humidity measured with an HMP155A probe and barometric pressure obtained from a Vaisala CS106. Both station have a refresh rate of 1 min. We will also include voltage and current readings from the batteries and both drive motors. We recognize the importance of driver annotations of important events and conditions occurring during data recording. These, along with driver IDs and other metadata, will be included with their timestamps for each dataset run.
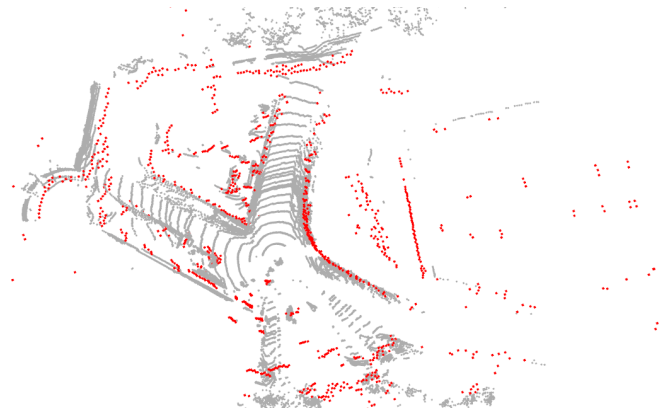

Fig. 4. Lidar point cloud (grey) calibrated against extracted radar point cloud (red) using CACFAR [39] as the extractor.

F. Ground Truth

Given the planned scale of the dataset, it would be practically impossible to supplement it with GT maps. Indeed, seasonal changes would demand repeated scanning of the environment with a survey-grade stationery 3D laser before every deployment. Moreover, heavy snowfall can cause significant changes to the environment, even on a span shorter than some of the proposed trajectories. Since localization and mapping are interconnected problems, and considering the various combinations of sensors provided, we focus our efforts on providing precise GT poses instead of a GT map.

As noted in Section III-B, a static GNSS antenna will be located in an open-sky area. The coordinates of this antenna will be determined with a PPK method in a geodesic coordinates system in the NAD83, MTM zone 7 projection.[4] Data from the three mobile antennas is recorded in the National Marine Electronics Association (NMEA) format, enabling the computation of the full 6-Degrees of Freedom GT trajectories. PPK correction will be applied to the data, as the alternative RTK method is less flexible due to its baseline restrictions and requirement for continuous signal. On the contrary, the PPK method does not require a strong connection between the three antennas on the UGV and the base station, making it particularly suitable for boreal forests. A geodetic pillar or a tripod fixed throughout the data recordings will ensure accurate and reproducible results for the GT.

IV. PROPOSED DATASET USAGE

We envision the primary use of our dataset for 3D odometry and metric localization. Such applications align with other autonomous driving datasets; however, we believe that the multi-seasonal conditions in a boreal forest will challenge established odometry and SLAM pipelines. The recorded data will also present a good opportunity for terrain-based power estimation. Last but not least, the comprehensive recorded data might be useful in diverse tasks, such as semantic segmentation, terrain classification, traversability estimation, and multi-sensor fusion.

V. CONCLUSION AND FUTURE WORK

This paper proposes the FoMo dataset for robot navigation in sub-arctic environments. By repeating the same routes through the fall-winter-spring freeze-thaw cycle, research into autonomy that is robust against significant environmental variation can advance. The FoMo dataset will contain about 6 km of paths at each recording session and 42 km in total. By pairing the sensor data from the UGV with the weather data available at Montmorency Forest, researchers will be able to investigate the effects of ambient weather on the traversability of the terrain. The PPK GNSS ground truth poses will be used for quantitative evaluation of odometry and localization pipelines. We anticipate research that studies each sensor modality individually, as well as sensor fusion approaches. The public leaderboard will be available on the dataset website after the final release.

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