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# LiDAR Odometry and Mapping Beyond RTK Accuracy

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## **Title of the thesis**

# **LiDAR Odometry and Mapping Beyond RTK Accuracy**

## **Topic of the thesis**

Out of the five basic senses that humans use to experience the world, vision accounts for 80% of the information input that our brains operate with [1]. Naturally, robotics research aims to replicate this and develop systems that can not only collect high-quality visual data but also create rich artificial representations of the world, enabling autonomous systems to confidently reason about their environment.

This work will focus on the use of 3D Light Detection and Ranging (LiDAR) sensors in outdoor settings. When mounted on an arbitrary mobile base and moved around a target environment, the sensor collects information about the geometry of the scene, which can be merged in order to create a general 3D model. However, this process depends on accurate displacement measurements that are not trivial to obtain. An existing solution relies on Global Navigation Satellite System (GNSS) localization, corrected using Real-Time Kinematic positioning (RTK), and orientation from an Inertial Measurement Unit (IMU). Together, these create an Inertial Navigation System (INS) whose output can be interpreted as the 3D transformation between sensor poses at discrete time steps. Even though this represents the state-of-the-art technology for outdoor localization, with centimeter-level position error, its accuracy is unsatisfactory when it comes to high-quality pointcloud registration. Additionally, this is not feasible for all outdoor scenes, because GNSS accuracy varies heavily depending on surroundings and signal strength.

We will investigate methods that address the limitations of the INS-based registration, by using the visual information in the scene, such that the system is less reliant on a sensor with fluctuating uncertainty. Previous research in this area [2] indicates that visual cues alone should be enough to achieve reliable displacement estimation, enabling the computation of odometry from LiDAR data, as well as creating a 3D map of the explored environment. A comparison between LiDAR odometry and GNSS localization is also within the scope of this work. The research questions that we aim to answer are the following:

- What metrics exist for measuring the accuracy of pointcloud registration?
- Can methods that use only visual information achieve higher quality pointcloud registration (3D mapping) than RTK-based merging?
- To what extent is LiDAR-based odometry an alternative to GNSS localization?

The work will be carried out in collaboration with Sodex Innovations GmbH, who provide the sensor rig (LiDAR, RGB cameras, GNSS + RTK + IMU) as well as several existing datasets consisting of sensor data collected while exploring outdoor rural environments. The project will span approximately 15 weeks, and is tentatively structured as shown below, subject to change brought by results at different stages.

Stage	Estimated Duration	Description
Introduction	2 weeks	Familiarization with the existing sensors, datasets and related processes
Background investigation	3 weeks	Exploring existing solutions, initial experimentation on available data
Design and Development	4 weeks	Iterative implementation and testing of new approaches
Analysis	4 weeks	Evaluation and comparison between the solutions developed at different iterations
Final write-up	2 weeks	Reporting methods, implementation and results

### **Keywords**

LiDAR odometry, LiDAR mapping, pointcloud registration, GNSS, RTK

### **References**

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# Chapter 1

## Introduction

Like many scientific terms that we encounter in our daily activities, *robotics* describes a broad collection of technologies and stands at the intersection of key research directions. Motivated by practicality, disciplines that appear completely unrelated find themselves building upon advancements in other fields, diluting boundaries and joining forces to enable otherwise-impossible advancements.

What constitutes a *robot*, then? In its inceptive use by Karel Čapek [1] in 1921, the word stemmed from the Slavic *robota*, meaning “servitude” or “forced work”, and referred to a human-like mechanical system working on factory assembly lines. This concept, however, dates from earlier centuries. Around 1495, Leonardo Da Vinci envisioned a mechanical knight controlled by a series of pulleys, that was able to perform simple movements [2]. Testifying to the industrial revolution and the computational breakthroughs of the last few decades, modern-day humanoid robots can perform acrobatics [3], interact with humans in constrained scenarios [4] [5] [6] and even replicate human facial expressions [7]. Still, a device ought not necessarily appear human-like in order for it to be labeled as a robot. Autonomous vacuum cleaners, space rovers or crop-monitoring drones fall under the same category. At this stage, a complete taxonomy would have to address dozens of physical (size, shape, mobility, locomotion system, etc.) and non-physical (autonomy, perception abilities, use-case, etc.) characteristics, and none of these would independently convey the meaning that we intuitively associate to the notion of *robot*. Without assessing whether an exhaustive, generic definition is even possible, we can synthesize the above by affirming that a *robot* is an artificial system that performs one or more tasks and is able to evaluate its state or gather information from its environment.

## 1.1 Robotic perception

This formulation highlights two essential aspects of a robotic agent (Fig. 1.1): actuation, seen as some form of dynamic physical ability, allowing the agent to enact the desired behavior, and perception, the ability to observe changes in the environment.

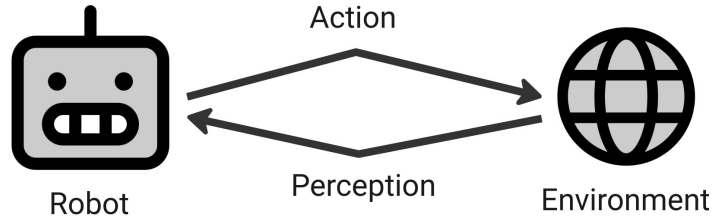


Figure 1.1: A simplified interpretation of the robotics paradigm. The interaction between an agent and its environment can be seen as a two-way flow: the agent alters the environment through its actions, and uses perception to observe it.

Sensing modalities have largely different contributions to the perception mechanism. To this extent, the phrase *visual dominance* was introduced by F. Colavita [8], whose study demonstrated that humans focus more on the visual component when presented with an audiovisual stimulus, and following research has strongly confirmed this tendency [9] [10]. Unsurprisingly, a similar pattern is emerging in the case of robots, thanks to the reduced cost, familiarity and wide availability of cameras. In many situations, visual stimuli provide most of the necessary information, and this has motivated the development of various image processing algorithms.

Technological innovation in the last century has led to the situation in which artificial sensors surpass humans in both the range of signals that are perceived, as well as the accuracy of the measurements. A relevant example is the class of Light Detection and Ranging (LiDAR) sensors which retrieve three-dimensional information about the environment at a very high frequency and with rather negligible measurement errors, in the form of *point clouds* (Fig. 1.2). Among many applications, this type of sensors can be used to construct virtual representations of a specific environment, enabling engineers to experiment with a realistic model, evaluate construction progress or validate a finished project.

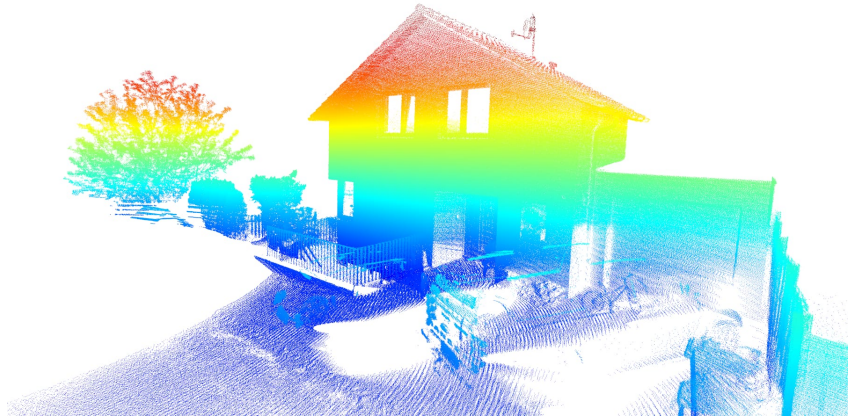


Figure 1.2: An example point cloud (points are colored by height), capturing the 3D representation of an outdoor scene. Multiple individual scans are placed into the same coordinate system to obtain a dense spatial representation.

## 1.2 Problem definition

The current work addresses a common and well-known problem in the area of Field Robotics, namely Simultaneous Localization and Mapping (SLAM), and combines the practicality of an industrial solution with a perception-based approach.

SDX-Compact (Fig. 3.1) is the main product of Sodex Innovations GmbH, consisting of multiple sensors that collect spatial and visual data. This module can be easily mounted on an arbitrary vehicle in order to expand its perception capabilities and convert it into a surveying device. While the vehicle is moving, the LiDAR sensor captures 3D scans of the surroundings, as well as related metadata (timestamps, localization information, signal intensity etc.). Because the rig includes a high-accuracy Inertial Navigation System (INS), the localization and orientation data can be used to join the collected point clouds and create a global 3D map of the traversed space.

Nonetheless, this suffers from two main limitations:

- Reliance on unstable signal: internally, the INS depends on information from a Global Navigation Satellite System (GNSS) receiver, which is limited to outdoor spaces and whose availability varies depending on weather conditions and surroundings (e.g. thick vegetation, tall buildings, bridges).
- Unsatisfactory accuracy: when merging point cloud data, positioning or localization errors introduce inconsistencies in the final 3D model, which hinders precise planning and construction.

Our work aims to address these limitations by introducing a component that utilizes the information collected by the LiDAR sensor in conjunction with the existing data. Three research questions have been formulated to guide this process:

1. What metrics exist for measuring the accuracy of point cloud registration? In this context, registration refers to placing a pair of related point sets in a common reference frame.
2. Can methods that use only visual information achieve higher quality point cloud registration (3D mapping) than merging based on Real-Time Kinematics (RTK)? Usually, GNSS systems provide meter-level accuracy. In the current scenario, however, the system is corrected using Real-Time Kinematics, such that the expected error is at centimeter-level.
3. To what extent is LiDAR-based odometry an alternative to GNSS localization? Previous research indicates that the spatial information present in 3D point clouds could be used to compute the relative displacement between consecutive scans, resulting in the ability to estimate odometry (an essential component of robotic localization) without dedicated sensors such as wheel encoders or accelerometers.

The main contribution of the project consists of developing an original framework for localization and mapping based on data collected with an industrial sensor rig. The results are more generic than if a particular physical robotic system were involved, and thus are relevant for virtually any robotic application with a similar setup.

The following chapters of this document will cover related research directions and efforts that our work builds upon (Chapter 2), a detailed description of the components and algorithms involved in developing the project (Chapter 3), an evaluation of the method based on its results (Chapter 4), as well as a series of conclusions that were drawn from the overall process (Chapter 5).



# Chapter 2

## Background and Literature Review

The goal of this chapter is to present the research context in which our project was conducted, by looking at common methods for each of the main components and highlighting those that inspired the current approach.

### 2.1 Simultaneous Localization and Mapping (SLAM)

SLAM constitutes a key research area in robotics, because it is a foundational building block for autonomous operation. This problem occurs when the robot does not have prior access to a map of the environment, so it must construct one while keeping track of its current position (*online* SLAM). If the goal is to optimize the entire sequence of poses along the robot path, this is known as the *full* SLAM problem. [11]

Usually, the problem is discretized along the time dimension, such that at time  $t$  we aim to compute the posterior function  $p(x_t, M | z_{1:t}, u_{1:t})$ , where  $x_t$  is the current state,  $M$  is the map,  $z_{1:t}$  represents the set of measurements collected so far, and  $u_{1:t}$  the control sequence. As each of these variables can have different concrete representations, depending on the task and the available sensors, a broad range of approaches have been proposed.

Aulinas et al. [12] note that the earliest methods rely on probabilistic models derived from the recursive Bayes rule, as such formulations can provide intuitive representations of the various noisy components involved in a robotic system. When employing the Kalman Filter (KF) [13] or its variations, the robot state, measurements and control inputs are modeled as multi-dimensional Gaussians, whose covariances describe the associated uncertainty. The algorithm alternates between *predictions*, when the state is modified based on  $u_t$ , and *updates*, when the prediction is evaluated against the latest observation  $z_t$ , and the

state hypothesis is updated accordingly. The Extended Kalman Filter (EKF) maintains this structure but can accommodate non-linearities in the displacement or measurement functions by using local linear approximations. Such methods have been successfully applied for indoor [14], aerial [15], and underwater [16] robots.

Particle Filter (PF), introduced by Del Moral [17], is a probabilistic approach that relies on the Monte Carlo method. Instead of an analytical form, the uncertainty is accounted for by considering a large set of samples (representing potential states) and weighting them based on measurement likelihood. This has a higher computational cost than the standard KF methods, but is not affected by any linearization limitations. Nie et al. [18] implemented a LiDAR SLAM algorithm based on PF localization, albeit for 2D mapping.

Another large group of methods is represented by *Visual SLAM*, when cameras are the main (and sometimes only) sensor used. As early as 1980, Moravec [19] developed a robot capable of estimating its motion by matching features in images captured at discrete poses, in a stop-and-go fashion. In 2007, SLAM was being performed using a single handheld camera [20] [21], triggering a separation from the popular, offline, Structure from Motion (SfM) techniques. The solution is even more robust when a stereo system is available [22], as this helps avoid the geometrical limitations of monocular vision.

## 2.2 Point cloud Registration

Before discussing LiDAR-based approaches in more detail, let us review the task of point cloud registration. Given two sets of points  $P, Q$  in arbitrary reference frames, representing (at least partially) the same scene, the goal is to find the transformation  $\mathbf{T} \in \text{SE}(3)$  (translation and rotation) that best aligns the points. This can be expressed as an optimization problem:

$$\underset{\mathbf{T}}{\operatorname{argmin}} J(\mathbf{T}P, Q)$$

where  $J$  is a custom cost function. The particular case where known point correspondences are provided has a closed-form solution [23], but the Iterative Closest Point (ICP) algorithm [24] removes this constraint by alternating between correspondence generation — each point in  $P$  is paired with its nearest neighbor from  $Q$  — and minimizing the point-pair distances. This approach is by far the most widespread, thanks to its simplic-

ity, computational efficiency (e.g., using a k-d tree for closest-point search) and many available variations [25] [26].

Chen and Medioni [27] proposed a “point-to-plane” minimization, while Segal et al. [28] formulated a generalized cost function by considering the probabilistic model underlying the point sets, and implemented a “plane-to-plane” minimization. Other variants modify the point selection strategy [29] [30], apply a weight to each pair [31], prune the set of the correspondences [32] [33] or employ a different minimization algorithm [34].

A different class of solutions operates by discretizing the space into voxels and estimating a normal distribution using the points in each voxel. Introduced in 2003, the Normal Distributions Transform (NDT) [35] algorithm is the main competitor to ICP, enabling registration to be performed without the need for point-to-point correspondences. Magnusson et al. [36] extended this work to 3D scans, and performed a thorough comparison between this and ICP [37] for the challenging task of registering point clouds captured in underground mines, where few usable features are present. More recently, the method has been applied for outdoor mapping [38], and as the basis for a Lidar Odometry and Mapping solution [39].

Neural Networks can also be used for point cloud registration, by creating correspondences based on features extracted by a descriptor architecture [40] [41]. This is particularly useful when no initial estimate of the transformation between the two point sets is available — a scenario that the other approaches cannot directly handle.

## 2.3 LiDAR-based Odometry and Mapping

Despite their high price range, LiDAR sensors have gained significant popularity in the last decade, becoming the go-to solution for autonomous mobility. Unlike cameras, LiDARs are not dependent on ambient lighting, so they can operate in total darkness, and they provide high-frequency, reliable 3D information without the need for additional processing. Basic applications include obstacle detection [42] [43], but the amount of information they provide makes them excellent for localization and mapping purposes.

A key reference is LiDAR Odometry and Mapping (LOAM), the work of Zhang and Singh [44], who used a motorized, 2-axis LiDAR scanner to generate 3D pointclouds. To register consecutive scans, they perform feature extraction (sharp edges or planar patches), identify correspondences to the previous scan, and find the optimal transformation using the Levenberg-Marquardt method. To account for displacement during the

beam sweep, points are reprojected by linear interpolation, assuming constant velocity — this is known as *motion/distortion compensation*. Mapping takes place in parallel, at a slower rate, and the current scan is registered to the map created so far. At that time, this implementation achieved the best results <sup>1</sup> on the KITTI Odometry Benchmark [45]. V-LOAM [46] improved this solution by introducing a visual odometry component based on a fish-eye camera.

A few years later, LeGO-LOAM [47] extended the feature extraction process by performing segmentation on a range image generated from the 3D point cloud. Clusters are filtered by size, in order to discard features belonging to potentially noisy points. Another modification is that the parameters of the transformation between consecutive scans are optimized separately:  $t_z, \theta_{roll}, \theta_{pitch}$  are computed using planar feature correspondences, then fixed during the optimization of  $t_x, t_y, \theta_{yaw}$ , which only uses edge features. The method is compared to LOAM and achieves higher accuracy in outdoor scenarios, while being an order of magnitude faster.

F-LOAM [48] proposes a two-step motion compensation process. For odometry computation, the constant velocity model is used, but the points are re-corrected using the optimized pose before being registered to the map. Correspondences are weighted based on the “local smoothness” of the feature, and the non-linear optimization is solved using the Gauss-Newton method. The map is not updated at every scan, but only when the translational change reaches a predefined threshold. This is a common keyframe selection technique inherited from Visual Odometry.

A slightly different approach introduces the use of inertial sensors, leading to LiDAR-Inertial Odometry (LIO). This aims to compensate for the lack of reliable 3D features in specific environments, as accelerometers can provide satisfactory motion estimates for short displacements. FAST-LIO [49] applies such a technique for a drone equipped with a high-frequency solid-state LiDAR, by performing tightly-coupled fusion: instead of using the IMU output to correct the scan registration, it is applied on the features extracted from the point cloud. COIN-LIO [50] introduces a photometric error component, based on the beam intensity values returned by the LiDAR. A monochrome “intensity image” is constructed and filtered such that matching can occur between consecutive frames, and these new correspondences extend the residual vector that is minimized for odometry computation. The approach achieves state-of-the-art performance on a dataset of

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<sup>1</sup>[https://www.cvlibs.net/datasets/kitti/eval\\_odometry.php](https://www.cvlibs.net/datasets/kitti/eval_odometry.php)

geometrically-degenerate scenes (ENWIDE <sup>2</sup>).

In the class of deep-learning techniques, we highlight Deep Matching LiDAR Odometry (DMLO) [51], which translates the registration problem into a supervised machine learning task. Point clouds are projected into a 2D map using cylinder encoding, with range and intensity values as channels, and a Convolutional Neural Network (CNN) architecture is trained to predict correspondences from pairs of projections. Training samples are constructed from a subset of the target dataset, and the method proves robust across different LiDAR hardware, but does not surpass LOAM on the KITTI sequences. In comparison to [52], this solution does not leave the geometric problem to the inner workings of the CNN.

The approach that our work draws most inspiration from is KISS-ICP [53], a LiDAR-only odometry framework built around point-to-point ICP. This method proposes a few modifications that cooperate towards a hardware-agnostic solution, with a small number of adjustable parameters. The first contribution is a constant velocity motion estimation, which provides the optimization step with an initial guess. The same motion estimation is used for distortion compensation. Secondly, feature extraction is replaced by two stages of voxel-based down-sampling: the first down-sampled point cloud is used to extend the map, while the even lower-resolution set is registered against the existing map to compute the pose estimate. Perhaps the key component is an adaptive distance threshold for correspondence outlier removal. This threshold is updated based on the deviation between the predicted and optimized pose, acting as a form of uncertainty estimation. Additionally, the optimization problem employs a robust kernel, whose scale parameter is related to the adaptive threshold.

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<sup>2</sup><https://projects.asl.ethz.ch/datasets/enwide>

# Chapter 3

## Methodology

This chapter will address the core contributions of our project. We present the hardware involved in sensor fusion, describe the data acquisition procedure, then introduce our final solution, by detailing the research and implementation process, as well as design decisions that had to be made along the way.

### 3.1 Hardware

In this context, hardware refers to the set of sensors used for data collection, determined by the existing industrial setup. The data capturing system is controlled by an Nvidia Jetson board, which operates as a middle-man for time synchronisation between the sensors, and coordinates the various data streams. Even though the solution was designed such that it does not inherently rely on any particular device, the relationship between hardware capabilities, data quality and final output makes it crucial to understand the sensors involved in the process. Beyond the components described below, the setup includes three industrial grade ArkCam Basic+ wide angle cameras which provide a 1920x1080 RGB stream over Ethernet. These are not utilised within this project, but represent a noticeable motivation for future work directions.

#### 3.1.1 LiDAR Sensor

The SDX-Compact (Fig. 3.1) is equipped with a Pandar XT32 [54] LiDAR sensor, manufactured by Hesai Technology. This is a mechanical rotating LiDAR with a full 360° horizontal field of view and 32 beams distributed vertically, at 1° resolution. With our settings, the sensor produces 10 complete scans per second, resulting in a horizon-

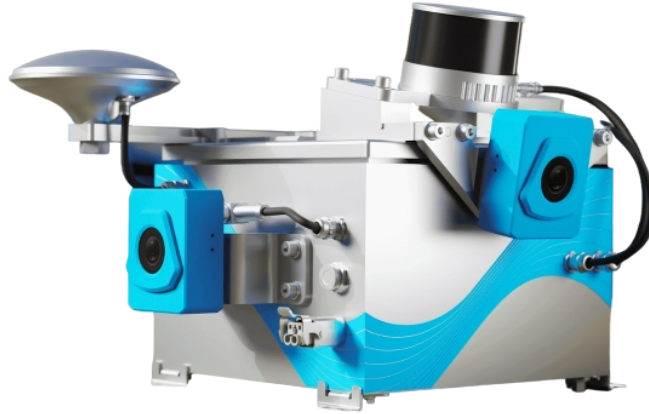


Figure 3.1: The SDX-Compact manufactured by Sodex Innovations GmbH. The set of sensors consists of a 3D LiDAR scanner, three RGB cameras and a high-accuracy positioning system. Image source: GeoLanes

tal resolution of  $0.18^\circ$ . The maximum operational range is 120m, decreasing to 50m for low-reflectivity targets. The official specifications state a typical accuracy of  $\pm 1\text{cm}$ , with precision  $\pm 0.5\text{cm}$ , in a static environment. For each beam, the strongest return is processed, leading to 640,000 points being generated per second. The high output bandwidth is handled by an Ethernet connection, over which points are sent as UDP packets. The sensor also supports PTP synchronisation, essential for high-quality sensor fusion.

The same device has been used for LiDAR odometry applications in the past [55], and has similar specifications to other popular scanners, such as Velodyne VLP-32C, Ouster OS1-32 or Robosense Helios 32.

### 3.1.2 GNSS/INS receiver

Another component of the sensor stack is the Septentrio AsteRx SBi3 Pro+ GNSS/INS receiver [56], which provides global positioning and orientation data at a rate of 100Hz. Internally, this relies on two distinct mechanisms.

The localization information comes from a dual antenna GNSS module compatible with several GNSS constellations (e.g., GPS<sup>3</sup>, GLONASS, Galileo), to ensure optimal worldwide coverage. In standalone mode, the advertised typical accuracy is 1m, but the receiver also acts as an NTRIP (a protocol for differential GPS) client, gathering correction information, in order to achieve centimeter-level accuracy.

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<sup>3</sup>Throughout this paper, GNSS and GPS are used interchangeably to refer to the global localization sensor, regardless of the underlying satellite system used during data collection.

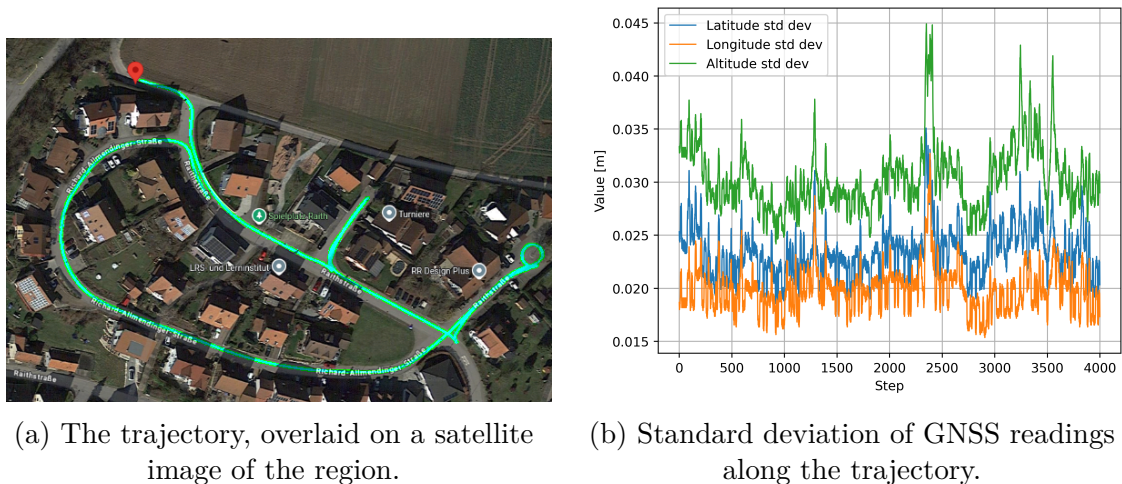


Figure 3.2: An example dataset collected in rural Germany (Lienziegen).

An Inertial Measurement Unit (IMU) module records acceleration data and provides the remaining orientation angles (roll, pitch, yaw) to compute the complete pose, in 6 Degrees of Freedom (DoF). This is integrated with the absolute GNSS measurements using the patented FUSE+ technology [57], resulting in an orientation error below 5-10°.

Like any system reliant on satellite communication, this will suffer significantly in situations where the signal propagation is disturbed (heavy clouds, “urban canyons”, thick vegetation, spoofing), even leading to loss of *GNSS fix*.

To conclude this section, we recognize and underline the importance of accurate extrinsic calibration between the LiDAR and the local INS coordinate frame, which has to be performed prior to any reliable data collection procedure. Given the radically different modalities of these two sensors, this is not a trivial task [58] and lies outside the scope of the current work.

## 3.2 Data acquisition and pre-processing

Data is collected by mounting the sensor rig on the roof of a vehicle, and driving around a target area at a relatively low speed (e.g., up to 40km/h). (Fig. 3.2) In comparison with other public datasets [59] [60], capturing data in non-urban environments introduces some challenges — scenes dominated by vegetation, with few identifiable features, uneven terrain — while minimizing others — negligible amount of dynamic objects, no tall buildings that could affect GNSS signal propagation.

The raw sensor output is uploaded to a cloud storage facility, and is later processed into *data frames* that fuse the available information (Fig. 3.3). This can occur because



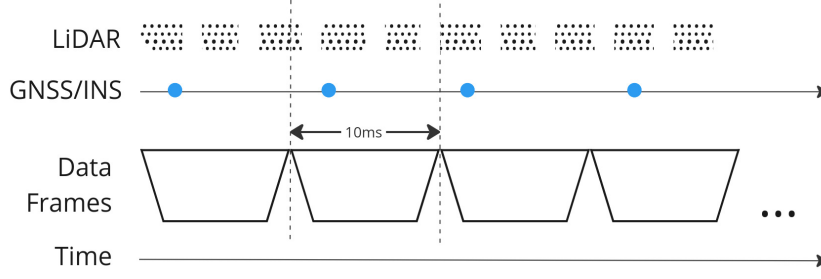


Figure 3.3: The data synchronisation process.

Time is discretized into fixed-size intervals, resulting in data frames of custom resolution.

These are populated with information from the two sensors: LiDAR points arrive in groups, as UDP packets, while GNSS readings have a frequency of approx. 100Hz. We employ a data frame size of 10ms to ensure that each interval has an associated GNSS measurement, and place all corresponding packets in the same data frame.

the sensors are PTP-synchronized on initialization, and all recorded data is timestamped.

The next pre-processing step consists of dividing the sequence of data frames such that we operate on individual scans (also known as sweeps) produced by the LiDAR. A scan corresponds to a complete  $360^\circ$  rotation, which takes 100ms, so we join the points in 10 consecutive data frames to obtain a single scan.

Every INS reading undergoes a map projection, to obtain  $x, y, z$  coordinates in the East-North-Up frame. We consider the frame of the GNSS receiver as the *ego* coordinate system. The roll  $\phi$ , pitch  $\theta$  and yaw angles  $\psi$  determine the absolute orientation, so we compute a global pose  ${}^W\mathbf{T}_{ego} \in \text{SE}(3)$  as:

$${}^W\mathbf{T}_{ego} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix} = \text{Translation}(x, y, z) \cdot \text{Rot}_z(\psi) \cdot \text{Rot}_x(\theta) \cdot \text{Rot}_y(\phi)$$

where  $\text{Rot}_k(\alpha)$  is the transformation matrix corresponding to a rotation of  $\alpha$  around axis  $k$ . Because the sensor provides error estimates in the form of global one-sigma values  $\{\sigma_x, \sigma_y, \sigma_z, \sigma_\phi, \sigma_\theta, \sigma_\psi\}$ , we construct the covariance matrix

$$\Sigma = \text{diag}(\sigma_x^2, \sigma_y^2, \sigma_z^2, \sigma_\phi^2, \sigma_\theta^2, \sigma_\psi^2)$$

and transform it using the adjoint map of the rotation component

$$\Sigma_{ego} = \text{Adj}(\mathbf{R}, \mathbf{0}) \cdot \Sigma \cdot \text{Adj}(\mathbf{R}, \mathbf{0})^T$$

where

$$\text{Adj}(\mathbf{R}, \mathbf{t}) = \begin{bmatrix} \mathbf{R} & \mathbf{0} \\ [\mathbf{t}]_\times \mathbf{R} & \mathbf{R} \end{bmatrix} \text{ and } [\mathbf{t}]_\times = \begin{bmatrix} 0 & -t_3 & t_2 \\ t_3 & 0 & -t_1 \\ -t_2 & t_1 & 0 \end{bmatrix}$$

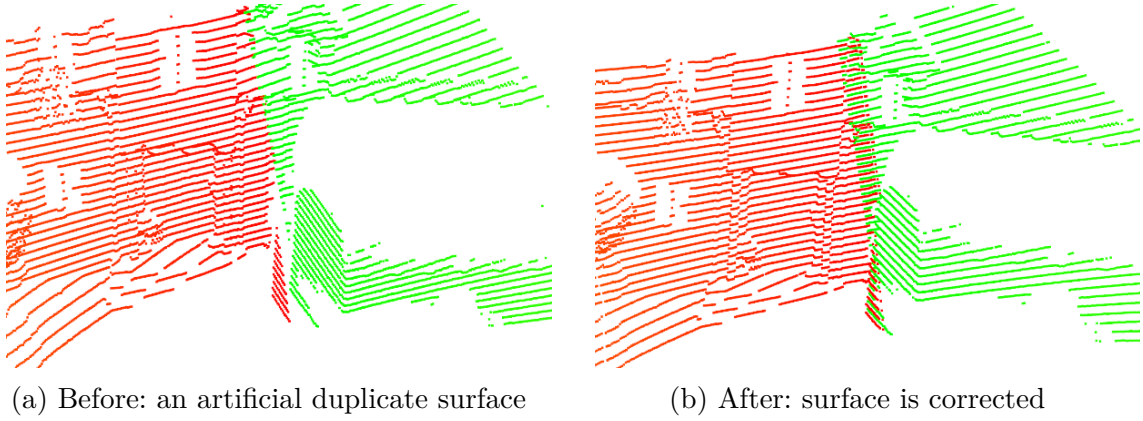


Figure 3.4: Motion artifacts and the result of motion compensation.

Green: points from the beginning of the sweep. Red: points from the end of the sweep. Without motion compensation, the vertical surface yields two conflicting clusters, so the scan cannot be used for accurate mapping in the global frame.

A LiDAR range reading  $r$ , captured at azimuth  $\alpha$  with an elevation angle of  $\phi$ , can be converted to a 3D location in the LiDAR frame:

$$\text{LiDAR} \mathbf{p} = \begin{bmatrix} p_x \\ p_y \\ p_z \end{bmatrix} = \begin{bmatrix} r \cos \phi \sin \alpha \\ r \cos \phi \cos \alpha \\ r \sin \phi \end{bmatrix}$$

If  ${}^{ego}\mathbf{T}_{\text{LiDAR}}$  is the pose of the LiDAR in the ego frame (from extrinsic calibration), we can compute the location of a point in the ego frame:

$$\begin{bmatrix} {}^{ego}\mathbf{p}_{\text{LiDAR}} \\ 1 \end{bmatrix} = {}^{ego}\mathbf{T}_{\text{LiDAR}} \begin{bmatrix} \text{LiDAR} \mathbf{p} \\ 1 \end{bmatrix}$$

At this stage, it is worth discussing the distortion effect that occurs when a rotating LiDAR sensor is moved at a relatively high velocity. Because it operates in a relative coordinate frame and different beams of the sweep are fired at different times, the beams corresponding to azimuth  $0^\circ$  will fire approximately 100ms earlier than the beams corresponding to azimuth  $359^\circ$ . Placing the resulting points in the same coordinate frame would lead to undesired artifacts, such as duplicate or warped structures. (Fig. 3.4a)

This open research problem [61] is commonly addressed by estimating the sensor pose change during a sweep [62] [53], and IMU integration proves satisfactory [63], given the short time interval involved. In our case, the ego poses  $\{{}^W\mathbf{T}_{i,0}, {}^W\mathbf{T}_{i,1}, \dots, {}^W\mathbf{T}_{i,m}\}$  computed from INS measurements during sweep  $i$  are used to bring all points into the frame defined by  ${}^W\mathbf{T}_{i,0}$ . A point  ${}^{i,k}\mathbf{p}$  belongs to data frame  $k$ , so it will be replaced by:

$$\begin{bmatrix} {}^{i,0}\mathbf{p} \\ 1 \end{bmatrix} = {}^{i,0}\mathbf{T}_{i,k} \begin{bmatrix} {}^{i,k}\mathbf{p} \\ 1 \end{bmatrix} = ({}^W\mathbf{T}_{i,0})^{-1} {}^W\mathbf{T}_{i,k} \begin{bmatrix} {}^{i,k}\mathbf{p} \\ 1 \end{bmatrix}$$

We also experimented with approaches that do not rely on the absolute pose measurements for subsections of the sweep, such as interpolation using point timestamps or point indices (based on the order in which the points are returned), but these did not yield better results. A potential drawback of our method is that it disregards the localization noise, which could prove counterproductive if the GNSS receiver has low accuracy.

Through this step we are effectively removing the need for sub-scan information and creating a simpler data structure in which each scan is associated a single  ${}^W\mathbf{T}_{ego}$  pose (from the first data frame), and the points in a sweep can be treated as a unified set.

Without loss of generality, we transform the sequence of global poses  $\{{}^W\mathbf{T}_0, {}^W\mathbf{T}_1, \dots, {}^W\mathbf{T}_n\}$  into the frame of the first pose, by multiplying each pose with  $({}^W\mathbf{T}_0)^{-1}$ , to obtain  $\{\mathbf{T}_0, \mathbf{T}_1, \dots, \mathbf{T}_n\}$ . Naturally,  $\mathbf{T}_0$  will always be  $\mathbf{I}_4$ , which simplifies the initialization of the odometry estimation. The covariance of each pose is adjusted with the adjoint of  $({}^W\mathbf{T}_0)^{-1}$ .

### 3.3 Solution architecture

At its core, the odometry and mapping solution that we propose requires minimal input: a sequence of point clouds captured by a moving LiDAR scanner, and a timestamp for each scan. If available, absolute localization/INS measurements can be used as additional input.

Let  $\mathfrak{P} = \{P_0, P_1, \dots, P_n\}$  represent the set of point clouds that we operate on, with point coordinates  $P_k = \{\mathbf{p}_{k,i} | \mathbf{p}_{k,i} \in \mathbb{R}^3\}$  expressed in the local frame,  $\mathfrak{s} = \{s_0, s_1, \dots, s_n\}$  the corresponding timestamps, and  $\hat{\mathfrak{T}} = \{\hat{\mathbf{T}}_0, \hat{\mathbf{T}}_1, \dots, \hat{\mathbf{T}}_n\}$  the ground truth poses at which each scan was captured. In an ideal setting, a point cloud registration algorithm would take  $P_i$  and  $P_{i+1}$  as input and return the transformation  $\Delta\hat{\mathbf{T}}_i = \hat{\mathbf{T}}_i^{-1}\hat{\mathbf{T}}_{i+1}$ , i.e., the ground truth displacement between consecutive poses. This would correspond to a perfect odometry model, and the complete trajectory could be reconstructed by accumulating the computed displacement. Unfortunately, with the exception of some simulation environments, such an approach is not actually feasible. As we have already seen, LiDAR output is not perfect, especially in dynamic scenes, and some scenarios are simply unsuitable for odometry estimation based on 3D features [64].

The output of our solution can be formulated as  $\mathfrak{T} = \{\mathbf{T}_0, \mathbf{T}_1, \dots, \mathbf{T}_n\}$ . Pose  $\mathbf{T}_k \in \text{SE}(3)$  represents the estimated location and orientation of the *ego* frame from which the points  $P_k$  were observed. The complete *map* estimate, represented as a larger point cloud in global coordinates, is the set of all points, each transformed according to their respective pose:

$$M(\mathfrak{T}, \mathfrak{P}) = \left\{ \mathbf{p}_{k,i}^* \mid \begin{bmatrix} \mathbf{p}_{k,i}^* \\ 1 \end{bmatrix} = \mathbf{T}_k \begin{bmatrix} \mathbf{p}_{k,i} \\ 1 \end{bmatrix}, \mathbf{p}_{k,i} \in P_k, k \in \overline{0 \dots n} \right\}$$

This uncovers two possible evaluation directions, which also constitute the high-level aims of our method. On one hand, the output trajectory  $\mathfrak{T}$  should match the actual path of the system as accurately as possible. On the other, the final map  $M(\mathfrak{T}, \mathfrak{P})$  should not hide or damage small details in the scene, to obtain a high-quality 3D reconstruction. Although not immediately obvious, these can result in conflicting requirements, but they anticipate an underlying optimization problem.

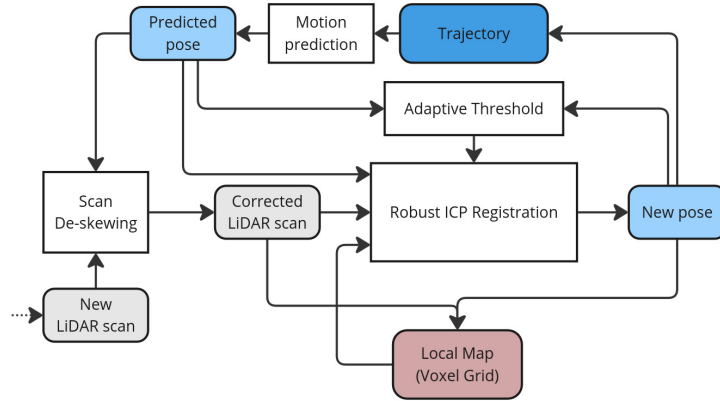


Figure 3.5: The KISS ICP pipeline.

An incoming scan is motion-compensated using the displacement between the previous estimated poses, then it is downsampled and registered against the local map. The pose estimated by the ICP algorithm is added to the trajectory, and the adaptive threshold is updated by evaluating the accuracy of the motion estimation. This determines the ICP outlier removal threshold, improving the system’s ability to react to unexpected motions.

### 3.3.1 Overview

The final architecture is the result of a series of experiments. The process began with a LiDAR-only framework, immitating the KISS-ICP [53] implementation. (Fig. 3.5) In this approach, scans are processed sequentially, attempting to compute the optimal pose at each step, and the map is built incrementally. This is computationally efficient and becomes essential when a robot operates in an unknown environment, as it provides

the best localization estimates at any given time. In the absence of absolute positioning information, however, this diverges from the ground-truth trajectory (Fig. 3.6), creating a distorted map.

Early efforts focused on introducing the GPS readings as a constraint at each step, alongside motion prediction and registration results. This led to experimenting with each component, as well as methods for combining the respective poses, while regularly monitoring the quality of the output trajectories and maps. As the solution was developed, it was additionally tested on more challenging scenarios, by adding artificial noise to the GPS readings, or skipping some of them altogether.

Later on, we also considered addressing the pose estimation problem holistically, instead of in an incremental fashion, and experimented with architectures based on factor graph optimization, where nodes are linked using registration and GPS constraints. The same building blocks are needed, but the relationship between them is guided by the graph paradigm. Eventually, this was adapted to obtain a hybrid solution, which combines the advantages of the two frameworks in a very intuitive manner.

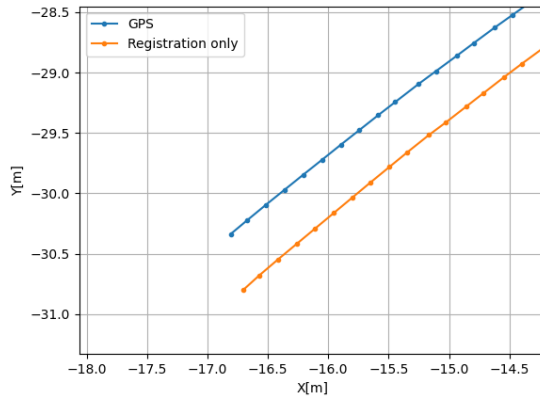


Figure 3.6: When the GPS information is not used, the trajectory computed based on LiDAR data diverges. Here, after 300 scans (approx. 30 seconds), the last location is approx. 0.5m away from the corresponding GPS position.

### 3.3.2 Reconciling motion prediction, GNSS and registration

Before discussing the components in detail, we would like to provide a general picture of the rationale behind combining the pose estimates that we operate on. We assume that for every scan  $P_k$  we can compute three poses in the world frame, and aim to generate  $\mathbf{T}_k$  as a function of these:

1. A registration-predicted pose  $\mathbf{T}_k^{\text{ICP}}$ , from a point cloud registration method that optimizes map alignment between scans in the global frame.

2. An absolute localization pose  $\mathbf{T}_k^{\text{GPS}}$ , generated by the INS sensor.
3. A motion-predicted pose  $\mathbf{T}'_k$ , output by the algorithm described in section 3.3.3.

Each of these serves a different purpose: using only  $\mathbf{T}_k^{\text{ICP}}$  would lead to a high-quality 3D map, while diverging from the actual locations;  $\mathbf{T}_k^{\text{GPS}}$  estimates the absolute position and orientation, but its accuracy varies depending on the environment; the  $\mathbf{T}'_k$  pose can help filter out noise in the GNSS data and smoothen the trajectory, but comes from a motion prediction mechanism that cannot operate in the absence of other sensors.

In an initial trial, we observed what happens when the GPS pose is used in the initialization step of the registration algorithm, with the intuition that this could prevent trajectory divergence without significantly affecting map quality. However, this leads to an unwanted behavior. At first, the registration is not affected by the input pose, converging to the pure  $\mathbf{T}_k^{\text{ICP}}$ . As the map grows, the divergence is not constrained, so it reaches the stage where a  $\mathbf{T}_k^{\text{GPS}}$  pose is a very poor initial guess for registration, which gets stuck in a local minimum. Depending on the displacement between scans and the nature of the 3D scenes, this can even happen after just a few scans.

A subsequent idea was to treat  $\mathbf{T}_k^{\text{ICP}}$  as a local refinement for  $\mathbf{T}_k^{\text{GPS}}$ , by applying an interpolation mechanism, as defined in Equation 3.1. If  $\mathbf{T}_k = \varphi(\mathbf{T}_k^{\text{GPS}}, \mathbf{T}_k^{\text{ICP}}, \alpha)$ , the interpolation parameter  $\alpha$  controls how much the registration pose is allowed to alter the GPS prior — when  $\alpha = 1$ , we obtain the pure registration-based trajectory. This approach can prevent trajectory divergence while improving map quality, for small values of  $\alpha$ , e.g., 0.1, but because  $\alpha$  is fixed, it does not address the problem of varying GPS noise or faulty registration results.

This can also be formulated as an optimization problem, by defining

### 3.3.3 Motion prediction

The first component that we analyse addresses the problem of predicting the next pose in the trajectory. Given the trajectory computed so far  $\{\mathbf{T}_0, \mathbf{T}_1, \dots, \mathbf{T}_t\}$ , we are looking for  $\mathbf{T}'_{t+1}$  that estimates the location and orientation of scan  $P_{t+1}$  in the world frame.

This influences two other elements of the framework: motion compensation and point cloud registration. In the absence of IMU data, the displacement between consecutive scans can be interpolated to correct individual points. Point cloud registration uses this predicted pose as an initial guess, for faster convergence, as we will see in a later section.

If the scans are captured at small, equal intervals, as is usually the case for LiDAR sensors, the movement can be approximated by a constant velocity model. The displacement between the previous two scans is propagated using  $\Delta \mathbf{T}'_t \approx \Delta \mathbf{T}_{t-1} = \mathbf{T}_{t-1}^{-1} \mathbf{T}_t$ , which leads to  $\mathbf{T}'_{t+1} = \mathbf{T}_t \Delta \mathbf{T}_{t-1}$ . In our case, the time steps are not necessarily equal, and we would like to correct this pose estimate using the GPS measurements, when available, so we experimented with a Kalman Filter for computing the location component of  $\mathbf{T}'_{t+1}$ . The state  $\mathbf{x}_k \sim \mathcal{N}(\bar{\mathbf{x}}_k, \mathbf{P}_k)$  is formulated as:

$$\begin{aligned}\bar{\mathbf{x}}_k &= [x_k, y_k, z_k, v_{x_k}, v_{y_k}, v_{z_k}]^T \\ \mathbf{P}_k &= \text{diag}(\sigma_{x_k}^2, \sigma_{y_k}^2, \sigma_{z_k}^2, \sigma_{v_{x_k}}^2, \sigma_{v_{y_k}}^2, \sigma_{v_{z_k}}^2)\end{aligned}$$

Over a time step  $\Delta t$ , this changes according to a linear model:

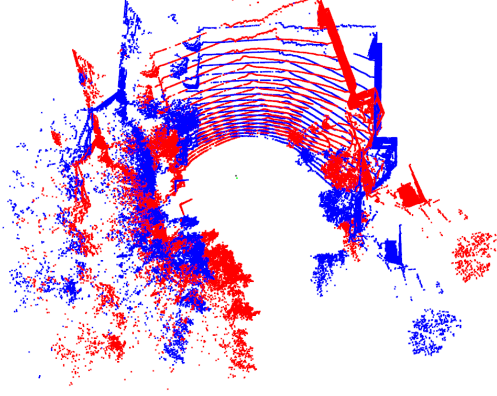
$$\begin{aligned}\hat{\bar{\mathbf{x}}}_{k+1} &= \mathbf{F}(\Delta t) \cdot \bar{\mathbf{x}}_k \\ \hat{\mathbf{P}}_{k+1} &= \mathbf{F}(\Delta t)^T \cdot \mathbf{P}_k \cdot \mathbf{F}(\Delta t) + \mathbf{Q}(\Delta t)\end{aligned}$$

where  $\mathbf{F}(\Delta t) = \begin{bmatrix} \mathbf{I}_3 & \mathbf{I}_3 \Delta t \\ \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix}$  and  $\mathbf{Q}(\Delta t)$  is the estimated process noise, which scales with the time interval. In the update step, we compute the new mean and covariance using a measurement  $\mathbf{z}_k \sim \mathcal{N}(\mathbf{z}_k, \mathbf{R})$ , by applying a Kalman gain:

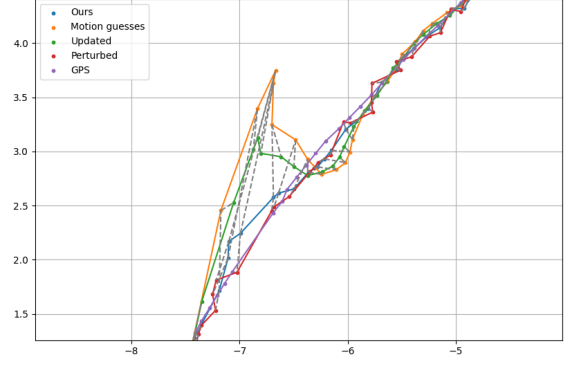
$$\begin{aligned}\mathbf{K} &= \hat{\mathbf{P}}_{k+1} \mathbf{H} (\mathbf{H} \hat{\mathbf{P}}_{k+1} \mathbf{H}^T + \mathbf{R})^{-1} \\ \bar{\mathbf{x}}_{k+1} &= \hat{\bar{\mathbf{x}}}_{k+1} + \mathbf{K} (\mathbf{z}_k - \mathbf{H} \hat{\bar{\mathbf{x}}}_k) \\ \mathbf{P}_{k+1} &= (\mathbf{I} - \mathbf{K} \mathbf{H}) \hat{\mathbf{P}}_{k+1}\end{aligned}$$

The  $\mathbf{z}_k$  vector consists of a location  $[x_{\text{GPS}}, y_{\text{GPS}}, z_{\text{GPS}}]^T$  and velocity values  $\frac{1}{\Delta t} [x_{\text{GPS}} - x_k, y_{\text{GPS}} - y_k, z_{\text{GPS}} - z_k]^T$ , assuming linear displacement. The Jacobian  $\mathbf{H}$  with respect to the state vector is  $\mathbf{I}_6$ , and the covariance of the measurement noise  $\mathbf{R}$  can be estimated using the covariance of the GNSS reading. If no GNSS reading is associated with the current scan, the pose estimate is retrieved from the predicted position  $\hat{\bar{\mathbf{x}}}_{k+1}$ , and the update step is performed based on the pose computed after the registration procedure.

This type of motion prediction method suffers from several disadvantages which outweigh its benefits for our use case. Firstly, it does not address the rotation component of the poses. Some possible workarounds include copying the orientation from the previous pose and letting the registration component correct that — this has been observed



(a) Registration failure case, when the rotation between consecutive scans (red and blue) is estimated incorrectly. The ICP algorithm converges to an erroneous local minimum.



(b) If the motion model is too confident in its velocity estimate, or uneven time intervals are not handled correctly, the motion prediction will overshoot. Trajectory starts from bottom.

Figure 3.7: Challenges of using a Kalman Filter motion model.

to fail when a larger time gap occurs, especially for curved trajectories (Fig. 3.7a) —, using the rotation returned by the INS, or having a separate method for computing the new rotation. Secondly, it introduces the need for reliable noise estimation (Fig. 3.7b), such that the model is reactive to unexpected movement, while filtering out measurement noise. Process noise covariance  $\mathbf{Q}(\Delta t)$  and the measurement input covariance  $\mathbf{R}$  require approximations which are difficult to balance for a general solution. Therefore, using the estimated uncertainty of the predicted pose in further computations would only propagate potential sources of error.

The approach that we propose relies on the differential properties of the  $\text{SE}(3)$  manifold. For any  $\mathbf{M} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \in \text{SE}(3)$ , there is a corresponding twist  $\hat{\xi} = \begin{bmatrix} [\mathbf{w}]_{\times} & \mathbf{v} \\ \mathbf{0}^T & 1 \end{bmatrix} \in \mathfrak{se}(3)$  which can be computed through the logarithmic map  $\hat{\xi} = \log(\mathbf{M}) := \begin{bmatrix} \mathbf{V}^{-1}(\mathbf{w})\mathbf{t} \\ \text{Log}_{\text{SO}}(\mathbf{R}) \end{bmatrix}$ , where  $\mathbf{V}(\mathbf{w}) = \mathbf{V}(\theta\mathbf{u}) := \mathbf{I}_3 + \frac{1-\cos\theta}{\theta} [\mathbf{u}]_{\times} + \frac{\theta-\cos\theta}{\theta} [\mathbf{u}]_{\times}^2$ . The inverse operation, the exponential map, is defined as  $\mathbf{M} = \exp(\hat{\xi}) := \begin{bmatrix} \text{Exp}_{\text{SO}}(\mathbf{w}) & \mathbf{V}(\mathbf{w})\mathbf{v} \\ \mathbf{0} & 1 \end{bmatrix}$ .  $\text{Log}_{\text{SO}}()$  and  $\text{Exp}_{\text{SO}}()$  are the logarithmic and exponential maps that convert between  $\mathbf{w} \in \mathbb{R}^3$  and  $\mathbf{R} \in \text{SO}(3)$ . All of this allows the introduction of an interpolation function, with a parameter  $t \in [0, 1]$ :

$$\varphi(\mathbf{M}_1, \mathbf{M}_2, \alpha) := \mathbf{M}_1 \exp(\alpha \cdot \log(\mathbf{M}_1^{-1} \mathbf{M}_2)) \quad (3.1)$$

In our case, using  $\mathbf{T}_{t-1}$  and  $\mathbf{T}_t$  to compute  $\mathbf{T}'_{t+1}$  is actually a matter of extrapolation,



because we expect  $\alpha$  to be approximately 2 at most steps, which would lead to unstable behaviour in the Lie group transformation. To avoid this, we first compute  $\mathbf{T}_{t+1}'' = \mathbf{T}_t \mathbf{T}_{t-1}^{-1} \mathbf{T}_t$ , and then obtain  $\mathbf{T}_{t+1}' = \varphi\left(\mathbf{T}_t, \mathbf{T}_{t+1}'', \alpha_t - 1\right)$ , where  $\alpha_t = \frac{s_{t+1} - s_{t-1}}{s_t - s_{t-1}}$ .

# Chapter 4

## Results

## Chapter 5

## Conclusion

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# Acronyms

**CNN** Convolutional Neural Network.

**DoF** Degrees of Freedom.

**EKF** Extended Kalman Filter.

**GLONASS** Global Navigation Satellite System (Russian).

**GNSS** Global Navigation Satellite System.

**GPS** Global Positioning System.

**ICP** Iterative Closest Point.

**IMU** Inertial Measurement Unit.

**INS** Inertial Navigation System.

**KF** Kalman Filter.

**LiDAR** Light Detection and Ranging.

**LIO** LiDAR-Inertial Odometry.

**LOAM** LiDAR Odometry and Mapping.

**NDT** Normal Distributions Transform.

**PF** Particle Filter.

**PTP** Precision Time Protocol.

**RTK** Real-Time Kinematics.

**SLAM** Simultaneous Localization and Mapping.

**UDP** Universal Datagram Protocol.

# Glossary

**Field Robotics** The area of robotics that focuses on robots operating in unstructured outdoor environments for tasks like agriculture or exploration.

**GNSS fix** The desirable situation in which a connection to the satellite system is established, such that live localization information can be transmitted.

**k-d tree** A data structure for organizing entries in a  $k$ -dimensional space using a tree structure. When  $k$  is not very large, it provides logarithmic look-up time.

**keyframe** An image frame or 3D scan that is used for odometry estimation. Because modern sensors usually operate at higher frequencies than needed for most algorithms, it is a reasonable decision to skip frames based on a predefined pattern or condition, without sacrificing accuracy.

**odometry** The process of computing relative displacement of a robot using on-board sensors.

**point cloud** A set of point coordinates obtained as the output of a scanning sensor.

**registration** The process of aligning multiple point clouds in a single coordinate system such that matching features are as close as possible.

**sensor fusion** The process of combining information from multiple sensors, to augment the knowledge about the environment and increase the level of autonomy.

**Structure from Motion (SfM)** The task of reconstructing a 3D scene and a sequence of camera poses from a set of images.

**surveying** The work of examining and recording the area and features of a piece of land in order to construct a map, plan, or detailed description thereof.

**voxel** A cuboid-shaped region in 3D space; a 3D cell.