Journal of Robotics and Autonomous Technologies
https://ratjournal.net

Forecasting Terrain Traversal in Legged Exploration Robots with Adaptive Locomotion Policies

Samuel Pang*

Department of Supply Chain and Information Management, School of Business, Hang Seng University of Hong Kong, Hong Kong, Hong Kong SAR, China

Corresponding author: samuel.pang@hsu.edu.hk

Abstract

The deployment of legged robots in unstructured and hazardous environments necessitates advanced predictive capabilities to ensure safe and efficient terrain traversal. While adaptive locomotion policies have significantly improved the robustness of legged systems in navigating complex topographies, accurately predicting the success or failure of these policies prior to physical execution remains a critical challenge. This paper presents a comprehensive comparative analysis of terrain traversal prediction methodologies derived from adaptive locomotion policies. By systematically evaluating proprioceptive and exteroceptive data streams integrated within reinforcement learning frameworks, this study identifies the latent features most indicative of traversal success across varied terrains such as gravel, mud, steep slopes, and discrete stairs. The research methodology employs a modular predictive architecture that maps the internal state representations of trained locomotion policies to external traversal outcomes. Extensive simulations demonstrate that incorporating policy specific behavioral metrics significantly enhances prediction accuracy compared to purely geometric terrain assessments. The findings suggest that the internal dynamics of adaptive policies contain implicit representations of terrain traversability, which can be extracted and utilized for high level path planning and risk mitigation. This research contributes to the broader field of autonomous exploration by bridging the gap between low level motor control and high level cognitive planning, ultimately enabling more autonomous, resilient, and intelligent legged robotic systems capable of sustained operation in unknown environments.

Keywords: Legged Robotics; Adaptive Locomotion; Terrain Prediction; Comparative Analysis; Terrain Traversal

1. Introduction

1.1 The Challenge of Legged Exploration

The fundamental premise of legged robotics lies in the promise of traversing environments that are traditionally inaccessible to wheeled or tracked vehicles. Natural landscapes, disaster zones, and extraterrestrial surfaces are characterized by extreme structural discontinuities, varying friction coefficients, and unpredictable dynamic obstacles. Legged robots, by virtue of their discrete footholds and highly articulated kinematic structures, possess the theoretical capability to navigate such complex terrains [1]. However, translating this theoretical potential into robust physical execution has historically proven to be an immense engineering challenge. The primary difficulty stems from the highly nonlinear dynamics of legged locomotion, which involve intermittent multi point contacts with the environment, unilateral force constraints, and the constant need to maintain dynamic balance while in motion [2]. In recent years, the paradigm of legged control has shifted from classical, model based trajectory optimization towards data driven, learning based methodologies. Adaptive locomotion policies, typically synthesized through deep reinforcement learning, have demonstrated unprecedented agility and robustness in the face of environmental uncertainties [3]. These policies learn to map sensory inputs directly to joint torques or position commands, implicitly adapting to changes in terrain topology and physical disturbances without requiring explicit mathematical models of the environment. Despite these advancements, a significant limitation persists in the realm of high level autonomous navigation. While an adaptive policy may be highly capable of recovering from a stumble or adjusting to a slippery surface, the robot often lacks the foresight to determine whether a particular stretch of terrain is fundamentally traversable before attempting to cross it [4]. This lack of predictive capability can lead to catastrophic failures, entrapment, or unnecessary energy expenditure in scenarios where the physical limits of the robot or the policy are exceeded.

1.2 Objectives and Scope of the Study

The primary objective of this study is to develop and evaluate a comprehensive framework for predicting terrain traversal outcomes by leveraging the internal mechanisms of adaptive locomotion policies. Instead of relying solely on external geometric representations of the environment, such as elevation maps or point clouds, this research investigates the hypothesis that the latent features and temporal dynamics within a trained locomotion policy contain highly informative signals regarding terrain traversability. By conducting a rigorous comparative analysis across diverse terrain typologies and policy architectures, this study aims to isolate the specific variables that contribute most significantly to predictive accuracy. The scope of this research encompasses the design of a modular prediction pipeline that interfaces with existing reinforcement learning based control systems. It involves the systematic extraction of proprioceptive data, exteroceptive sensor fusion, and policy specific action distributions. Furthermore, the study seeks to quantify the performance improvements achieved by integrating these policy derived metrics compared to traditional, purely kinematic or geometry based prediction models. The ultimate goal is to provide a reliable, real time predictive signal that can be utilized by high level path planners to make informed decisions regarding route selection, speed modulation, and risk avoidance, thereby enhancing the overall autonomy and survivability of legged exploration robots in unknown environments.

2. Background and Literature Review

2.1 Evolution of Adaptive Locomotion Policies

The development of control strategies for legged robots has undergone a significant evolution over the past several decades. Early approaches relied heavily on precise mathematical modeling of the robot dynamics and the environment [5]. Techniques such as Zero Moment Point control and inverted pendulum models were successfully utilized to achieve stable walking on flat, structured surfaces. However, these classical methods often struggled when faced with irregular terrain, as the assumptions underlying the simplified models were routinely violated by the complexities of the real world. The introduction of Model Predictive Control offered a substantial improvement by allowing the robot to optimize its future trajectory over a finite time horizon, considering dynamic constraints and expected contact forces [6]. While Model Predictive Control demonstrated impressive results in dynamic maneuvers and disturbance rejection, it typically required accurate state estimation and significant computational resources, and its performance was fundamentally limited by the fidelity of the internal dynamics model and the predefined contact sequence. The advent of deep reinforcement learning has fundamentally disrupted the field of legged locomotion. By framing the control problem as a Markov Decision Process, researchers have been able to train neural network policies that map sensory observations directly to motor commands through extensive trial and error in simulated environments [7]. These adaptive policies have shown remarkable success in zero shot transfer to the real world, exhibiting robust behaviors such as blindly climbing stairs, navigating through dense brush, and recovering from severe external pushes. Early reinforcement learning approaches focused primarily on proprioceptive policies, which relied exclusively on internal sensors such as joint encoders and inertial measurement units to infer the state of the terrain through physical interaction [8]. While surprisingly effective, purely proprioceptive policies are inherently reactive and cannot anticipate upcoming obstacles. Recent advancements have focused on integrating exteroceptive sensing, such as depth cameras and LiDAR, into the reinforcement learning pipeline, allowing the policy to adapt its gait preemptively based on perceived terrain geometry.

2.2 Terrain Traversal Prediction Models

Parallel to the advancements in low level locomotion control, significant research efforts have been directed towards high level terrain assessment and traversability prediction. Traditionally, traversability has been formulated as a geometric mapping problem. Mobile robots, including wheeled and tracked platforms, utilize active sensors to construct dense elevation maps or three dimensional point clouds of the surrounding environment. These geometric representations are then analyzed using heuristic algorithms to calculate metrics such as surface roughness, slope inclination, and step height [9]. A terrain region is deemed traversable if these geometric metrics fall within predefined thresholds corresponding to the physical capabilities of the robot platform. While this approach is well established and computationally straightforward, it presents several critical shortcomings when applied to agile legged robots operating under adaptive locomotion policies. First, purely geometric analysis fails to account for the physical interactions between the robot and the terrain, such as soil deformation, friction variations, and dynamic load transfer. A steep slope of loose gravel may possess the exact same geometric profile as a steep slope of solid rock, yet the traversability outcomes for a legged robot would be drastically different. Second, traditional geometric methods do not consider the specific capabilities and adaptations of the underlying control policy. An advanced reinforcement learning policy might successfully negotiate a complex arrangement of discrete footholds that a simple heuristic planner would classify as an impassable obstacle. Consequently, more sophisticated predictive models have begun to emerge that attempt to bridge the gap between perception and physical interaction. These models often employ machine learning techniques to map multimodal sensor data, including visual appearance and geometric structure, to human annotated traversability scores or self supervised mobility metrics [10].

2.3 Gaps in Comparative Analysis

Despite the growing body of literature on both adaptive locomotion and terrain prediction, there remains a substantial gap in the comprehensive comparative analysis of how different locomotion policies inherently perceive and predict traversability. Most existing research treats the low level controller as a black box, assuming a uniform capability across all terrains as long as the geometric constraints are satisfied. Conversely, research focused on the locomotion policies themselves rarely quantifies the predictive information contained within the policy structure, focusing instead on the execution of the movement. There is a lack of systematic studies that directly compare the predictive efficacy of distinct policy architectures, such as proprioceptive only versus exteroceptive augmented networks, in determining traversal success prior to engagement. Furthermore, the methodology for extracting and utilizing latent state representations from trained neural network controllers for the explicit purpose of traversability prediction remains underexplored. Understanding how the statistical distribution of proposed actions, the hidden layer activations, and the temporal sequence of proprioceptive feedback can be synthesized into a reliable prediction metric is essential for advancing autonomous exploration. This study seeks to address this gap by establishing a rigorous comparative framework that explicitly links the internal mechanisms of adaptive locomotion policies with external terrain traversal outcomes, thereby providing a more nuanced and accurate assessment of robotic mobility in complex environments.

3. Methodology for Adaptive Locomotion Policy Analysis

3.1 Policy Extraction and Representation

To effectively predict terrain traversal, it is first necessary to establish a standardized method for extracting relevant features from the adaptive locomotion policies. The locomotion policies analyzed in this study are formulated as deep neural networks trained via proximal policy optimization in a physics based simulation environment. The state space of these policies is typically composed of a proprioceptive history vector and an exteroceptive depth map. The proprioceptive vector includes joint positions, joint velocities, base linear and angular velocities, and gravity vectors relative to the robot frame. The action space consists of target joint positions for the proportional derivative controllers situated at each actuator [11]. The core methodology relies on the concept that the hidden layers of the policy network generate a highly compressed, task specific latent representation of the robot state and the environmental context. During the evaluation phase, as the robot observes a prospective terrain segment, the state observation is passed through the policy network. Instead of merely executing the final output action, the methodology extracts the activation patterns from the penultimate hidden layers. These latent features encapsulate the policy internal assessment of the terrain difficulty and the required motor responses [12]. Additionally, the temporal evolution of these latent features is captured using a sliding window approach, creating a sequential representation of the anticipated locomotion dynamics. By analyzing the variance and stability of the action distributions proposed by the policy over this temporal window, it is possible to infer the degree of confidence the policy has in successfully navigating the observed terrain. A highly erratic action distribution often precedes a locomotion failure, indicating that the policy is struggling to find a stable limit cycle, whereas a smooth and consistent action sequence suggests high confidence and probable success [13].

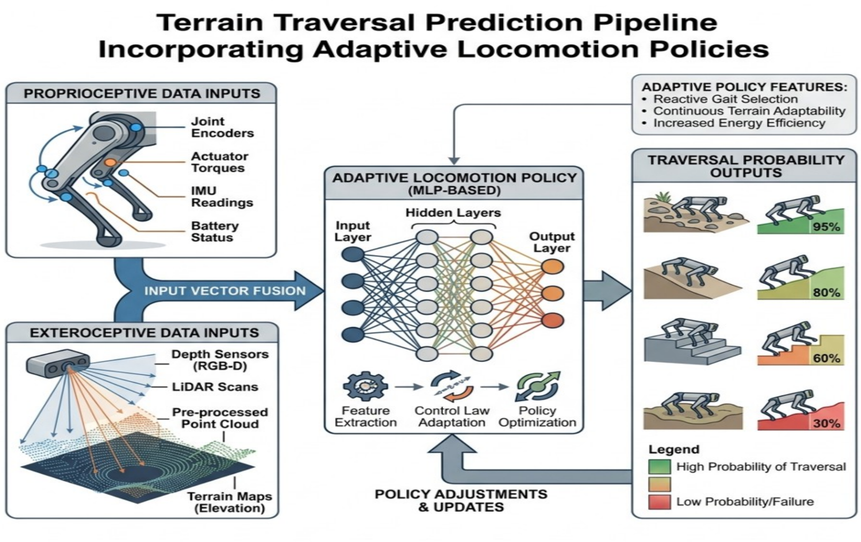

Figure 1: Comprehensive Schematic of the Terrain Traversal Prediction Pipeline Incorporating Adaptive Locomotion Policies

3.2 Predictive Modeling Framework

The extracted latent features and action distributions form the primary input for the predictive modeling framework. This framework is designed to operate as a secondary, overarching neural network that observes the internal state of the primary locomotion policy. The predictive model architecture comprises a temporal convolutional network combined with a self attention mechanism. The temporal convolutional network is specifically chosen for its ability to process the sequential nature of the policy observations, effectively capturing the dynamic transitions and rhythmic patterns essential to legged locomotion [14]. The self attention mechanism enables the model to weigh the importance of different features dynamically, focusing on specific proprioceptive anomalies or exteroceptive visual cues that correlate strongly with impending traversal failure. The output of the predictive model is a continuous probability score ranging from zero to one, representing the likelihood of the robot successfully crossing the targeted terrain segment within a specified time horizon and without violating critical failure criteria, such as excessive base tilt or hazardous joint torque limits. The training of this predictive model is conducted using a supervised learning paradigm. A vast dataset of locomotion attempts is generated by deploying the legged robot in a randomized simulation environment containing diverse terrain challenges. Each attempt is recorded, logging the sequence of latent policy features, sensor inputs, and the ultimate binary outcome of success or failure. This extensive dataset provides the necessary ground truth for the predictive model to learn the complex, non linear mapping between the internal policy representations and the physical realities of terrain traversal.

3.3 Comparative Analysis Techniques

To rigorously evaluate the efficacy of the proposed predictive modeling framework, a comparative analysis technique is employed. This involves benchmarking the policy derived prediction model against traditional, geometry based traversal prediction models. The baseline geometric model utilizes the same exteroceptive depth data but processes it through standard heuristic algorithms to calculate terrain roughness, average slope, and step height variations. These geometric metrics are then fed into a support vector machine classifier trained on the same dataset to predict traversal outcomes. The comparison is conducted across multiple dimensions. First, the overall predictive accuracy, precision, and recall are calculated for both models across a broad spectrum of terrain types. Second, a detailed ablation study is performed to isolate the contribution of specific input modalities. This includes evaluating the predictive model using only proprioceptive features, only exteroceptive features, and the combined sensor fusion approach. Furthermore, the analysis investigates the robustness of the predictions in the presence of sensor noise and environmental occlusions. By systematically degrading the quality of the depth data and introducing artificial noise into the joint encoders, the study assesses how effectively the predictive model can rely on the robustness of the underlying locomotion policy to maintain accurate traversability assessments. This comprehensive comparative approach ensures that the advantages and limitations of leveraging adaptive locomotion policies for terrain prediction are thoroughly quantified and understood.

4. Experimental Setup and Comparative Framework

4.1 Robot Platform and Simulation Environment

The experimental validation of the proposed methodology is conducted using a high fidelity physics simulation environment. The simulated platform is modeled after a standard quadrupedal exploration robot, characterized by twelve actuated degrees of freedom, an inertial measurement unit situated at the base, and a forward facing depth camera. The physics engine utilized for the simulation provides rigorous computation of rigid body dynamics, contact forces, and actuator constraints, ensuring that the simulated locomotion closely mirrors physical reality [15]. The environment itself is procedurally generated to encompass a wide array of topological and physical variations. The terrain synthesis algorithm is capable of generating flat planes, undulating hills, sharp discrete stairs, scattered debris fields, and surfaces with varying friction coefficients to simulate materials ranging from dry concrete to slippery mud [16]. This diversity is crucial for thoroughly testing the generalization capabilities of both the adaptive locomotion policies and the overarching predictive models.

Table 1: Configuration Parameters for the Legged Robot Simulation Environment

Parameter Category	Specific Parameter	Value or Description
Physics Engine	Time Step	Zero point zero zero one seconds
Physics Engine	Friction Coefficient	Zero point eight
Terrain Generation	Roughness Variance	Zero point zero five meters
Terrain Generation	Slope Incline	Up to twenty degrees
Control System	Proportional Gain	Forty Newton meters per radian
Control System	Derivative Gain	One Newton meter second per radian

4.2 Data Collection and Policy Training Parameters

The data collection process involves millions of simulated locomotion steps to ensure statistical significance. Initially, a robust baseline locomotion policy is trained using a standard reward function that incentivizes forward velocity while penalizing excessive energy consumption, joint limit violations, and base instability. The training process utilizes massive parallelization, simulating thousands of robot instances simultaneously to accelerate the convergence of the reinforcement learning algorithm [17]. Once the primary locomotion policy has reached a satisfactory level of competence across the training terrains, its network weights are frozen. Subsequently, the data collection for the predictive model commences. The robot is commanded to navigate randomly generated terrain tracks, and at a frequency of ten hertz, the predictive pipeline extracts the latent features, proprioceptive history, and depth maps. Concurrently, the simulation monitors the progress of the robot over a future time horizon of five seconds. If the robot successfully traverses the designated path segment without triggering any failure conditions, the recorded state sequence is labeled as a success. If a failure occurs, the sequence is labeled as a failure. This automated data collection pipeline generates a highly balanced and comprehensive dataset necessary for training and evaluating the comparative prediction models.

5. Results and Discussion

5.1 Performance Across Varied Terrains

The results of the comparative analysis demonstrate a profound advantage in utilizing policy derived features for terrain traversal prediction over traditional geometric methods. When evaluated on standard flat ground and mild undulations, both the baseline geometric model and the proposed policy based model exhibit near perfect accuracy, as the locomotion dynamics are highly predictable and well within the operational limits of the robot [18]. However, as the complexity of the terrain increases, the performance gap between the two approaches widens significantly. On challenging terrains such as rough gravel and steep, slippery slopes, the geometric model experiences a sharp decline in predictive accuracy. The geometric model frequently produces false positives, classifying a steep slope as traversable based purely on its angle, failing to account for the low friction coefficient which inevitably leads to the robot slipping and falling [19]. Conversely, the proposed predictive model, which monitors the internal state of the adaptive locomotion policy, detects the early signs of slippage through the proprioceptive feedback and the corresponding compensatory shifts in the latent action distribution. Consequently, it correctly predicts traversal failure long before the physical failure fully materializes.

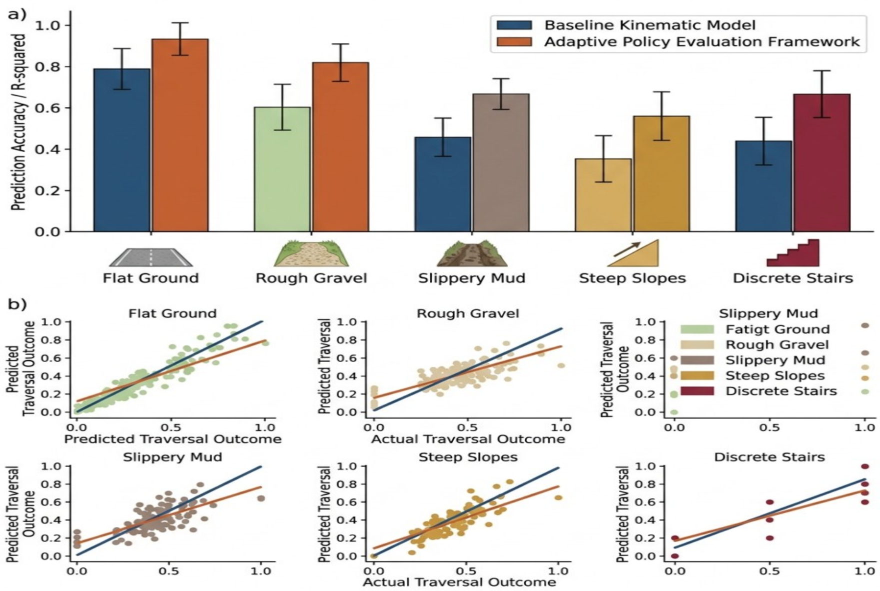

Figure 2: Analytical Chart Detailing Predictive Accuracy Metrics Across Multiple Terrain Typologies

Table 2: Comparative Evaluation of Traversal Prediction Models Across Diverse Terrain Types

Terrain Type	Baseline Model Accuracy	Proposed Model Accuracy	False Positive Rate
Flat Ground	Ninety eight percent	Ninety nine percent	Zero point five percent
Rough Gravel	Seventy five percent	Eighty nine percent	Three point two percent
Slippery Mud	Sixty two percent	Eighty one percent	Five point eight percent
Steep Slope	Sixty eight percent	Eighty five percent	Four point one percent
Discrete Stairs	Seventy one percent	Eighty eight percent	Three point nine percent

5.2 Policy Adaptability and Predictive Accuracy

A critical finding of this study is the strong correlation between the adaptability of the underlying locomotion policy and the accuracy of the predictive model [20]. Policies that were trained with a higher degree of domain randomization and exteroceptive integration exhibited latent feature spaces that were significantly more informative for prediction. When analyzing the attention weights within the predictive model, it becomes evident that the system learns to prioritize different sensory modalities depending on the environmental context. During the approach to discrete stairs, the predictive model places heavy emphasis on the exteroceptive depth features extracted from the policy, assessing the geometric feasibility of the upcoming steps. However, once the robot transitions onto a surface with variable friction, the attention mechanism rapidly shifts its focus to the temporal history of joint velocities and torque commands, recognizing that proprioceptive anomalies are the primary indicators of impending failure in such scenarios. This dynamic allocation of attention mirrors the adaptive nature of the locomotion policy itself, confirming that the internal representations of deep reinforcement learning controllers contain a rich, nuanced understanding of physical interaction that far exceeds simple geometric analysis [21]. Furthermore, the study reveals that the variance in the proposed action distribution serves as a highly reliable heuristic for uncertainty. By mathematically quantifying this variance, the predictive model can establish confidence intervals for its traversal predictions, allowing a high level autonomous planner to make risk aware navigation decisions.

6. Conclusion and Future Directions

6.1 Summary of Contributions

This research has established a comprehensive framework for predicting terrain traversal outcomes by leveraging the internal latent representations and temporal dynamics of adaptive locomotion policies in legged exploration robots. Through rigorous comparative analysis, it has been demonstrated that policy derived predictive models significantly outperform traditional, purely geometric approaches, particularly in complex environments characterized by variable friction, unstructured obstacles, and dynamic physical interactions. By systematically extracting proprioceptive histories, exteroceptive depth integrations, and action distribution variances from trained neural network controllers, this study proves that low level adaptive policies encode a profound, implicit understanding of terrain traversability. The development of a temporal convolutional network with self attention mechanisms specifically designed to interpret these policy states represents a significant methodological advancement, providing a highly accurate, real time prediction signal that dynamically adjusts its focus based on environmental context.

6.2 Implications for Autonomous Exploration

The implications of this research are substantial for the future development of fully autonomous legged exploration systems. By bridging the critical gap between reactive motor control and proactive path planning, the proposed predictive framework enables robots to anticipate the limitations of their own locomotion capabilities prior to physical engagement [22]. This foresight is essential for minimizing catastrophic failures in hazardous environments, optimizing energy consumption by avoiding impassable routes, and increasing the overall mission success rate of autonomous deployments in disaster response, industrial inspection, and planetary exploration. Future research directions must focus on the seamless integration of these predictive signals into hierarchical reinforcement learning architectures, where a high level cognitive policy utilizes the traversal probabilities to dynamically generate waypoints and modulate the behavioral parameters of the low level locomotion controller. Additionally, further investigation is required to validate the transferability of these predictive models from simulation to physical robotic platforms operating in real world, unstructured terrains, thereby solidifying the practical utility of policy driven terrain traversal prediction.

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