Autonomous Culvert Inspection on the Erie Canal using Legged Robots

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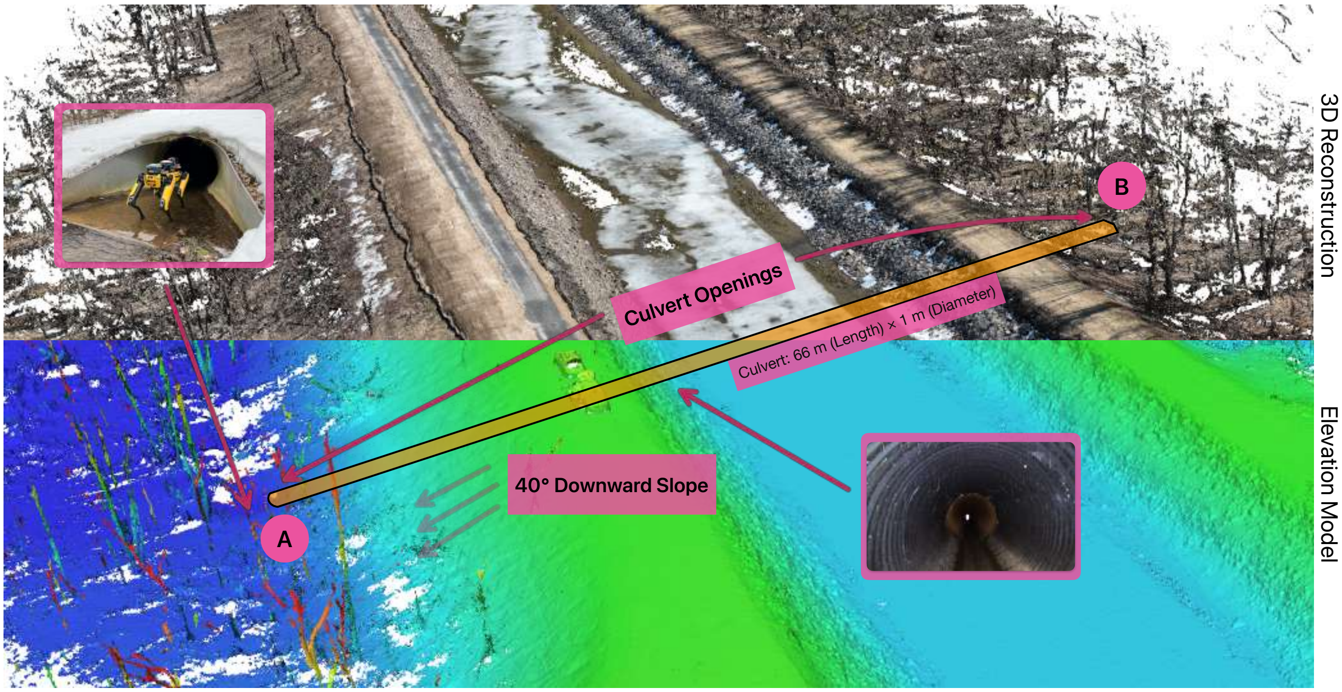

Fig. 1: Site-view from Culvert 110, western division, Erie canal - top is the 3D reconstruction and bottom is the elevation map.

Abstract— **Culverts under the Erie Canal perform the essential function of mitigating overflows and regulating water drainage around the canal. The Erie Canal was built in 1825 with modifications made every few decades. There are more than 350 culverts along the Erie Canal that goes from Buffalo, NY to New York City. Culverts need to be regularly inspected for damage due to aging, inclement weather, and strong water flow. Such inspections are currently performed manually, which is extremely tedious, cannot be done often due to scale, and vary in quality depending on the person performing the inspection.**

To address these challenges, we are working with the New York Canals Corporation to perform an autonomous inspection of the culverts using a legged robot. Through our experimentation, we have identified two primary challenges in this application. First, there is limited lighting inside a culvert, making it very hard to visually capture images that have any distinct features. This is an issue for both robot localization as well as inspection. Secondly, the banks of the canal that we need to navigate to get to the culvert are extremely steep (above 40-degree incline) and vary in terrain conditions based on the season. We have inspected the culverts in snowy conditions, wet and slushy conditions, as well as dry conditions. It is important for the robot to safely navigate to the culvert before it can inspect it.

Through work over the last six months, we have preliminary results as well as directions addressing both these challenges. This work presents our methodologies to perform safe and stable locomotion along the bank and adaptive light control to effectively illuminate the scene for good image capture. We will also describe our approach to integrate proprioception and exteroception into a learning framework for stable locomotion in uneven terrain.

I. INTRODUCTION

The Erie Canal is a historic waterway in upstate New York that connects the Hudson River to Lake Erie. Completed in 1825, the culverts beneath these banks are designed to divert excess drainage water. Unfortunately, these culverts have experienced structural degradation over time [1], [2], as shown in one of the NYCC (New York Canal Corporation) structure inspection reports in Figure 4. These structural degradations, such as surface corrosion, spalling, and seepage, can lead to culvert failure, potentially causing significant damage to the communities and ecosystems. Culverts are generally located in critically hazardous zones beneath the canals, making it difficult for humans to perform manual inspection. In addition, environmental complexities such as steep slopes and rugged terrain raise additional safety concerns for humans entering the culverts during manual inspection.

Legged robots are increasingly being adapted to address the challenges associated with manual inspections in structurally hazardous spaces [3], [4]. Their ability to traverse complex environments such as confined spaces, uneven ter-

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Fig. 3: Active illumination and exposure control on Boston Dynamics Spot and Unitree Go2 robots, inspecting Culvert 110 under Erie Canal.

rain, and GPS-denied areas, makes them ideal for inspecting culverts that are inaccessible or hazardous to humans. The autonomous navigation of legged robots through diverse and complicated environments has gained attention in recent years to accomplish critical tasks such as payload delivery [5], search and rescue [3], [6], environmental inspection [7], agricultural tasks [8], and others. Legged robots like Boston Dynamics SPOT, Unitree Go1/Go2, and Anybotics ANYmal provide basic legged locomotion, enabling them to walk on reasonably flat terrains. The primary challenge in using them for off-road navigation is to incorporate a detailed understanding of the terrain and use this for stable locomotion. Such stable locomotion will in turn allow us to deploy them in realistic applications such as culvert inspection.

In this work, we are collaborating with NYCC to collect data and perform experiments on their canal sites with various culverts (culvert 101, 102, 103, and 110) using Boston Dynamics SPOT and Unitree Go2 robots as shown in Figure 3. The experiments performed in this work are primarily from culvert 110. Figure 1 shows a digital elevation model (DEM) of the experiment site. To carry out an end-to-end autonomous inspection, the legged robot equipped with stereo cameras, LiDARs and a custom-built LED light for active illumination descends a 7-meter-long, 30-degree downward slope in rugged terrain, reaches the culvert located at Point A, and proceeds to Point B to complete the full inspection of task, and returns to Point A autonomously.

Our goal is an end-to-end solution for a legged robot to autonomously navigate the terrain and safely inspect the culvert. There are several components to achieving this goal. Currently, we have made progress on two modules that address the fundamental challenges of performing accurate state estimation in dark regions and achieving stable locomotion in tedious terrain. The modules are as follows :

- **Stable Navigation**: This module incorporates a context-aware learning architecture designed to generate high-level command velocities and predict stable gaits for a legged robot. It enables the legged robot to navigate safely and in a stable manner in an offroad environment such as the banks of the Canal. This module has been tested in simulation and has shown promising results compared to the baseline controllers.
- **Active Illumination**: This module develops an active illumination and exposure control scheme that uses online Bayesian optimization to set the optimal external light intensity and exposure time. The system runs onboard the robot in an event-triggered fashion. Preliminary results show a 47-197% improvement in feature tracking when using our method compared to Auto-exposure with max external light and no external light, respectively.

II. Related Work

A. Subterranean exploration using Legged Robots

The DARPA Subterranean (SubT) challenge [9], [10] has demonstrated various robotic exploration and inspection systems like [11], [12], [13] that demonstrate the capability of quadruped robots to navigate through sewers, tunnels, and cave spaces. Further, legged robots' locomotion capability has been validated [14], [15] across complex, uneven, and varying terrain while ensuring safety and efficiency.

With the hardware advancements in the industry, these robots have not been left untouched from performing some of the extreme navigation tasks like [16], [17]. Perpetual observation of terrain is essential to achieve robust and collision-free navigation of a robot. Sensor-based perception using exteroception has been exploited over the years that could result in a high-level but coursed characterization of a specific terrain. Leveraging sensor-based perception works like [18], [19] utilizes images to determine risk-aware path planning for a legged robot. However, these methods, without any additional signal of terrain difficulty results in a lack of internal feedback and could make the robot's body unaware of its current state. To overcome these issues, [20] couples both exteroceptive and proprioceptive parameters of a robot to adapt between different gaits.

B. Stable legged locomotion

Fundamental physics provides a solid foundation to assess the stability of a physical object. Evaluating physical concepts like the center of gravity, establishing equilibrium, and the moment of force acting on the body determines the state. Furthermore, a more formal notion of stability is explored through the analysis of a zero moment point (ZMP). The ZMP has been extensively used as a quantitative metric to analyze and understand the stability of various legged locomotions since it was introduced by Vukobratovi and Stepanenko [21]. But with legged robots, on volatile surfaces, it's more complicated. Robots like Boston Dynamic's Spot acquire state-of-the-art SDK to stabilize their state. However, we have learning-oriented literature that utilizes various stability modules from robot proprioception for supervision to estimate terrain properties for ensuring safe and robust navigation. Works like [20] provide resistance to the robot's motion using proprioceptive readings as the vibration cost, which could determine the stability of the robot. On the other hand, [2] uses direct proprioceptive measures to regulate between a holonomic and non-holonomic action space to reduce the risk of entrapment. Some of the quantification relies on a more detailed analysis [30] of the proprioceptive parameters. On the other hand, simulated observations [17], [22] tend to be useful in regulating the robot's locomotion. In our Navigation-Stack module, we incorporate the trade-off between the slips and the velocity acquired by the robot when traversing different terrains.

Failed bituminous coating along the invert | Uneven grouted transition with minor displacement | Widespread minor surface corrosion

3 inches deep cracking | 1 ft long spalling | Seepage

Fig. 4: Structure Inspection Report completed by NYCC on 11/14/2023 at Culvert - 110 (Royalton). The inspection was carried out manually by the inspector using hand tools, including a digital camera, folding ruler, hammer, and tape rule. The report illustrates various degradation landmarks inside the culvert.

C. Effect of illumination and exposure on robot perception

Environment illuminance plays a critical role in the performance of visual estimation methods, which heavily rely on feature detection and matching. Illuminance directly influences image brightness and camera exposure, ultimately affecting image quality and feature tracking performance. This impact is particularly pronounced in subterranean environments such as caves, mines, and underground structures.

Standard vision sensors, including monocular, RGB-D, and stereo cameras, rely on auto-exposure (AE) to adjust settings like exposure time (shutter speed), gain (ISO), and aperture. While AE performs well in typical scenarios, it struggles in extreme environments. The primary limitation of AE stems from its objective: maintaining a mean pixel intensity around 50%, aiming for neither over nor under-exposure. This approach, however, may not be optimal for robot vision tasks. The goal in these applications is to reliably detect and match stable features, which a neutrally exposed image doesn't necessarily guarantee.

D. Active exposure control

Several exposure control methods have been proposed [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33]. [23], [25] controls camera exposure-time while [30], [34] controls both exposure-time and gain. Some of these methods propose image utility metrics that aim to quantify the quality of images from a feature detection and matching perspective like M_{shim} [25], $M_{softperc}$ [23] and NEWG [34]. These metrics typically revolve around using image gradients as most feature detectors exploit gradients for key-point detection.

III. AUTONOMOUS CULVERT INSPECTION USING LEGGED ROBOTS

Figure 8 shows the overall architecture of our method, including Navigation-Stack for stable navigation and Perception-Stack for the culvert vision inspection. The architectural details are as follows:

*1) **Stable Navigation**:* During the training, Navigation-Stack inputs a stream of RGBD images and the robot's proprioception data $\mathbf{P}_t$ (joints, hips, and feet slips) recorded in an unsupervised fashion. The framework encodes these readings into two backbones sel maps [35] and a vanilla encoder for proprioception resulting in sets of random sequences S_t with visual tokens $\mathbf{F}_t^{\text{visual}}$ and proprioceptive features $\mathbf{F}_t^{\text{proprio}}$ stacked together. As an intermediate step, a pointer network is defined to assign the weighted confidence Confidence_t between these sets and select the dominating ones to train. Finally, we use the trained contextual relationship $\mathbf{c}_t$ as the input to a neural network that provides the optimal command velocity and height of the robot. The loss function our training scheme uses to select optimal sequences is a trade-off between the velocity and slip measurement from the robot's proprioception. The slip parameter is a sensor reading from the Spot that determines the offset of the robot's legs from the base. This parameter has been widely used in various learning-based legged locomotion frameworks [20] [22]. To train our Navigation-Stack model in simulation, we use the IsaacSim [36] simulator with varying terrain configured according to the difficulty levels as shown in Figure 7. We train our model on terrain configured using only 10% difficulty level and test our model on 100% difficulty.

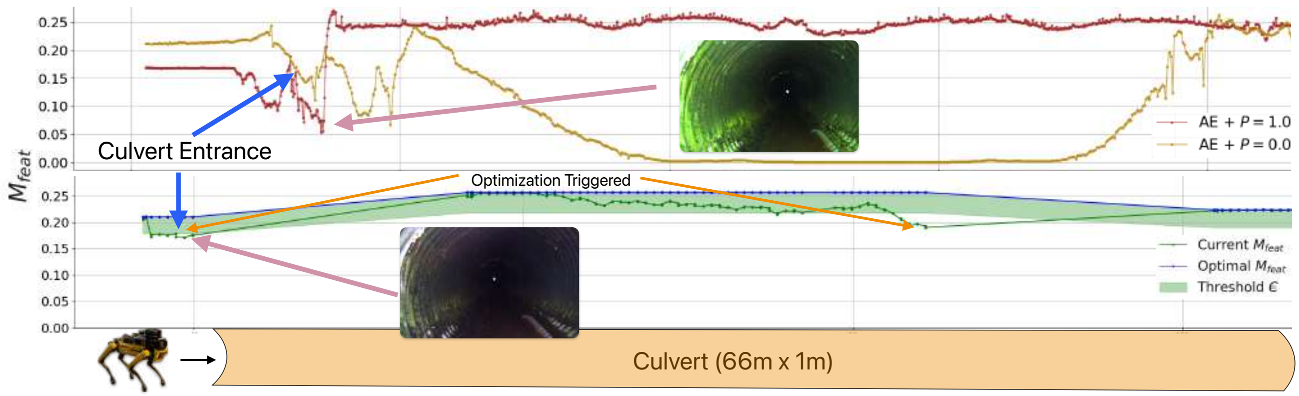
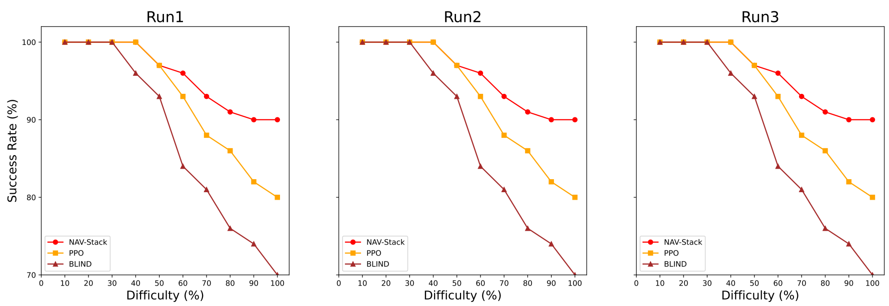
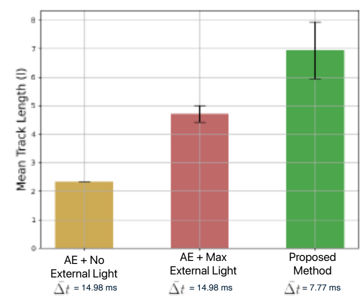


Fig. 5: Change in image utility (using M_{feat}) as the robot enters the culvert is shown in the 3 settings, AE with no external light results in underexposed images while adding a fixed (100%) light introduces artifacts such as a greenish hue. Finally, with Perception-Stack, the overall image utility is consistent, and the sudden dips and greenish hue at the culvert entrance are prevented.



(a) Simulation Results: Our high level controller achieves better success rates when compared with two IsaacSim's native locomotion baselines. The PPO baseline was trained using privileged knowledge from both exteroception and proprioception.



(b) Feature tracking performance (l = track length) of the 3 settings where our algorithm shows improved feature tracking and lower exposure-times ($\bar{\Delta}t$ = mean exposure-time).

Fig. 6: Combined simulation and tracking performance results.

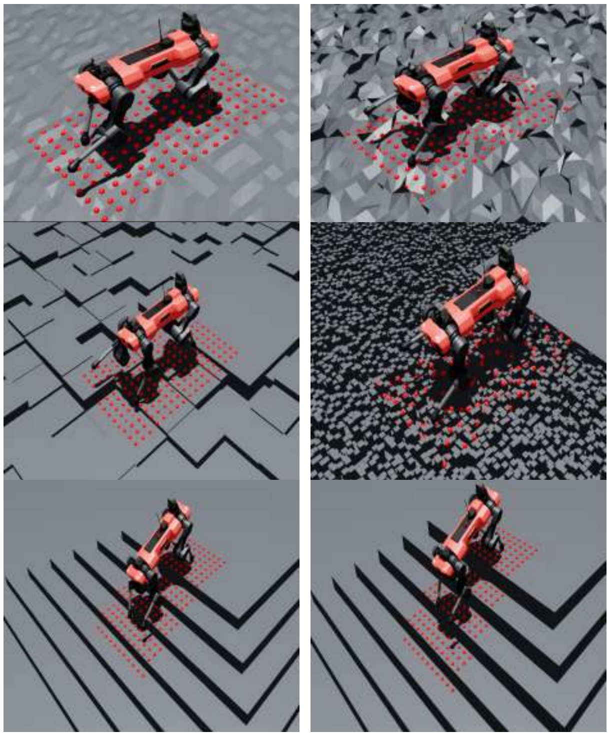
*2) **Active Illumination**:* The exposure control methods mentioned in subsection II-D, adjusting camera parameters like shutter speed and gain, often fall short in challenging low-light or varying-light conditions. Insufficient scene radiance can necessitate excessively long exposures or high gains, leading to reduced frame rates and increased noise. Integrating an onboard light source offers a promising solution by augmenting scene illumination. However, naive control of onboard lighting can introduce undesirable artifacts such as specular reflections and overexposure, while also consuming significant robot power. Careful tuning and control are essential to mitigate these drawbacks.

$$M_{\text{feat}} = \left(\frac{1}{N} \sum_{i=1}^{N} R_i \right) \cdot \left(\frac{1}{N} \sum_{i=1}^{N} Q_i \right)^2 \qquad (1)$$

We propose a novel feature detector-based image utility metric and use it as a cost function of our online, event-triggered Bayesian optimization. To quantify image utility, we utilize R2D2 [37] as the base feature detection network. We compute the product of the mean repeatability and the square of the mean reliability that yields a single scalar value M_{feat} (Equation 1). We evaluated M_{feat} performance and compared it against other benchmark metrics, demonstrating a strong correlation with feature matching performance. The overall Perception-Stack's architecture is illustrated in Figure 8. Our algorithm begins with Bayesian optimization (BO) to compute the optimal configurations (external light intensity P^* and exposure time Δt^*), which provides the optimal score (M^*_{feat}). These settings are then executed by the vision system, and images are received by an image quality assessment module, which checks the current score and compares it with the previous optimal score. A threshold ϵ ($\epsilon > 0$) is provided by the user, which determines the tolerance. As the robot moves and if $M^*_{feat} - M_{feat} > \epsilon$, it indicates that the previous optimal solutions are not sophisticated enough to accommodate the dramatic changes in the scene. This triggers the reactivation of the BO to refine the control variables P^* and Δt^* to improve the image quality.

IV. Experimental Setup and Preliminary Results

To evaluate Navigation-Stack performance, we train a network using the schema shown in Figure 8. For simulation, we use IsaacLab and create multiple terrain types with varying



Difficulty: 10% Difficulty: 100%

Fig. 7: NAVstack and all the baselines were trained on multiple terrains with a difficulty of 10% only. However, we evaluate the performances on the same terrains with difficulty up to 100%.

difficulties Figure 7 to address the real-world scenario from our problem scenario. For a fair comparison, we train our model and all other baselines on the same terrains with a difficulty level of 10% and evaluate all the tests on 100% difficulty. We compare Navigation-Stack performance with two other baseline policies from IsaacSim Omniverse. The *Blind* policy was trained over the same training scenario by only using proprioception, whereas the *PPO* baseline was equipped with a height scanner as an exteroception signal. We evaluate all methods based on the success rate and base and body oscillation of the robot while maneuvering through variable terrain. We conducted three experiments, keeping the starting and end points the same for all baselines and ours. The results can be seen in 6a.

We performed real-world experiments in the culvert to evaluate the robustness of our illumination control module (Perception-Stack). Our algorithm is deployed on the Spot robot equipped with a FLIR Blackfly S camera and controllable 50W LED. Implemented using ROS2, PyTorch, and Scikit-learn, our algorithm runs online on an onboard NVIDIA Jetson. The optimization process takes about 20 seconds, depending on the chosen hyper-parameters. We conducted several tele-operated missions beneath the Erie Canal, capturing images under 3 camera configurations with fixed gain: (1) AE with no external lighting (built-in AE only), (2) AE with fixed external lighting (LED at constant 100%), and (3) our algorithm. Feature tracking performance for each setting is shown in 6b while change in M_{feat} is shown in Figure 5. The two baselines result in sub-optimal performance; without external light, image utility and feature tracking is poor, although the use of external light (at max intensity) improves feature tracking, it introduces artifacts such as a greenish hue. Our method achieves superior average track lengths (47-197% improvement) and reduced exposure times by 52% (effectively reducing motion blur) while preventing artifacts due to reflections and over-exposure.

V. Challenges and Future Work

Our experiment insights have demonstrated the potential usage of the proposed modules in real-world applications. We anticipate several challenges to resolve before testing the complete stack at the site.

- **Real-World deployment of Navigation-Stack**: Ongoing work is on adapting the learnt model in simulation to real-world experiments in multiple offroad environments including the culvert. Future work includes incorporation of detailed terrain information (snow, marshy soil, dampness) as well as generalizing the learnt model across various legged robots.
- **Adaptive Planning in Navigation-Stack:** We identified further locomotion improvements by adding another stack in our pipeline for stable path planning of the robot in an adaptive manner. As discussed in subsection II-B, there is a prior work on estimating stability margins using ZMP and GIIM metrics. We are in the process of using these signals to estimate the stability margin based path planner for efficient and stable locomotion in our environment.
- **Water and Biofilm Hazards:** Wet surfaces inside culverts can hinder traction and visual inspection due to biofilm layers. The irregular traction makes the culvert slippery and prone to failure and creates a reflection on the water surface. Accurately identifying and adapting to such scenarios requires specific characterization, modeling and adaptation to both the perception and navigation stacks.
- **Continuous illumination controls:** The proposed illumination control strategy was implemented in an event-triggered recursive optimization pipeline and temporarily pause robot movement to determine optimal settings before proceeding to the next way-point. We aim to further improve our algorithm by applying a continuous control method and reducing the computing time to ensure a smooth maneuver.
- **Visual Features for Degradation Detection:** We aim to scale our Perception-Stack by incorporating vision algorithms to detect the degradations such as corrosion, seepage, and spalling of culvert surfaces. This requires specifications of the size and type of damages to be identified and a detailed characterization of visual detection algorithms to accomplish such detections.
- **System Engineering**: In spite of using state-of-the-art sensors, we still identified networking issues due to the structural complexities inside the culvert and other environmental factors. Culverts often block GNSS

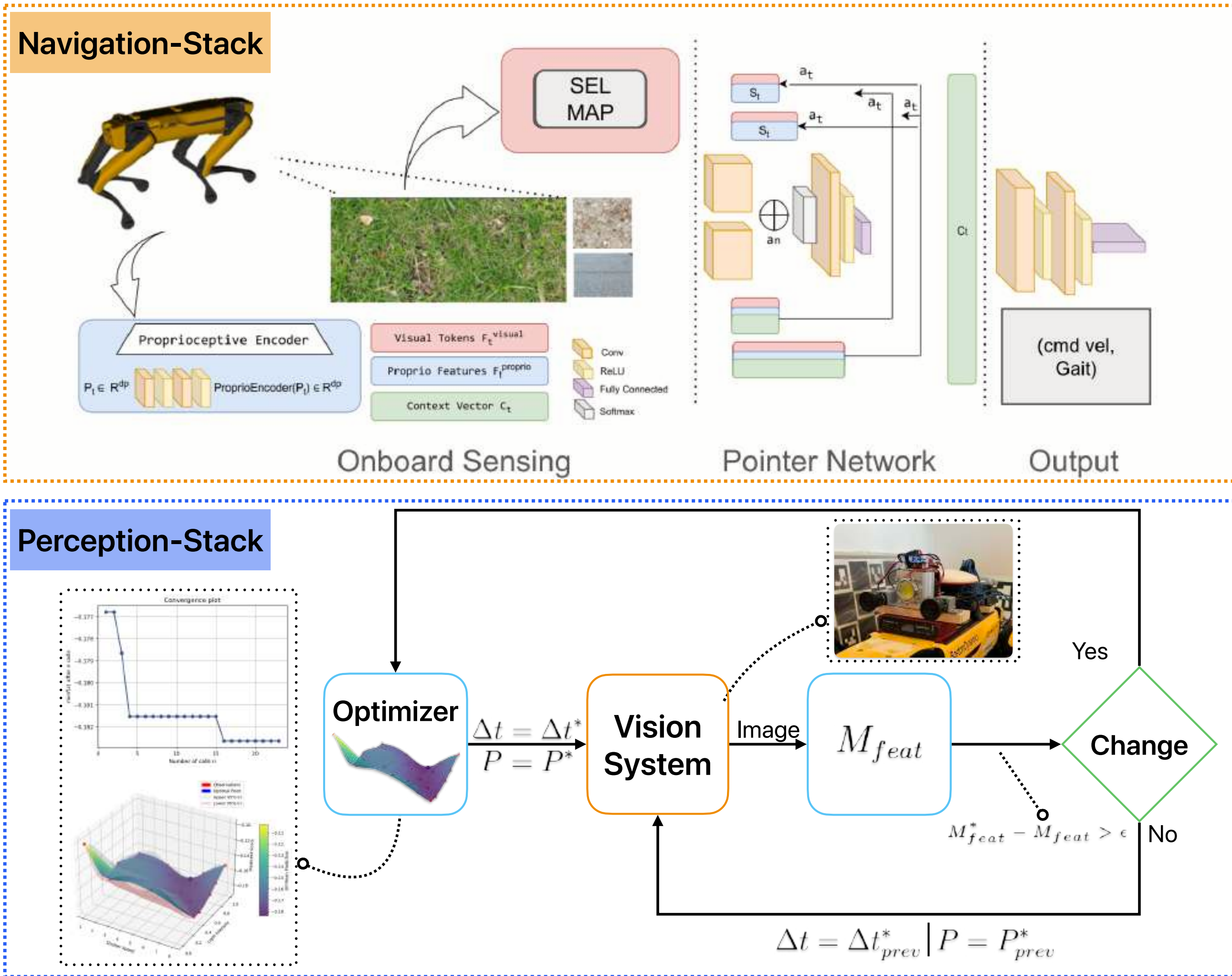


Fig. 8: Complete overview of our pipeline. Navigation-Stack offers high-level control and stable locomotion, while Perception-Stack provides active illumination and exposure control for improved robot perception and estimation.

signals, requiring alternative localization methods, such as inertial navigation systems or mesh networks for communication. Our autonomy stack needs to be self sufficient as well as robust to such losses for long-term deployment in realistic environments.

VI. Conclusion

In this work, we introduced an end-to-end autonomy pipeline for a culvert inspection in the Erie Canal using Boston Dynamics Spot robot. Our ongoing efforts demonstrate the capability of a legged robot to perform inspection tasks that are hazardous for humans. The two modules presented in this work provide a solution to the navigation problem on steep, rugged slopes and active adaptation of light control inside the culvert. We also present our current challenges and the future directions we have identified during our experiments.

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References

[1] M. El-Taher, "The effect of wall and backfill soil deterioration on corrugated metal culvert stability," Ph.D. dissertation, Queen's University, 2009.

[2] A. Faber, "https://www.superiorrivers.org/the-role-of-culverts-in-our-watersheds/," Ph.D. dissertation, Superior Tivers, 2020.

[3] C. D. Bellicoso, M. Bjelonic, L. Wellhausen, K. Holtmann, F. Günther, M. Tranzatto, P. Fankhauser, and M. Hutter, "Advances in real-world applications for legged robots," *Journal of Field Robotics*, vol. 35, no. 8, pp. 1311–1326, 2018.

[4] G. Haddeler, J. Chan, Y. You, S. Verma, A. H. Adiwahono, and C. M. Chew, "Explore bravely: Wheeled-legged robots traverse in unknown rough environment," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2020, pp. 7521–7526.

[5] M. Figliozzi and D. Jennings, "Autonomous delivery robots and their potential impacts on urban freight energy consumption and emissions," *Transportation research procedia*, vol. 46, pp. 21–28, 2020.

[6] M. Eich, F. Grimminger, and F. Kirchner, “A versatile stair-climbing robot for search and rescue applications,” in *2008 IEEE international workshop on safety, security and rescue robotics*. IEEE, 2008, pp. 35–40.

[7] H. Kolvenbach, C. Bärtschi, L. Wellhausen, R. Grandia, and M. Hutter, “Haptic inspection of planetary soils with legged robots,” *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 1626–1632, 2019.

[8] N. S. Naik, V. V. Shete, and S. R. Danve, “Precision agriculture robot for seeding function,” in *2016 international conference on inventive computation technologies (ICICT)*, vol. 2. IEEE, 2016, pp. 1–3.

[9] M. Tranzatto, T. Miki, M. Dharmadhikari, L. Bernreiter, M. Kulkarni, F. Mascarich, O. Andersson, S. Khattak, M. Hutter, R. Siegwart *et al.*, “Cerberus in the darpa subterranean challenge,” *Science Robotics*, vol. 7, no. 66, p. eabp9742, 2022.

[10] K. Ebadi, L. Bernreiter, H. Biggie, G. Catt, Y. Chang, A. Chatterjee, C. E. Denniston, S.-P. Deschênes, K. Harlow, S. Khattak *et al.*, “Present and future of slam in extreme environments: The darpa subt challenge,” *IEEE Transactions on Robotics*, vol. 40, pp. 936–959, 2023.

[11] H. Kolvenbach, D. Wisth, R. Buchanan, G. Valsecchi, R. Grandia, M. Fallon, and M. Hutter, “Towards autonomous inspection of concrete deterioration in sewers with legged robots,” *Journal of field robotics*, vol. 37, no. 8, pp. 1314–1327, 2020.

[12] T. Roucek, M. Pecka, P. Cızek, T. Petrıcek, J. Bayer, V. Šalansky, T. Azayev, D. Hert, M. Petrlık, T. Báca *et al.*, “System for multi-robotic exploration of underground environments ctu-cras-norlab in the darpa subterranean challenge,” *arXiv preprint arXiv:2110.05911*, 2021.

[13] K. Otsu, S. Tepsuporn, R. Thakker, T. S. Vaquero, J. A. Edlund, W. Walsh, G. Miles, T. Heywood, M. T. Wolf, and A.-A. Agha-Mohammadi, “Supervised autonomy for communication-degraded subterranean exploration by a robot team,” in *2020 IEEE aerospace conference*. IEEE, 2020, pp. 1–9.

[14] M. Wermelinger, P. Fankhauser, R. Diethelm, P. Krüsi, R. Siegwart, and M. Hutter, “Navigation planning for legged robots in challenging terrain,” in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2016, pp. 1184–1189.

[15] A. Agarwal, A. Kumar, J. Malik, and D. Pathak, “Legged locomotion in challenging terrains using egocentric vision,” in *Conference on robot learning*. PMLR, 2023, pp. 403–415.

[16] L. Wellhausen and M. Hutter, “Artplanner: Robust legged robot navigation in the field,” *arXiv preprint arXiv:2303.01420*, 2023.

[17] Z. Fu, A. Kumar, A. Agarwal, H. Qi, J. Malik, and D. Pathak, “Coupling vision and proprioception for navigation of legged robots,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 17 273–17 283.

[18] A. J. Sathyamoorthy, K. Weerakoon, T. Guan, M. Russell, D. Conover, J. Pusey, and D. Manocha, “Vern: Vegetation-aware robot navigation in dense unstructured outdoor environments,” in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2023, pp. 11 233–11 240.

[19] A. J. Sathyamoorthy, K. Weerakoon, M. Elnoor, A. Zore, B. Ichter, F. Xia, J. Tan, W. Yu, and D. Manocha, “Convoi: Context-aware navigation using vision language models in outdoor and indoor environments,” *arXiv preprint arXiv:2403.15637*, 2024.

[20] M. Elnoor, A. J. Sathyamoorthy, K. Weerakoon, and D. Manocha, “Pronav: Proprioceptive traversability estimation for legged robot navigation in outdoor environments,” *IEEE Robotics and Automation Letters*, 2024.

[21] M. Vukobratović and J. Stepanenko, “On the stability of anthropomorphic systems,” *Mathematical biosciences*, vol. 15, no. 1-2, pp. 1–37, 1972.

[22] K. Weerakoon, A. J. Sathyamoorthy, M. Elnoor, and D. Manocha, “Vapor: Legged robot navigation in unstructured outdoor environments using offline reinforcement learning,” in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 10 344–10 350.

[23] Z. Zhang, C. Forster, and D. Scaramuzza, “Active exposure control for robust visual odometry in HDR environments,” in *2017 IEEE International Conference on Robotics and Automation (ICRA)*. Singapore, Singapore: IEEE, May 2017, pp. 3894–3901. [Online]. Available: http://ieeexplore.ieee.org/document/7989449/

[24] S. Zhang, J. He, B. Xue, J. Wu, P. Yin, J. Jiao, and M. Liu, “An Image Acquisition Scheme for Visual Odometry based on Image Bracketing and Online Attribute Control,” in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. Yokohama, Japan: IEEE, May 2024, pp. 381–387. [Online]. Available: https://ieeexplore.ieee.org/document/10611141/

[25] I. Shim, J.-Y. Lee, and I. S. Kweon, “Auto-adjusting camera exposure for outdoor robotics using gradient information,” in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*. Chicago, IL, USA: IEEE, Sep. 2014, pp. 1011–1017. [Online]. Available: http://ieeexplore.ieee.org/document/6942682/

[26] B. Han, Y. Lin, Y. Dong, H. Wang, T. Zhang, and C. Liang, “Camera Attributes Control for Visual Odometry With Motion Blur Awareness,” *IEEE/ASME Transactions on Mechatronics*, vol. 28, no. 4, pp. 2225–2235, Aug. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10040760/

[27] S. Zhang, J. He, Y. Zhu, J. Wu, and J. Yuan, “Efficient Camera Exposure Control for Visual Odometry via Deep Reinforcement Learning,” *IEEE Robotics and Automation Letters*, vol. 10, no. 2, pp. 1609–1616, Feb. 2025. [Online]. Available: https://ieeexplore.ieee.org/document/10816543/

[28] J. Kim, Y. Cho, and A. Kim, “Exposure Control Using Bayesian Optimization Based on Entropy Weighted Image Gradient,” in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. Brisbane, QLD: IEEE, May 2018, pp. 857–864. [Online]. Available: https://ieeexplore.ieee.org/document/8462881/

[29] I. Mehta, M. Tang, and T. D. Barfoot, “Gradient-Based Auto-Exposure Control Applied to a Self-Driving Car,” in *2020 17th Conference on Computer and Robot Vision (CRV)*. Ottawa, ON, Canada: IEEE, May 2020, pp. 166–173. [Online]. Available: https://ieeexplore.ieee.org/document/9108676/

[30] J. Tomasi, B. Wagstaff, S. L. Waslander, and J. Kelly, “Learned Camera Gain and Exposure Control for Improved Visual Feature Detection and Matching,” *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 2028–2035, Apr. 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9353970/

[31] K. Lee, U. Shin, and B.-U. Lee, “Learning to Control Camera Exposure via Reinforcement Learning,” in *2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. Seattle, WA, USA: IEEE, Jun. 2024, pp. 2975–2983. [Online]. Available: https://ieeexplore.ieee.org/document/10657210/

[32] R. Gomez-Ojeda, Z. Zhang, J. Gonzalez-Jimenez, and D. Scaramuzza, “Learning-Based Image Enhancement for Visual Odometry in Challenging HDR Environments,” in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. Brisbane, QLD: IEEE, May 2018, pp. 805–811. [Online]. Available: https://ieeexplore.ieee.org/document/8462876/

[33] X. Liu, Z. Gao, H. Cheng, P. Wang, and B. M. Chen, “Learning-based Low Light Image Enhancement for Visual Odometry,” in *2020 IEEE 16th International Conference on Control & Automation (ICCA)*. Singapore: IEEE, Oct. 2020, pp. 1143–1148. [Online]. Available: https://ieeexplore.ieee.org/document/9264401/

[34] J. Kim, Y. Cho, and A. Kim, “Proactive Camera Attribute Control Using Bayesian Optimization for Illumination-Resilient Visual Navigation,” *IEEE Transactions on Robotics*, vol. 36, no. 4, pp. 1256–1271, Aug. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9098963/

[35] P. Ewen, A. Li, Y. Chen, S. Hong, and R. Vasudevan, “These maps are made for walking: Real-time terrain property estimation for mobile robots,” *IEEE Robotics and Automation Letters*, vol. 7, no. 3, pp. 7083–7090, 2022.

[36] “Nvidia isaac sim,” in *https://developer.nvidia.com/isaac/sim*. NVIDIA.

[37] J. Revaud, C. De Souza, M. Humenberger, and P. Weinzaepfel, “R2D2: Reliable and Repeatable Detector and Descriptor,” in *Advances in Neural Information Processing Systems*, vol. 32. Curran Associates, Inc., 2019. [Online]. Available: https://proceedings.neurips.cc/paper/2019/hash/3198dfd0aef271d22f7bcddd6f12f5cb-Abstract.html