

Feasibility and Performance Analysis of Ground-penetrating Radar Integration for Autonomous Navigation of Quadruped Robots

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Ground-penetrating radar (GPR) enables robust navigation in environments where vision and light detection and ranging systems fail as a result of environmental degradation. Despite this, the integration of GPR onto quadrupedal platforms remains a challenge. Therefore, we analyzed the feasibility of GPR-based navigation for quadruped robots and developed a sensor-integrated framework that mitigates the noise inherent in legged locomotion. By leveraging real-time kinematic telemetry for antenna–ground height correction and hardware-synchronized blanking gates to inhibit noise during foot-strike events, our approach addresses critical challenges in dynamic sensor acquisition. The analysis of the Carnegie Mellon University-GPR dataset showed that multimodal data fusion significantly improved localization performance. By integrating GPR-derived subsurface feature matrices (time–frequency representations of buried reflections) with inertial measurement unit and encoder data, the system showed a weighted root mean square error of 0.568 m, representing a 74.5% improvement over unimodal GPR-only localization. These results show that subsurface electromagnetic features provide stable localization benchmarks even in feature-sparse indoor environments. Deep-learning-based architectures, such as a GPR-based difference- and similarity-driven odometry estimation network, showed higher precision (0.449 m root mean square error), showing the potential for advanced sensor development. The results of this study provide a reference for developing robust, redundant navigation systems, proving that GPR integration is a viable solution for quadrupedal robots operating in smoke, dust, or GPS-denied subterranean corridors.

1. Introduction

Autonomous navigation in complex and unstructured environments remains a major challenge in robotics.⁽¹⁾ Vision-sensor-based autonomous navigation is significantly affected by environmental appearance changes. For example, snow, dust, flooding, or artificial lighting obscures or alters visual features, leading to navigation failures.⁽²⁾ Although light detection and ranging (LiDAR) sensors are robust to illumination changes,⁽³⁾ their performance degrades in

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the presence of airborne particulates.⁽⁴⁾ Moreover, featureless areas without distinct markers cause the positional accuracy of simultaneous localization and mapping (SLAM) systems to decrease.⁽⁵⁾

Other than visual and optical line-of-sight sensors, acoustic and seismic methods for subsurface sensing are widely used in geotechnical surveying. However, they have operational trade-offs for robotic state estimation. In ultrasonic and acoustic inspection techniques, wave propagation across acoustic impedance boundaries is important. The severe impedance mismatch of the techniques between air and ground media requires direct transducer contact or fluid coupling, preventing high-speed noncontact acquisition during locomotion.⁽⁶⁾ To address this mismatch, seismic and microseismic methods are used for deep penetration (tens to hundreds of meters) using low-frequency elastic waves, but their low spatial resolution (wavelengths spanning several meters) and susceptibility to foot-strike ground vibrations hinder the methods from being used for high-rate, submeter robot localization.⁽⁷⁾ In contrast, ground-penetrating radar (GPR) transmits ultra-wideband (UWB) electromagnetic waves that operate effectively in noncontact (air-coupled) topologies with high sampling frequencies (> 100 Hz) and decimeter-scale spatial resolutions necessary for real-time mobile state estimation.

For noncontact operation, high-rate data acquisition, and submeter localization accuracy, quadruped robots are used since they can move across discontinuous and uneven terrain and thus are well suited for environments inaccessible to wheeled robots.⁽⁸⁾ Commercially available quadruped robots, such as Boston Dynamics' Spot and the Swiss Federal Institute of Technology's ANYmal, employ stereo cameras and three-dimensional LiDAR sensors to perceive their surroundings.^(9,10) Such sensors enable the robots to operate in open areas with stable illumination, but they introduce failure modes, such as odometry drift in featureless environments, sensor blinding from specular reflections, and tracking loss caused by dynamic obstacles.

To reduce such failures in various applications, GPR is widely used. GPR sensors transmit signals into the ground and measure reflections from subsurface features with varying electrical properties.⁽¹¹⁾ Because subsurface structures change more slowly than surface appearances, GPR provides stable features for localization over time.⁽¹²⁾ Studies with wheeled autonomous robots using localizing GPR (LGPR) have shown localization errors of less than 4.3 cm root mean square (*RMS*) at highway speeds of up to 100 km/h.⁽¹³⁾ More recently, factor graph methods have been introduced for accurate localization with single-channel GPR sensors in indoor environments where GPS is not available, showing average errors of 2.23 m with unimodal data and 0.568 m when fused with inertial measurement unit (IMU) and encoder data.⁽¹²⁾

In legged robotic navigation, GPR has not yet been extensively integrated despite its technological advancements. In robotic navigation, the periodic vibrations of walking introduce artifacts into sensor readings,⁽¹⁴⁾ whereas variations in leg position cause fluctuations in sensor-to-ground distance, affecting travel time measurements.⁽¹⁵⁾ In addition, the relatively large size of GPR arrays and associated hardware poses challenges for payload-limited quadruped platforms.^(8,16) Although these issues have been observed, systematic experimental studies remain absent and theoretical work on signal processing adaptations is limited.

To address the above limitations, we examined existing localization methods that employ GPR sensors and evaluated their relevance to quadruped robot design and operating

environments. In previous studies, general legged navigation⁽¹⁶⁾ or wheeled GPR mapping⁽¹⁷⁾ was examined. However, the interference introduced by leg impacts and vertical gait sway needs to be addressed. Therefore, to improve quadruped autonomous navigation, we developed a hardware–software signal-conditioning framework that integrates real-time kinematic–inertial pose feedback for time-zero correction with hardware-synchronized blanking gates to suppress the transient noise caused by foot-strike effects. In the framework, nonstationary adaptive filtering driven by quadruped locomotion phase data is introduced to effectively suppress chassis resonance and preserve subsurface electromagnetic signatures. In this study, GPR-derived subsurface feature matrices (SFMs) and deep temporal architectures such as a GPR-based difference- and similarity-driven odometry estimation network (GPR-OdomNet) with multimodal fusion reduce positioning fluctuations by 74.5% (a weighted *RMSE* of 0.568 m) in feature-sparse and visually degraded corridors.

2. Literature Review

2.1 Localization of GPR

The propagation velocity of electromagnetic waves in subsurface media is determined by the relative dielectric permittivity of the soil, with the speed of light in vacuum being approximately 0.30 m/ns.⁽⁴⁾ Dry sandy soils exhibit permittivity values between 3 and 5, resulting in velocities of 0.13–0.17 m/ns, and clay-saturated soils show values near 40, reducing velocities to less than 0.05 m/ns. Therefore, accurate soil permittivity measurement is essential for estimating reflector depth and interpreting the hyperbolic diffraction patterns generated as the antenna passes over subsurface features.⁽¹⁸⁾

LGPR systems utilize prebuilt subsurface maps and particle swarm optimization to align new scan data with stored data. Conventional LGPR systems show cross-track localization accuracies of 4.3 cm *RMS* at speeds up to 100 km/h, surpassing the differential GPS performance.^(11,12) However, reliance on raw amplitude measurements makes them sensitive to soil moisture, freeze–thaw cycles, and water tables.⁽¹²⁾ To overcome these limitations, factor graph models are used to localize robots directly from GPR images without requiring GPS or preexisting maps. Such models are compatible with quadruped motion measurements, making them promising for legged platforms.⁽¹³⁾ The GROUNDED dataset, which includes localizing GPR scans recorded in clear, snowy, and rainy weather, is widely used as a benchmark for evaluating LGPR systems under various weather conditions. The dataset contains images of routes captured in clear, snowy, and rainy weather, which show the challenge of maintaining consistent localization (Fig. 1). The corresponding trajectory map shows how LGPR data can be used to evaluate translational and rotational errors, as well as lateral and longitudinal deviations, which are critical for both autonomous vehicles and quadruped robots navigating confined corridors.⁽¹⁴⁾

2.2 Quadruped robot navigation

Quadruped control enables a transition from manually engineered predictive controllers to learned policies transferred from simulation to hardware through domain randomization.^(9,13)

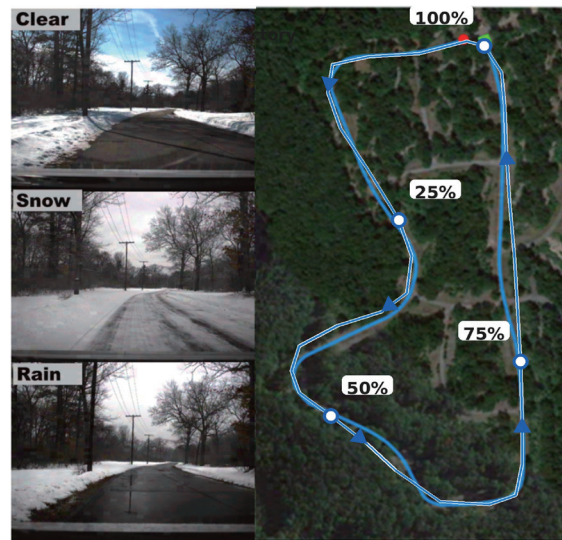


Fig. 1. (Color online) Camera images of the same route captured during three runs in clear, snowy, and rainy weather. The blue solid line represents a route on satellite image reference (common and nominal route trajectory) in clear, snowy, and rainy conditions. The blue–white line with arrows represents the annotated route-progress path. Circular markers and 25, 50, 75, and 100% labels indicate normalized progress along the route.⁽¹⁵⁾

For example, ANYmal, equipped with a depth camera, traverses stairs, vegetation, and deformable terrain faster than human hikers, integrating exteroceptive and proprioceptive states to recover from sensor failures.⁽⁹⁾ Similarly, Boston Dynamics' Spot adopts LiDAR and IMU sensors. Although Spot successfully navigated narrow tunnels, areas lacking visual features caused SLAM drift, presenting the potential of GPR to overcome such limitations.⁽¹⁶⁾

In quadruped navigation, a factor graph-based fusion algorithm plays an essential role. In particular, this algorithm is vital for the integration of sensors with different sampling frequencies and loop-closure constraints. Through the fusion of the global navigation satellite system (GNSS), LiDAR, and IMU signals, an accuracy of 1–2 m is obtained even under limited satellite visibility, such as in forests. Subsurface features can also be included in factor graphs to improve localization when GNSS and LiDAR are unavailable.⁽¹⁹⁾ Path planning strategies are also used in drawing skeleton maps for the systematic scanning of areas of interest and can be extended to subsurface exploration with GPR sensors.⁽²⁰⁾ However, this method has limited terrain adaptation, as kinematic strategies cannot detect subsurface or buried obstacles. In this case, GPR is employed as it accurately senses such obstacles.

2.3 Signal processing in GPR-based robot navigation

For GPR data preprocessing, background removal, de-wowling, spreading, exponential compensation, and denoising are conducted using wavelet or bandpass filters.^(13,21) Localization methods, such as the SFM method, are also used to model signals in the frequency domain, since the SFM method resists amplitude variations and shows a localization error of 0.568 m, which is less than 2.23 m when using unimodal GPR data.⁽¹²⁾ Unlike raw radar images that fluctuate with soil moisture, SFM is used to convert signals into a time–frequency map that isolates the unique electromagnetic signatures of underground structures. This spectral representation provides a

stable subsurface fingerprint, enabling the robot to track its position accurately across changing soil conditions.

Deep learning models are widely used for advanced GPR-based localization. GPR-OdomNet, for instance, reduces localization error to 0.449 m on the Carnegie Mellon University (CMU)-GPR dataset on the basis of similarity and difference between consecutive brightness modulation scans, presenting a 10.2% improvement over other methods.⁽²²⁾ Transformer-based models such as GPRFormer also enable 30–50% improvements in Mars analog terrain, underscoring the potential of deep learning in subsurface localization.⁽²³⁾ In addition, when convolutional neural network (CNN)–recurrent neural network (RNN) models are applied to railway subgrade defect detection, temporal information in GPR is used for quadruped gait-based localization.⁽²⁴⁾ The CMU-GPR dataset is a valuable source for evaluating these algorithms. Collected in GPS-denied indoor environments, the dataset includes single-channel GPR, wheel encoder, red-green-blue camera, IMU, and ground truth data across a variety of surfaces, enabling the robust training and evaluation of localization models.⁽²⁵⁾ GPR has been implemented on wheeled robots for autonomous subsurface mapping. A robot equipped with LiDAR and GPR shows mapping accuracies of ± 3 cm and provides radargrams of subsurface features.⁽²⁶⁾ GPR has been applied to lunar terrain exploration, correcting inertial navigation system drift, and improving localization accuracy in simulated environments.⁽²⁷⁾

Quadruped robots have also been deployed in subterranean mines using LiDAR-inertial odometry and terrain segmentation. Although effective in many trials, dusty and featureless tunnels caused localization uncertainty, suggesting that GPR could provide absolute subsurface positioning under such conditions.⁽²⁷⁾ Beyond Earth, GPR-based localization has been explored for planetary rovers. The GPRFormer network reduces odometry error by 30–50% in Mars analog terrain, showing the relevance of GPR methods for both wheeled and legged robots in unstructured environments.⁽²³⁾ While CNN- and Transformer-based models achieve high localization accuracy on offline benchmark datasets, their direct onboard execution on payload-constrained quadruped computers requires explicit optimization for subsecond edge inference.⁽²⁸⁾

3. Methodology

3.1 Literature review

We conducted a literature review to assess the feasibility, signal dynamics, and localization accuracy of GPR systems integrated into quadrupedal robots. Articles on hardware-in-the-loop experiments performed in outdoor or field environments and were published between 2017 and 2026 were collected from IEEE Xplore, Web of Science, Scopus, and arXiv. The specific topics selected for inclusion were the use of GPR mounted on mobile platforms, the validation of odometry or pose estimation against independent ground-truth instruments such as real-time kinematic-GNSS or robotic total stations, and the provision of complete sensor specifications including center frequency, antenna topology, and coupling parameters. Studies that employed GPR only for stationary target classification without evaluating robot motion or state estimation were excluded.

3.2 Sensor-integrated framework

On the basis of the literature review results, an integration framework was designed to fuse subsurface electromagnetic data with proprioceptive robotic states. The sensors used included a single-channel, UWB GPR antenna operating between 500 MHz and 1 GHz. To maximize electromagnetic energy transfer into the ground and minimize impedance mismatches, the antenna was coupled to ANYmal using resistively loaded blades or flexible suspensions that conformed to terrain variations.

To assess mechanical compatibility, the dimensions and payload requirements of the quadruped platform and GPR system were evaluated.⁽²⁹⁾ Industrial quadruped robots considered in this framework, including ANYmal C (length of 0.93 m, width of 0.53 m, standing height of 0.89 m, and ground clearance of 0.50 m) and Boston Dynamics' Spot (length of 1.10 m, width of 0.50 m, standing height of 0.84 m, and ground clearance of 0.45 m), provide sufficient underslung payload capacity for the integration of compact GPR sensors.⁽³⁰⁾ The proposed single-channel UWB GPR transceiver module measures 0.30 m in length, 0.23 m in width, and 0.18 m in height, with a mass of 3.2 kg. The 0.23-m-wide antenna module beneath the robot's main torso maintains a 0.25–0.30 m operational clearance above the ground surface, ensuring that the sensor footprint remains entirely within the chassis boundary without interfering with kinematic leg swing trajectories.⁽³¹⁾

Antenna size and form factor are critical in adapting GPR technology in legged robotic platforms.⁽²⁹⁾ LGPR systems developed for road vehicles employ antenna arrays spanning up to 1.52 m in width to cover full-lane geometries, far exceeding the typical torso width of quadruped robots. In contrast, the dimensions of the single-channel UWB antenna evaluated in this study are 0.23 m in width, corresponding to 45% of the robot's torso width, and a weight of 3.2 kg. These characteristics enable the sensor to meet the payload and dimensional constraints of modern quadruped platforms.⁽³⁰⁾ Although compact single-channel antennas provide a lower spatial gain than large multi-element arrays, their reduced footprint enables chassis integration without compromising mobility. Such compact configurations also enable submeter localization accuracy in confined and GNSS-denied environments.⁽³¹⁾

Raw radar traces (e. g., A-scans that are single one-dimensional radar traces recorded at one antenna position, showing how strongly the signal is reflected as a function of two-way travel time, meaning the time the pulse takes to travel down to a reflector and back) were processed through a deterministic signal conditioning chain to improve the signal-to-noise ratio. This included de-wow filtering to remove low-frequency bias, bandpass filtering to suppress out-of-band noise, exponential compensation to correct for spreading and attenuation, and background removal to eliminate static ringing and air-ground reflections. Conditioned A-scans were stacked into B-scans (a two-dimensional image made by placing successive A-scans side by side along the robot's path. The horizontal axis is distance traveled, the vertical axis is travel time corresponding to depth, and brightness shows reflection strength), from which subsurface feature matrices were derived using short-time Fourier transform (STFT). These matrices captured spectral peaks representing dielectric scatterers. The depth of reflectors was calculated from the two-way travel time and propagation velocity, with corrections applied for antenna

elevation offsets caused by leg compliance and terrain slopes. Real-time kinematic telemetry was injected into the pipeline to adjust the time-zero datum of each pulse, ensuring accurate depth estimation under dynamic locomotion. Figure 2 shows an up-slope locomotion experiment conducted using the Boston Dynamics quadruped robot, Spot. The sequence in the figure shows the robot traversing an inclined surface while maintaining stable body posture and foothold placement, presenting the effectiveness of quadrupedal locomotion in negotiating uneven terrain. Such terrain-adaptive mobility is important for GPR-equipped quadruped platforms that operate in complex outdoor and subterranean environments, where reliable localization must be maintained during continuous changes in elevation and ground conditions.⁽¹⁷⁾

Localization was achieved through a factor graph optimization framework. Graph nodes were identified to represent robot poses, while edges encoded constraints from GPR, IMU, and encoder data. Cross-correlation between successive subsurface feature matrices provided displacement vectors that were fused with proprioceptive measurements. Localization was implemented using a factor graph framework in which nodes represented robot poses and edges encoded constraints derived from GPR, IMU, and encoder measurements. The robot trajectory was then estimated as a Maximum A Posteriori solution and optimized using a nonlinear least-squares solver. The optimization was executed at a cycle frequency of 10 Hz on edge-capable computing hardware. To enhance robustness, the adaptive weighting of sensor constraints was introduced, allowing IMU data to be dominant during rapid gait transitions and GPR constraints to be dominant in visually degraded or GNSS-denied environments.

3.3 Hardware–software integration

Quadrupedal locomotion introduced significant noise into GPR signals through body-pose oscillations and foot-strike impacts. Vertical chassis motion altered the antenna–ground distance, shifting reflector travel times, and mechanical shocks deformed antenna geometry and injected noise into receiver electronics. Mechanical shocks generated during foot-strike events produced high-frequency structural vibrations that propagated to the receiver electronics,

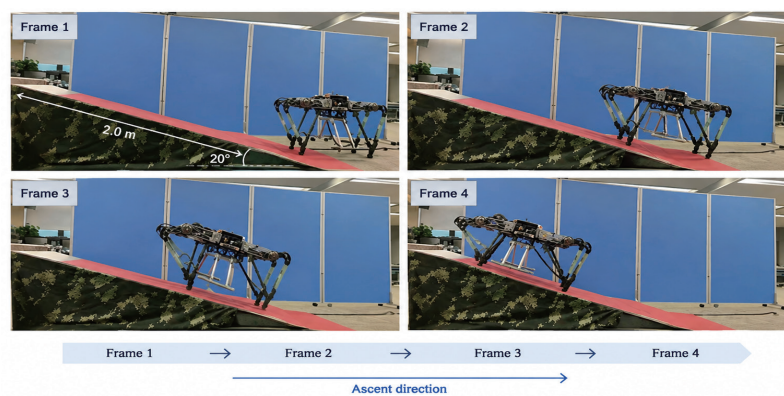


Fig. 2. (Color online) Four-stage up-slope experiment of Boston Dynamics' Spot, showing ascending direction and progression from Frames 1 to 4.⁽¹⁷⁾

resulting in signal clipping and spurious artifacts in the B-scans.⁽²⁹⁾ To mitigate them, our developed framework employed a hardware-level interrupt mechanism linked to the robot's locomotion controller. Upon contact detection, the framework's transistor–transistor logic signal activated a 5–10 ms blanking gate on the GPR transceiver to inhibit signal acquisition during peak structural deceleration.

The integration framework employs a combined hardware–software architecture designed to normalize raw GPR A-scans and maintain localization despite the dynamic, nonstationary movement of ANYmal. The system is structured around three conditioning stages, each supported by hardware synchronization and mechanical design considerations. To mitigate high-energy transients induced by foot-strike impacts, the framework incorporates an interrupt-driven blanking protocol. The robot's controller provides real-time gait phase telemetry, and upon the detection of a limb contact event, a transistor–transistor logic signal is issued directly to the GPR transceiver. The transceiver is inhibited for a duration of 5–10 ms, calibrated to encompass the primary mechanical ringing decay time of the antenna mounting assembly. This hardware-level gating prevents the saturation of the receiver's high-gain amplifiers during impact. The blanking gate is implemented through a dedicated microcontroller interface, ensuring deterministic timing and minimal latency between gait detection and transceiver inhibition.

For integration with the Spot and ANYmal platforms, a lightweight mounting structure was installed beneath the robot body to support the GPR antenna. The antenna was positioned in the robot's ground-clearance range while maintaining sufficient distance from metallic leg components to minimize electromagnetic interference. The spatial relationship between the antenna and the robot body was determined through calibration using the robot's pose measurements and external distance measurements during stationary setup. Before operation, a short stationary scan of approximately 5 s was performed to establish the radar time-zero reference and estimate the initial ground dielectric properties.⁽³²⁾ The GPR system was enclosed in a lightweight Ingress Protection 65-rated polyether ether ketone radome for protection against dust and water spray. The compact configuration was designed not to interfere with the robot's normal locomotion, self-righting behavior, or obstacle-climbing capability.

Vertical body sway (± 40 mm) changes the antenna–ground height and two-way travel times, corrupting spatial B-scan consistency. By incorporating real-time high-rate IMU and encoder data into processing, the time-zero reference of each A-scan is recalibrated before feature matrix conversion.⁽³²⁾ The antenna is mounted on a compliant suspension system that minimizes abrupt elevation changes, and IMU and encoder signals are routed through a real-time processing unit that synchronizes pose feedback with radar acquisition.

Mechanical ringing from the antenna housing and resistively loaded blades often overlaps with the frequency spectrum of subsurface dielectric scatterers. To address this, the framework employs a nonstationary adaptive filter that correlates radar trace anomalies with the gait cycle. The filter dynamically updates its coefficients to attenuate resonant harmonics associated with mechanical vibrations, preserving the primary signal window between 500 MHz and 1 GHz. Hardware design plays a complementary role: the antenna chassis is reinforced with vibration-damping materials, and resistive loading is optimized to reduce structural resonances. Together,

these hardware and software measures ensure that subsurface signals remain intact for cross-correlation-based odometry.

Conditioned radar signals are transformed into subsurface feature matrices by STFT. These matrices serve as observation nodes within a factor graph, which fuses electromagnetic subsurface data with proprioceptive sensors. Each node represents the robot's pose at a given time, whereas edges encode constraints from pre-integrated IMU data and displacement vectors derived from successive B-scans. Adaptive weighting is applied through a diagonal information matrix that adjusts confidence in GPR observations in accordance with environmental richness. In visually degraded but geologically heterogeneous terrain, GPR constraints dominate the pose estimation, while in smoother environments, inertial priors carry greater weight.

The factor graph framework is supported by edge-capable computing units such as the NVIDIA Jetson Orin Architecture (AGX) or Intel Next Unit of Computing (NUC) platform, which provide sufficient processing power to execute spectral feature extraction and graph optimization at 10 Hz. The GPR antenna is physically coupled to the Spot chassis using a modular mounting system that allows rapid reconfiguration for different terrains. This integration ensures that the quadruped platform maintains stable trajectory estimation by treating mechanical noise as a deterministic input to be corrected, rather than stochastic interference.

Localization accuracy was compared with that of real-time kinematic (RTK)-GNSS arrays and robotic total stations. The CMU-GPR dataset was used, assuming controlled GPS-denied environments with diverse surfaces such as concrete, industrial flooring, and car park. Evaluation was conducted on absolute and relative trajectory errors to quantify baseline GPR odometry performance, as well as comparative localization metrics across different sensor configurations, including IMU-only, kinematic-inertial, and GPR fusion. Dynamic stress tests, including slope traversal, variable soil moisture conditions, and corridor navigation, were also conducted.

The experimental results were analyzed to explore how sensor covariance limits evolved under different locomotion gaits and environmental perturbations and to define the operational boundaries of GPR odometry in GPS-denied subterranean environments.

4. Results

4.1 Literature review results

The performance of GPR was examined through a literature review to investigate localization sensors across diverse mobile platforms and validate GPR odometry against robotic total stations and RTK-GNSS. The results provided a reference for the design of the proposed navigation framework. A strong correlation between the complexity of the geological substrate and the accuracy of subsurface feature-based localization was observed. Homogeneous indoor environments, such as concrete basements, caused sparse electromagnetic scattering, leading to higher sensor data drift rates and the reduced reliability of spectral feature matching. In contrast, outdoor or industrial environments containing rebar, conduits, or variable soil textures generated

richer spectral matrices than indoor environments, enabling robust localization. This shows that the richness of the subsurface directly determines the reliability of STFT-based feature extraction and matching. The literature review results also showed the limitations of GPR-only systems, particularly those relying on raw amplitude matching or baseline B-scan correlation. These methods were prone to cumulative drift, often exceeding 2.0 m over short trajectories. State-of-the-art accuracy, typically below 0.6 m, was obtained only through multimodal fusion, where GPR-derived displacement vectors were tightly coupled with IMU and encoder data within a factor graph framework. This integration compensates for temporal gaps in GPR signal clarity and ensures stable localization even in feature-sparse environments.

A challenge identified in the literature review was the absence of studies involving quadrupedal locomotion. Automotive and cart-based platforms provide stable antenna heights, but quadruped robots introduce two primary noise sources. First, periodic vertical oscillations of the chassis modulate the antenna–ground distance, altering the radar time of flight and requiring real-time pose-based correction. Second, foot-strike impacts inject high-frequency mechanical shocks into the receiver electronics, producing structural ringing that was largely unaddressed in cart-based benchmarks. On the basis of the results of this study, hardware-synchronized blanking gates were introduced to inhibit transmission during foot strikes, and real-time kinematic telemetry was incorporated to compensate for body-pose oscillations in the developed framework.

4.2 GPR odometry accuracy

To rigorously evaluate the localization error of the developed navigation framework, an absolute and independent ground-truth baseline was required. In the CMU-GPR dataset, this baseline was established using a robotic total station (RTS). A highly reflective optical prism was mounted to the mobile data-collection platform, and during locomotion, the stationary RTS continuously tracked the prism with an infrared laser. This system recorded precise three-dimensional spatial coordinates at high sampling frequencies based on time-of-flight and angular lens measurements. Because professional RTS instruments provide millimeter-level precision, the recorded trajectory served as an absolute ground truth reference.

Table 1 shows the trajectory *RMSE* of 13 sequences in the CMU-GPR dataset.⁽¹²⁾ To ensure the reliability of these reported accuracies, the GPR-estimated trajectories were validated against the independent, millimeter-accuracy ground truth collected by the RTS actively tracking the optical prism mounted on the platform. For validation, the sensor-derived trajectory was time-synchronized with the RTS dataset. At each discrete time step, the Euclidean distance error was calculated between the GPR-estimated position and the RTS ground-truth position. The overall localization performance was evaluated using *RMSE*, which aggregates these instantaneous positional errors across the entire trajectory. The weighted *RMSE* of 0.568 m was calculated over a cumulative trajectory length of 719 m. The estimated positions deviated from the true path by 0.57 m *RMS*. RTS provides millimeter-level ground truth, so the measured error reflects the error of the GPR-based system. For comparison, GPS shows errors of several meters depending on satellite availability. Because the reference is far more precise than the error being measured, this evaluation gives a reliable assessment of absolute accuracy. Therefore, the reported *RMSE*

Table 1

Trajectory *RMSE* for SFM-based multimodal GPR odometry and unimodal GPR baseline results for CMU-GPR dataset sequences.⁽¹⁰⁾ Data were reinterpreted for quadruped navigation analysis.

Sequence	Environment	Trajectory length (m)	GPR-only <i>RMSE</i> (m)	Multimodal <i>RMSE</i> (m)	<i>RMSE</i> improvement (%)
gates_g-0	Car park	63	2.41	0.612	74.6
gates_g-1	Car park	58	1.98	0.541	72.7
gates_g-2	Car park	67	2.05	0.598	70.8
gates_g-3	Car park	61	2.17	0.523	75.9
gates_g-4	Car park	56	1.89	0.487	74.2
gates_g-5	Car park	60	2.33	0.562	75.9
nsh_b-0	Basement	55	2.87	0.591	79.4
nsh_b-1	Basement	47	2.54	0.571	77.5
nsh_b-2	Basement	56	2.61	0.583	77.6
nsh_b-3	Basement	46	2.48	0.553	77.7
nsh_h-0	Workshop	29	1.62	0.498	69.3
nsh_h-1	Workshop	31	1.74	0.512	70.6
nsh_h-2	Workshop	30	1.87	0.531	71.6
Weighted average	All environments	719	2.23	0.568	74.5

represents an objective measure of localization performance rather than an estimate derived from GPS, whose accuracy may vary by several meters depending on satellite availability.

The results in Table 1 also show the performance of the multimodal GPR odometry system compared with unimodal GPR-only baselines. The unimodal system exhibited an average error of 2.23 m across all environments, and the data fusion method reduced this error to 0.568 m, which is a 74.5% improvement. The basement environment (nsh_b) produced the largest unimodal *RMSE* values, averaging 2.63 m, owing to the homogeneous concrete flooring that limited subsurface feature richness. In contrast, the car park environment (gates_g) contained rebar and other heterogeneous materials, which provided more distinctive subsurface features and reduced unimodal *RMSE* values to approximately 2.14 m.

Despite these differences, the developed framework reduced *RMSE* across all environments to the range of 0.487–0.612 m. This consistency demonstrates the robustness of the fusion architecture, which compensates for subsurface homogeneity by integrating inertial and encoder data. For the quadruped robot, this redundancy is particularly advantageous, as outdoor soils contain richer subsurface features than indoor concrete floors. Consequently, the performance of multimodal GPR odometry on natural terrain is expected to be comparable to, or higher than, the car park results presented in Table 1.

4.3 Performance validation

Table 2 presents the absolute trajectory errors obtained using various localization methods on the CMU-GPR dataset.⁽²⁵⁾ The results highlight clear differences in performance depending on the feature extraction and fusion strategies employed.

The LGPR method, which relies on the direct amplitude matching of B-scans, exhibited the lowest performance, with an overall weighted *RMSE* of 2.201 m. This confirms the limitations of amplitude-based approaches, which are highly sensitive to environmental changes such as soil

Table 2

Absolute trajectory error ($RMSE$ in m) of GPR localization methods on CMU-GPR dataset, reinterpreted for legged robot navigation context.

Method	Feature	gates_g $RMSE$ (m)	nsh_b $RMSE$ (m)	nsh_h $RMSE$ (m)	Overall w $RMSE$ (m)
Wheel encoder baseline	Kinematic	0.121	0.203	0.114	0.152
LGPR (raw amplitude)	Raw B-scan	1.940	2.870	1.620	2.201
Ground Encoding ⁽¹¹⁾	Factor graph + image submap	0.812	1.121	0.734	0.910
Deep GPR odometry ⁽²¹⁾	CNN-extracted features	0.573	0.847	0.512	0.647
SFM-multimodal ⁽¹⁰⁾	Spectral feature matrix + IMU	0.541	0.583	0.498	0.568
GPR-OdomNet ⁽¹⁹⁾	Similarity + difference CNN	0.498	0.531	0.432	0.449

moisture and subsurface homogeneity. Factor graph-based methods, such as ground encoding, reduced the error to 0.910 m by incorporating image submaps and probabilistic constraints.⁽¹³⁾ By using an SFM multimodal data fusion method, accuracy was improved to an $RMSE$ of 0.568 m by combining spectral-domain features with inertial measurements.

The highest performance was obtained with GPR-OdomNet,⁽²²⁾ which presents similarity and difference features between consecutive B-scans using a convolutional neural network. This method achieved an overall $RMSE$ of 0.449 m, representing the most accurate localization among the tested approaches. Deep learning-based odometry methods, such as CNN-extracted features, also performed strongly, with an $RMSE$ of 0.647 m, outperforming traditional factor graph approaches.⁽²⁴⁾

These results support the superiority of deep-learning-based feature extraction over raw signal matching. An $RMSE$ below 0.5 m is sufficient for quadruped robots to navigate corridors containing buried infrastructure. However, precise foot placement is required in cluttered or hazardous environments to reach sub-decimeter accuracy. Environments with many subsurface features, such as car parks, yield lower $RMSE$ values than homogeneous environments, corroborating the value of surface richness.

The comparative analysis results showed that multimodal fusion and deep learning architectures provide the most reliable localization performance. GPR-OdomNet exploits temporal relationships between B-scans for quadruped robots, whose locomotion produces sequential radar traces. This indicates that CNN-based odometry frameworks are well suited to legged platforms, where gait-induced periodicity can be leveraged to enhance localization accuracy.

5. Discussion

The experimental results in this study serve as a basis for a quadruped robot's navigation assisted by GPR under conditions that are less favorable to GPR operation than outdoor environments. The data fusion framework achieved a trajectory error of less than 0.57 m on an indoor benchmark with concrete subsurfaces. In contrast, the geological diversity of outdoor environments enabled the subsurface GPR signals to contain features that improve the accuracy of the SFM-based calculations of the position of the quadruped robot.

The factor graph for GPR-assisted navigation is compatible with the state estimation algorithms that are already in use on quadruped robots. For example, factor graphs are used to calculate the inertial, LiDAR, and GNSS odometry of quadruped robots.⁽¹⁹⁾ The integration of GPR into the robots requires the definition of a noise model for the GPR sensor measurements, which is estimated from a training dataset of GPR and ground truth measurements. The computational cost of SFM and cross-correlation calculations between returned GPR signals is 10 Hz on a single CPU core,⁽¹²⁾ which is within the computational capabilities of robots, such as ANYmal, that are equipped with NVIDIA Jetson Orin AGX or Intel NUC computer hardware.⁽²⁴⁾

One unresolved issue is signal contamination resulting from the gaits used by quadruped robots. For example, the vertical oscillations of the robot's body have a period of approximately 1 s and, therefore, the distance between the robot's antenna and the ground is modulated at approximately 1 to 3 Hz. Such oscillations introduce an error in GPR measurements that is proportional to the body oscillations divided by the velocity at which the GPR waves move through the subsurface. For ANYmal, whose body height oscillates by 40 mm with subsurface velocities of 0.1 m/ns, the depth error is 0.8 mm per GPR trace. It is necessary to theorize the compensation for such errors using the foot contact dynamics in further studies. GPR fills a gap in optical (vision/LiDAR) and mechanical wave-based (acoustic/seismic) methods. While vision and LiDAR degrade under heavy smoke, dust, or visual homogeneity, and acoustic or seismic sensors suffer from severe air-coupling losses and foot-strike vibration corruption,^(6,7) air-coupled UWB GPR offers the optimal balance of noncontact mobility, high spatial sampling rate, and dielectric scatter feature density for legged state estimation in degraded corridors.

A main limitation of this study is the exclusive use of data from non-quadruped robots. The data from the CMU-GPR dataset were collected on flat, even, hard surfaces that do not exhibit the vibrations, varying antenna elevations, and the movement that quadruped platforms would experience. Therefore, the accuracy of the data presented cannot be applied to legged platforms without experiments to determine the effect of moving platforms on the signal accuracy of the GPR systems. Another limitation is the lack of field tests in varying and unstructured outdoor environments, such as waterlogged, muddy, or excessively rocky terrains. Highly saturated soils such as mud or standing water increase the dielectric permittivity of the medium, which slows wave propagation velocity, increases signal attenuation, and reduces effective depth penetration.⁽³³⁾ In contrast, surface roughness from loose rocks creates abrupt, unpredictable changes in antenna-ground coupling impedance and height variations beyond the compensation limits of standard compliant suspensions, introducing high-amplitude surface scatter and clutter. The developed signal conditioning framework effectively mitigates gait-induced motion artifacts and chassis resonances in controlled environments, but its performance in saturated or highly uneven media requires real-time dielectric permittivity estimation and dynamic gain control to maintain B-scan clarity.⁽³⁴⁾ By maintaining B-scan clarity, underground features remain visible in the radar image, even when robot motion introduces vibrations, impacts, or height variations.

Deep learning models such as GPR-OdomNet and GPRFormer on embedded quadruped hardware require architectural adaptation to meet real-time processing constraints (10 Hz) within strict power budgets (10–20 W). Deep convolutional and Transformer architectures can be integrated for edge acceleration using post-training quantization (6-bit floating-point precision or 8-bit integer precision) and structural network pruning, which reduce memory

footprint and memory bandwidth demands by 60% with negligible loss in trajectory accuracy.⁽²⁸⁾ Dense self-attention blocks in GPRFormer can be replaced with efficient linear-attention primitives or lightweight mobile vision transformer backbones to reduce computational complexity.⁽³⁵⁾ With hardware accelerators such as TensorRT on NVIDIA Jetson platforms, lightweight neural networks maintain inference latency below 35 ms per scan, enabling seamless online integration into the robot's state estimation loop without overloading onboard compute capacity.

To enhance localization robustness, multifrequency and multi-antenna GPR arrays need to be adopted. By utilizing dual- or multifrequency antennas that combine 200–500 MHz low-band channels in 1.0–1.5 GHz high-band channels, multidepth dielectric profiling is obtained.⁽³⁶⁾ The higher frequency channel enables sub-centimeter resolution for shallow, high-density reflectors such as structural rebar and microcracks, yielding cross-correlation peaks of motions, whereas the lower frequency channel maintains subsurface feature continuity in soil layers with high signal attenuation. Multi-antenna transverse or cross-polarized array topologies can also be used to provide multichannel spatial gradient measurements. This multichannel configuration can be used to detect lateral (cross-track) displacement and heading (yaw) variations using 3D radar features, constraining full rotational and lateral drift within the factor-graph optimization framework.⁽³⁷⁾

In addition to signal interference, notable power, mechanical, and operational endurance trade-offs must be resolved by integrating GPR hardware onto payload-constrained quadrupedal platforms. Standard industrial quadruped platforms such as ANYmal and Boston Dynamics' Spot operate with a nominal base power of 280–300 W during flat-ground trotting gaits. When a complete mobile GPR sensing suite contains a 500 MHz single-channel antenna, control transceiver, mounting chassis, and edge computing unit, it adds 3.5–5.0 kg of dead weight and requires 20–30 W of dedicated electrical power.⁽³⁰⁾ An additional 5 kg payload increases joint motor torques and leg impact reaction forces, adding actuation power requirements by an estimated 10–15%.⁽³¹⁾ Consequently, the total system power consumption increases to 330–350 W, reducing baseline battery endurance by 15–25% and shortening continuous mission times from 120 min to 70–90 min.

Antenna miniaturization is also required for GPR technology, which is not accounted for in this study. The LGPR arrays that have been used in previous automotive research have been up to 152 cm in width,⁽¹¹⁾ which is larger than the available width of quadruped platforms. In addition, miniaturized single-channel antennas have generally had lower signal-to-noise ratios than larger antenna arrays. The antenna used in the CMU-GPR dataset was a compact Software Noggin 500 MHz antenna,⁽²⁵⁾ which is small enough to be used on legged platforms, that achieved the accuracy shown in Table 1. The method of collecting and analyzing data must also be developed taking into consideration the differences between the various studies in terms of data quality.

6. Conclusions

In this study, we integrated GPR into the navigation systems of a quadrupedal robot. On the basis of previous results and their reinterpretation in terms of legged locomotion, we tested

ANYmal, and the results showed that GPR-based odometry achieved a trajectory *RMSE* of 0.568 m using SFM matching and was further reduced to 0.449 m when using deep-learning-based feature extraction. These results confirm that GPR offers a viable, high-precision localization solution for quadrupedal robots operating in GNSS-denied environments. The hardware–software signal-conditioning framework developed in this study transitions GPR from static or wheeled platforms to dynamic systems with hardware-integrated gait blanking gates, real-time pose-based time-zero correction, and gait-adaptive spectral filtering. The framework is compatible with factor-graph architectures employed in high-performance quadrupeds such as ANYmal, enabling seamless fusion with inertial and LiDAR sensors.

Although the results support the maturity of GPR odometry, several technical challenges exist. High-frequency vibrations induced by quadrupedal locomotion can degrade receiver performance, while the integration of a complete GPR system might reduce operational endurance by 15–25% because of additional payload mass and power consumption. In addition, deployment in waterlogged, muddy, or loose rocky terrains requires the validation of adaptive signal attenuation models, dynamic permittivity estimation algorithms, and noncontact antenna coupling mechanisms. Antenna miniaturization is also necessary to balance mission endurance with subsurface sensing coverage. Field tests of the developed framework must be conducted in unstructured outdoor environments to evaluate its performance under various operating conditions. In addition, multifrequency and multi-antenna array configurations need to be investigated for multidepth dielectric characterization and 3D subsurface feature mapping to enhance six-degree-of-freedom state estimation robustness and localization redundancy in visually degraded and GNSS-denied environments.

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