Autonomous Robotic System for Power Cable Tracking and Mapping Using Hybrid Localization in GPS-Denied and GPS-Rich Environments

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Abstract— **Accurate underground power cable mapping is essential for infrastructure maintenance and fault detection. However, traditional GPS-based localization is unreliable in GPS-denied environments, necessitating alternative localization strategies. This paper presents an autonomous robotic system that employs a hybrid localization framework, integrating RTK-GPS for outdoor positioning and ORB-SLAM3 for visual-based localization in GPS-denied environments. The system features a cable locator sensor for real-time power cable detection, while a human-in-the-loop GUI enables manual GPS corrections to mitigate positioning errors. The ORB-SLAM3 based localization module is integrated with GPS-based localization to ensure mapping consistency across varying operational conditions. Real-world experiments validate the system's capability to accurately track and map power cables in both GPS-rich outdoor areas and GPS-denied environments, demonstrating the effectiveness of this hybrid localization approach for robotic infrastructure inspection and maintenance.**

I. INTRODUCTION

The rapid advancements in robotics, automation, and artificial intelligence (AI) are accelerating the adoption of autonomous systems across industries, streamlining complex and labor-intensive tasks. Robotic solutions now play a crucial role in warehouse automation [1], [2], construction [3], [4], and robotic manipulation [5], [6]. In the utility sector, autonomous robotic systems are increasingly employed for infrastructure inspection [7] and maintenance [8], enhancing efficiency and operational reliability.

As urban landscapes expand, large-scale underground infrastructure—such as water pipelines and power distribution networks—becomes essential. Accurate mapping of these assets is critical for proactive maintenance, fault detection, and minimizing service disruptions. However, GPS-based localization struggles in dense urban environments, tunnels, and indoor spaces due to multipath effects and signal attenuation. While standard GPS provides almost 1.5-meter accuracy in open-sky conditions [9], its performance degrades significantly with obstructions. Alternative methods, including inertial navigation systems (INS) [10], ground-penetrating radar (GPR) [11], and multi-sensor integration [12], have been explored but face inherent limitations such as cumulative drift (INS), high implementation costs (GPR), and extensive pre-mapping requirements.

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(a) GPS rich (b) GPS Denied (c) Plotted Cable

Fig. 1: Cable plotting from GPS to non-GPS environment.

To address these challenges, this paper presents an autonomous robotic system for power cable tracking and mapping, capable of generating precise spatial representations on geospatial platforms like Google Maps (Fig. 1c). The system integrates a cable locator sensor for real-time underground cable detection and employs RTK-GPS for high-precision localization in GPS-rich environments. In GPS-denied regions, it seamlessly transitions to a visual-based localization framework using an RGBD camera with ORB-SLAM3, ensuring continuous and reliable operation across diverse environments.

A key challenge in power cable mapping lies in mitigating GPS inaccuracies and ensuring smooth integration between GPS-based and visual SLAM localization for consistent mapping. To address this, a human-in-the-loop graphical user interface (GUI) is incorporated, allowing operators to manually refine GPS-based positioning errors in real time. Furthermore, data from both RTK-GPS and ORB-SLAM3 is transformed into a unified global reference frame, ensuring seamless localization continuity across mixed GPS and GPS-denied regions.

Extensive real-world experiments validate the system's effectiveness in both GPS-rich environments and GPS-denied settings. Results demonstrate the robustness of the hybrid localization framework, with human-in-the-loop corrections significantly improving GPS accuracy. Additionally, failure scenarios are analyzed to identify limitations and inform future improvements. Despite these constraints, this research establishes a strong foundation for the development of autonomous robotic solutions for large-scale infrastructure inspection and mapping.

The remainder of this paper is organized as follows: Section II reviews related work, Section III details the system architecture and sensor selection, Section IV outlines the methodologies for cable tracking and mapping, Section V presents experimental validation, and Section VI summarizes key findings and future research directions.

II. LITERATURE

A. Underground Infrastructure Mapping Challenges

Traditional underground utility mapping methods are labor intensive and prone to errors. Zhang et al. highlighted that approximately 30% of the underground utility location data contains significant positional errors [15]. GPS technology exhibits well-documented limitations in underground environments, with position errors increasing significantly in urban canyons and underground spaces, often resulting in complete signal loss in tunnels, as documented by Patel et al. [16].

B. Autonomous Systems for Infrastructure Inspection

For underground cable detection, electromagnetic induction (EMI) sensors have demonstrated detection accuracies of up to 95% for energized cables at depths of up to 2 meters according to Goldberg and Smith [17], although performance degrades in environments with overlapping electromagnetic fields. Recent multisensor approaches aim to improve detection reliability in complex environments.

C. Localization Strategies

Real-Time Kinematic GPS (RTK-GPS) provides centimeter-level accuracy under optimal conditions, but requires continuous communication with base stations and unobstructed satellite visibility, as shown by Thompson et al. [18]. Visual SLAM techniques have emerged as alternatives for GPS-denied environments, with ORB-SLAM3 demonstrating robust feature extraction capabilities and improved mapping consistency, as documented by Campos et al. [19]. Liu et al. reported positional accuracy within 0.4 meters over 100-meter trajectories using ORB-SLAM3 without GPS assistance in underground environments [20].

Hybrid localization approaches leverage multiple technologies to improve robustness. Hassan et al. developed fusion algorithms combining RTK-GPS and visual SLAM data using an Extended Kalman Filter, demonstrating improved trajectory estimation across diverse environments [21]. These hybrid approaches maintain sub-meter accuracy even during temporary GPS outages.

D. Human-in-the-Loop Systems

Human oversight in autonomous mapping systems has improved reliability. Gonzalez et al. implemented human-in-the-loop interfaces that allowed operators to validate and refine robotic mapping outputs in ambiguous detection scenarios [22], reducing mapping errors compared to fully autonomous solutions.

E. Research Gaps

Integration methodologies for a seamless transition between localization approaches require further development, particularly for environments with intermittent GPS availability according to Thompson et al. [23]. In addition, robust mapping under varying soil conditions and electromagnetic interference scenarios presents ongoing challenges. The evolution toward fully autonomous systems that maintain high accuracy standards while requiring minimal human intervention represents a key research direction in the field.

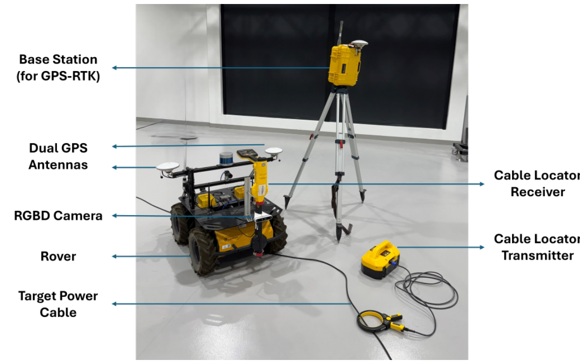


Fig. 2: The Complete Robotic system.

III. SYSTEM DESIGN

This section details the robotic system and sensor integration, illustrating component interactions in Fig. 2.

The system is based on Clearpath's Husky rover, equipped with RTK-GPS for precise localization. It employs dual GPS antennas on the rover and a fixed RTK base station as a reference. The base station requires approximately five minutes to initialize, introducing an initial GPS error of $\sim$1.5 meters. Since the rover's position is determined relative to the base station, any movement of the base station distorts its coordinates. The system operates within $\sim$100 meters, requiring base station relocation and re-initialization for extended coverage or when obstructions interfere with GPS signals. Correcting the base station's GPS error is crucial for maintaining localization accuracy.

For cable tracking, the system integrates the Vivax-Metrotech Vloc3-Pro locator, consisting of a transmitter and receiver module. The transmitter induces an electromagnetic signal into the cable, while the receiver, mounted on the rover, detects and provides real-time navigation signals for tracking the cable path.

In GPS-available environments, RTK-GPS ensures accurate localization, provided the base station error is corrected. In GPS-denied areas, the system switches to ORB-SLAM3, a vision-based SLAM algorithm. ORB-SLAM3 extracts keypoint features from an RGBD camera's image feed and uses depth information to estimate the rover's position within a fixed reference frame, enabling autonomous cable mapping without GPS.

To facilitate seamless sensor communication and data integration, the system is implemented using ROS-Noetic as its middleware. Custom ROS messages are designed for GPS data, cable locator readings, and ORB-SLAM3 outputs, ensuring efficient data exchange through ROS topics. A central control loop processes these sensor inputs in real time, generating velocity commands that autonomously navigate the rover along the cable path while simultaneously visualizing its trajectory in RViz or on digital mapping platforms like Google Maps.

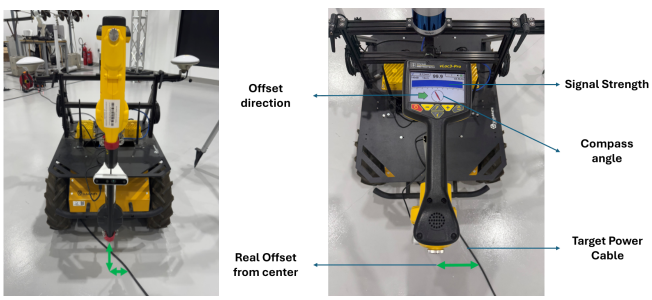
IV. Method

The previous section outlined the robotic system's key components, including the cable locator sensor, dual GPS antennas with a base station, and an RGBD camera.

This section first focuses on the cable locator sensor, detailing its output, integration into the ROS network, and role in rover navigation. Next, we address base station initialization errors, which introduce a ∼1.5-meter positioning offset and require frequent reinitialization. Accumulated errors can impact GPS-based localization and cable mapping accuracy, so we present a GUI-based solution for real-time GPS error correction.

Finally, we discuss mapping strategies for both GPS-rich and GPS-denied environments to ensure reliable cable tracking under varying operational conditions.

A. Cable locator sensor



(a) Front View (b) Top view

Fig. 3: Cable locator output

The outputs of the receiver, as illustrated in Fig. 3b, are defined as follows:

- **The Signal Strength:** Indicates the strength of the detected signal, with the bar color changing based on the level of distortion:
  - **Green** Low distortion.
  - **Blue** Minor distortion.
  - **Red** Excessive distortion.
- **Compass Angle:** Represents the angle of the target power cable relative to the receiver.
- **Offset Direction:** Indicates whether the target power cable is positioned to the left or right of the receiver.
- **Transverse angle:** proportional to the displacement/offset of the cable from the receiver's center point.

Additionally, the receiver provides real-time data on the current flowing through the target cable and its depth relative to the receiver.

A u-blox OBS421 Bluetooth module enables wireless data transmission to the Husky rover's onboard processor via a Bluetooth Serial Port Profile (SPP) connection. The received data is structured into a custom ROS message and published to a dedicated ROS topic at 7 samples per second for further processing.

The offset direction and transverse angle adjust the rover's angular velocity, keeping it aligned with the cable path. If the compass angle is high—indicating significant deviation—the system reduces linear velocity while increasing angular velocity to correct the trajectory.

B. Base station initialization

(a) Real View (b) GPS Error (c) GPS correction

Fig. 4: GPS error and offset correction

Fig. 4 highlights GPS positioning errors from base station initialization and their impact on rover localization.

In Fig. 4a, the rover's actual position (yellow circle) differs from its RTK-derived coordinates, revealing an initialization error. The base station initially registers at 24.7672199022° latitude, 55.3699049845° longitude, and the rover's computed position is 24.767097398° latitude, 55.369963286° longitude. In RViz (Fig. 4b), the simulated position appears slightly offset from the real-world reference. Reinitializing the base station without movement results in a new set of coordinates, 24.7672178915° latitude, 55.3699117274° longitude, shifting the rover's computed position to 24.7670953873° latitude, 55.3699700289° longitude. The difference between these two initialization events is 0.72 meters, and with repeated reinitializations, such errors can accumulate, further degrading localization accuracy.

To maintain accurate localization and precise power cable mapping, positional drift must be corrected. During the first initialization, an offset is identified by comparing the rover's real-world position with its simulated counterpart in RViz (Figs. 4a and 4b). For instance, while the rover may be near a landmark, such as a white square corner, its simulated position appears slightly misaligned, requiring adjustment.

To address this, a Python-based interface allows users to manually correct GPS positioning errors by adjusting offset values via keyboard inputs after initialization. This manual correction significantly reduces the error, ensuring that the rover's actual position closely matches its simulated position in the RViz environment, although minor residual errors may still exist (Fig. 4c).

For subsequent initializations, an automated script calculates offsets by analyzing differences between new and previous GPS coordinates, ensuring continuous correction. This prevents cumulative errors that could degrade localization over time.

By incorporating manual adjustments initially and automating corrections in later re-initializations, this approach maintains accurate rover positioning, preventing drift accumulation and ensuring reliable power cable mapping across large areas.

C. GPS based localization and mapping

To accurately map power cables, the rover must be localized within a defined reference frame. To achieve this, we establish a reference frame based on the GPS location of the rover, which we call as *GPS reference frame*, which can be set and saved according to user input. This stored GPS position serves as the origin for localization and mapping. For the coordinate system, we follow the East-North-Up (ENU) convention, where:

- The x-axis points toward true east.
- The y-axis points toward true north.
- The z-axis points upward (perpendicular to the ground).

When the cable locator detects a power cable, its GPS coordinates are recorded. However, for real-time visualization in ROS-based tools like RViz, these global coordinates must be converted into a Cartesian system.

To perform this transformation, we use *pymap3d* [14], an open-source geospatial library that converts GPS coordinates into relative ENU coordinates based on the rover's *GPS reference frame*. This ensures accurate real-time mapping.

Additionally, the recorded GPS positions can be directly used to overlay the detected cable path onto Google Maps or other GIS platforms, enabling large-scale mapping and analysis.

D. localization and mapping in GPS denied environment

The *pymap3d* library enables the transformation of GPS coordinates into relative Cartesian coordinates within the *GPS reference frame* and supports inverse conversion. This ensures accurate localization and mapping, even in areas with unreliable GPS signals.

For GPS-denied environments, we integrate ORB-SLAM3, a visual SLAM module that estimates the rover's position by tracking camera movement within a fixed *camera link frame*. Since the camera is rigidly attached to the rover, a transformation is applied to localize the rover's base. If the transformation between the *GPS reference frame* and *camera link frame* is known, the rover's absolute GPS position can be derived for accurate power cable mapping on GIS platforms.

The process starts with initializing the base station in a GPS-rich environment, assigning GPS coordinates to both the base and rover. Any positional error is corrected by adjusting GPS offsets using human feedback, ensuring accurate localization. Once refined, the *GPS reference frame* is established. As the rover moves along the cable, detected cable points are logged in GPS and converted into Cartesian coordinates for real-time RViz visualization.

When the rover enters a GPS-denied zone, ORB-SLAM3 maintains localization using the *camera link frame*. Since the transformation between the *GPS reference frame* and *camera link frame* is precomputed, the rover's Cartesian position is mapped back to the *GPS reference frame* for accurate GPS estimation of power cables.

By integrating GPS-based localization with ORB-SLAM3, seamless and precise localization is achieved across varied terrains, ensuring reliable power cable mapping and visualization on GIS platforms like Google Maps.

V. EXPERIMENTAL EVALUATION

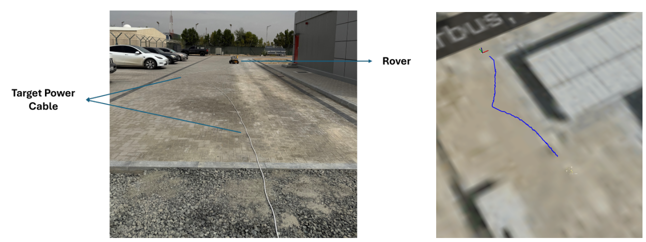
To assess the system's performance, controlled experiments were conducted across GPS-rich, GPS-denied, and transition environments.

A. Experimental Setup

The setup involved a live three-core power cable with a 2.5 mm conductor diameter and a total length of 91 meters. A Vivax-Metrotech Vloc3-Pro transmitter was attached at one end, while an electrical load was connected at the other to maintain circuit continuity.

As per Vloc3-Pro guidelines, a minimum radial separation of 10 meters between the transmitter and the rover-mounted receiver was required to prevent signal distortion. Additionally, a 10-meter safety buffer was maintained at the load termination point to minimize electromagnetic interference. This resulted in an effective cable length of 71 meters available for tracing and mapping. The system's accuracy in cable detection, real-time localization, and mapping was evaluated using this segment.

B. Scenario 1: GPS Rich environment (Outdoor Testing)



(a) Real View (b) Plotting

Fig. 5: GPS Rich Environment

In this scenario, the rover was tested in an open environment with strong GPS signals to validate the complete pipeline, fine-tune system parameters, and optimize motion control for precise cable tracking.

Through iterative testing, the following optimal parameters were determined:

- **Maximum Linear Speed:** 0.2 m/s (higher speeds led to overshooting sharp cable turns).
- **Maximum Angular speed:** 15°/s (higher values caused excessive zig-zag motion and instability).
- **Vloc3 transmitter frequency:** 65.5 kHz chosen to minimize interference from low-frequency noise).

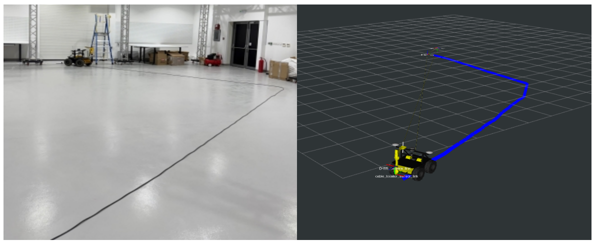
A proportional controller was implemented to dynamically adjust the rover's motion based on the transverse angle (cable displacement) and compass angle (cable direction) from the Vloc3 receiver:

- Straight sections (compass angle < 30°):
  - Linear speed: 0.2 m/s (maximum).
  - Angular velocity: proportional to transverse angle.
- Sharp turns (compass angle > 30°):
  - Linear speed: inverse proportional to compass angle.

– Angular velocity: 15°/s (maximum).

Whenever the rover crossed over the cable, the receiver's position was projected onto the ground and plotted on Google Maps. The experimental setup and corresponding cable path mapping are shown in Fig. 5.

C. Scenario 2: GPS Denied environment (Indoor Testing)



(a) Real View (b) Plotting

Fig. 6: GPS denied Environment

In the second experimental setup, the system was tested in a GPS-denied environment, such as an indoor laboratory. While motion parameters remained unchanged from outdoor trials, localization relied entirely on ORB-SLAM3 instead of GPS. Multiple trials were conducted with the power cable arranged in random configurations, including both straight sections and sharp turns. A representative example is shown in Fig. 6a, with the corresponding trajectory plotted in Fig. 6b.

To evaluate ORB-SLAM3's accuracy, the power cable was placed in a random layout, with start and end points physically marked and measured. The rover was positioned at the starting point, where a reference frame was established. It then followed the cable while logging its trajectory in the visualizer. Upon reaching the endpoint, the computed distance along the plotted trajectory was compared with the actual measured length. Repeated trials yielded the following results:

- **Actual Cable length:** 11.67 meters
- **Average Calculated length via simulator:** 11.43 meters.
- **Average time to track the cable:** 89.17 seconds.
- **Average velocity:** 0.13 m/s (lower than the maximum speed due to adaptive motion adjustments at the sharp turns).

For accurate localization, the environment must contain sufficient visual texture. In featureless settings (e.g., plain surfaces with minimal landmarks), localization errors increased significantly, leading to inaccuracies in both position tracking and trajectory plotting—consistent with the known limitations of texture-dependent VSLAM algorithms.

Even in visually rich environments, discrepancies between actual and computed cable lengths were observed. As seen in the plotted trajectory (Fig. 6b), the rover sometimes missed logging cable segments during sharp turns. Since the system records cable positions when the rover crosses over them, its motion dynamics occasionally caused it to bypass sections before a new crossover point was registered. This resulted in linear interpolation between recorded points, leading to a loss of finer trajectory details.

To address the above challenges, future work will focus on enhancing localization accuracy by integrating improved feature tracking within ORB-SLAM3, sensor fusion techniques (e.g., IMU-based corrections), and more advanced cable-mapping algorithms. These enhancements will improve cable tracing accuracy in complex environments.

D. Scenario 3: Transition from GPS-Rich to GPS-Denied Environment

(a) GPS rich (b) GPS Denied (c) Plotted Cable

Fig. 7: GPS-Rich to GPS denied

In the third experiment, the rover transitioned from an outdoor GPS-rich environment to an indoor GPS-denied environment while continuously tracking the cable. It started in a strong GPS signal zone (Fig. 7a), where a *GPS reference frame* was established (Fig. 7c). The starting position of the rover is highlighted in yellow. As the rover followed the cable into the indoor lab (Fig. 7b), GPS signals were lost, triggering an automatic switch to ORB-SLAM3-based visual localization. At this point, a *camera link frame* was created (Fig. 7c). The rover's position during the transition is also highlighted in yellow, marking its movement between localization methods.

This seamless transition between GPS-based and visual localization highlights the system's adaptability in environments with intermittent or no GPS coverage. The experimental setup and the final mapped cable trajectory are shown in Fig. 7.

E. Challenges and Future work

(a) GPS rich (b) GPS Lost (c) Plotted cable

Fig. 8: Failure Case

The experimental results confirm that the robotic system effectively maps power cables in both GPS-rich and GPS-denied environments, given sufficient visual texture for ORB-SLAM3. However, this assumption does not always hold in real-world scenarios. In areas with plain-textured walls or tall structures, localization becomes unreliable due to two primary challenges: (1) significant GPS inaccuracies caused by multipath effects in dense urban settings, and (2) ORB-SLAM3's failure to maintain accurate localization in featureless environments.

As shown in Fig. 8, these limitations impact the system's accuracy. For instance, in Fig. 8b, the rover loses GPS signals and switches to VSLAM, establishing a new frame (Fig. 8c). However, due to the lack of visual features, localization deteriorates, causing the plotted cable trajectory to deviate significantly from the actual path. In reality, the rover follows the walls and enters the lab through a large door, but the trajectory appears incorrect due to localization errors.

To overcome these challenges, future enhancements will explore integrating advanced localization techniques such as LiDAR-based SLAM, ultra-wideband (UWB) positioning, and multi-sensor fusion to improve performance in visually and GPS-challenged environments. Despite these constraints, the system provides a strong foundation for advancing autonomous power cable mapping and robotic infrastructure inspection.

VI. CONCLUSION

This paper presents an autonomous robotic system for power cable tracking and mapping in both GPS-rich and GPS-denied environments. By integrating RTK-GPS for outdoor localization and ORB-SLAM3 for visual-based localization, the system dynamically adapts to varying operational conditions. Additionally, a human-in-the-loop GUI enhances accuracy by enabling manual corrections to mitigate GPS positioning errors.

Real-world experiments validate the system's effectiveness, demonstrating reliable cable mapping across diverse environments. However, challenges arise in low-texture areas where ORB-SLAM3 struggles to maintain localization, affecting mapping accuracy. Addressing these limitations requires advanced localization techniques, such as LiDAR-based SLAM or UWB positioning, to improve robustness.

Despite these challenges, the proposed system lays a strong foundation for autonomous power cable mapping and robotic infrastructure inspection. Future work will focus on refining localization accuracy and expanding the system's capabilities for operation in complex and visually challenging environments.

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