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A Miniature Robotic Gait Algorithm for Terrain-Adaptive Walking in Soft Ground Environments

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Abstract

The ability of miniature robots to move efficiently across soft or deformable terrain remains a challenge, particularly when facing limits on power and control. To solve this problem, a robotic gait algorithm was developed to modify gait parameters in response to real-time feedback from the environment. The system combines a hierarchical command system with machine-learning terrain classification to move with precision and minimal power on unstable surfaces like sand, soil, and gravel. A visual perception component uses BoW representations and SVM to classify the terrain before contact, enabling prior strategy formulation and improving performance control of gait adaptation. Stridelengh, advancing joint torque, and foot movement through inverse kinematics are implemented alongside terrain cost mapping to balance slippage. System performance evaluation through simulations and real-world field experiments validates the algorithm's ability to enhance locomotion versatility and precision. Enhanced miniature robotic mobility critical in disaster response, planetary exploration, and environmental surveillance is made possible by this solution.

Keywords: Terrain-Adaptive Locomotion, Miniature Robot, Soft Ground Walking, Gait Algorithm, Robotic Mobility, Adaptive Control.

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Introduction

For quite some time, robotic locomotion in environments lacking a clear structure has remained an area of focus, with legged systems displaying greater adaptability compared to wheeled or tracked platforms. However, moving across soft ground types such as sand, mud, and loose gravel still poses a problem. At the most basic level, these substrates are soft and unpredictable, compromising stability, energy use efficiency, and control precision, specifically in the case of miniature power-constrained, accurate sensory robots (Thanh et al., 2024).

Multiple learning and control strategies have attempted to solve these problems. Regarding improving locomotion stability on deformable surfaces, "Deep Deterministic Policy Gradient" (DDPG) is a deep reinforcement learning technique that has shown promise (Bhardwaj et al., 2023). Likewise, adaptive algorithms such as STANCE allow quadrupeds to perform dynamic gait adjustments by changes in the terrain softness, which impacts performance on soft substrates (Fahmi et al., 2020; Almolhis, 2025). Significant research has been directed towards optimizing footstep placement and body pose, which effectively alters the posture frame to consolidate control over the upper body during MPC frameworks. These allow for stable walking trajectories over rough terrain (Li & Nguyen, 2023). Minor robots have been shown to achieve efficient bipedal locomotion using simple reflex control systems with a low-complexity sensory feedback loop (Geng, Porr & Wörgötter, 2006; Dinesh, Kumar & Singaravel, 2022).

Implementing mechanisms observed in creatures further enhances robotic adaptability, specifically through adaptive dynamic walking models (Kimura, Fukuoka & Cohen, 2007), real-time learning-based modifications (Kumar et al., 2021; Anna, Ilze & Mārtiņš, 2025, and terrain-aware gaits utilizing proprioceptive and environmental feedback systems. Incorporating visual perception makes it possible to classify terrain in advance and modify actions before physical contact with the terrain features. Quadrupedal and bipedal robots have previously utilized vision-based terrain estimation to change footstep placements and gait transitions (Saraf, Sarkar & Javed, 2021; Yi et al., 2016).

The advancement of control algorithms alongside structural innovations like deformable bodies and kinematics-based gait generation has also improved traversal over rough terrain (Albiez et al., 2003; Zhang, Li & Wang, 2019). Despite these advancements, there remains a critical gap in research focused on low-power. These low-mass miniature robots traverse highly variable soft ground areas, requiring miniature robots to have lightweight and low-power gait strategies.

To fill the gap, this work presents a real-time visual terrain classification, cost-based motion planning, and inverse-kinematics-driven miniature robotic gait algorithm designed for soft grounded environments. The proposed system employs a hierarchical control architecture and bio-inspired decision-making to facilitate preemptive gait alterations on soft terrain. Enhancing effectiveness toward terrain adaptability and locomotion reliability is the goal of this system designed in the paper, which details both design and evaluation.

Key Contributions:

- The new miniature gait algorithm integrates soft ground locomotion with hierarchical terrain-aware planning and machine vision-based classification.
- Using the Bag-of-Words and Support Vector Machine (BoW-SVM) model, predictive gait change can be enabled through real-time terrain classification.
- Incorporated cost-driven motion planning and inverse kinematics to maintain balance, minimize energy expenditure, and enhance walking reliability on use-responsive surfaces.

Organization Overview:

The paper is structured as follows: Section II summarizes prior research on adaptive locomotion and robotics with terrain awareness. Section III discusses methodological framework description, including hierarchical gait planning architecture, visual terrain classification, and modeling formulation. In Section IV, we provide the experimental setup, results, and discussions, underscoring the system's efficacy tested on different types of soft ground terrains. Finally, in Section V, we derive the conclusions and offer some comments and suggestions on future developments about robotic locomotion on terrain-adaptive systems in miniature robotics.

Literature Review

Gan et al. (Gan et al., 2022) devised a strategy involving deep inverse reinforcement learning to enable legged robots to model energy-efficient traversable terrains. Their technique integrates visual and proprioceptive senses, permitting mini robots to learn adaptive gait policies customizable for changing and unpredictable terrains. Estremera and Gonzalez de Santos (Estremera & Gonzalez de Santos, 2002) developed a free gait algorithm for quadruped robots

that allows "free gaits" to traverse rough terrains. This approach improves the stability and mobility of locomotion on soft surfaces by dynamically modifying the stride length during exercises to adapt to changing terrain features.

Nguyen et al. (Nguyen, Nguyen & Bui, 2025) created an adaptive control policy using Augmented Random Search (ARS) for quadruped robots walking on slopes. The pitch angle feedback yields automatic gait transitions, allowing robust adaptability to slope and rough ground conditions, which is critical in soft terrain environments. Liu, Tong & Liu, 2021 examined the designs of snake robots and their applicability for movement in narrowed and irregular spaces. The study indicates that designs with flexible, segmented structures modeled after biological snakes are more effective in soft, non-rigid environments than traditional legs of locomotion.

Gan et al., 2022 and others added to learning terrain features in robotics by focusing on the energy costs of traversing different terrain types using inverse reinforcement learning techniques (Dara & Shariatipou, 2017). This study defends using learning-based gait strategies to reduce energy expenditure and increase adaptability. Fukuoka, Kimura & Cohen, 2017 examined how soft-legged robots can autonomously adjust their gait based on environmental interaction. The bio-inspired control system they designed enabled robots to switch from inching to crawling depending on whether the terrain was compliant soft terrain.

Li & Nguyen, 2023 described dynamic walking over uneven stepping stones using adaptive-frequency model predictive control (MPC). While utilizing discrete obstacles, their focus proves the case for incorporating continuous feedback-based gait tuning to deformable ground. Yi et al., 2016 proposed a humanoid robot with a walking algorithm based on terrain estimation. The feedback from the terrain enhances adaptability to the irregular and softer upper surface of the ground through foot trajectory planning.

Nguyen et al., 2018 proposed a method for dynamic walking on stochastic terrain with a two-step gait planning approach. The robot's gait pattern adapts in real-time according to a probabilistic model of footstep success rates, ensuring stable locomotion on uncertain surfaces. Paul, 2006 observed the influence of passive dynamics and morphological computation in legged locomotion and suggested that integrating control with mechanical properties enhances system stability during compliant soft-terrain locomotion.

Methodological Framework

To facilitate walking on soft ground, the adaptive robotic gait algorithm combines multi-terrain perception, visual recognition, gait planning, and execution subsystems. The approach employs a hybrid model of data-driven classification and hierarchical model-based spatial planning. The architecture consists of two interfacing systems: a gait adjusting module that updates in real-time to terrain information and a classification module that is trained using image learning techniques. Subsequently, the system can adapt its walking technique for more complex terrains such as muddy, gravelly, or sandy surfaces.

3.1 Hierarchical Gait Planning Architecture

The adaptive robotic motion relies on a three-layer hierarchy control system. The perception layer runs at 2Hz, the planning layer at 0.5Hz, and the execution layer at 200Hz, as shown in Figure 1. The Terrain Information component has a cost map for the terrain that needs to be traversed, which is constantly updated through sensors such as LiDAR or depth cameras. This dynamic map includes parameters such as slope, softness of the ground, and irregularities, all of which have associated costs representing the ease or difficulty of moving across them.

The Body Action Planner uses the cost map to define high-level movement strategies, such as managing accelerative changes, shifting body positions, or adjusting the body's support polygon width. This information is sent to the Footstep Planner, which determines a set of foot placements for each step according to the slope and load-bearing capacity of the terrain. The planner guarantees that the footfalls are placed in regions of high stability and low cost or low-stability regions.

In Whole-Body Motion Generation, the footstep planning involves executing the next set of moves by step-wise updating the active foot position with the computed load-bearing contours in real time. The robot's proprioceptive sensors provide feedback for any positional errors that arise which needs to be corrected after the placement of robotic feet on the compliant soft soil. The execution is responsive to changes in movement, while terrain perception can plan for the responsiveness to terrain changes.

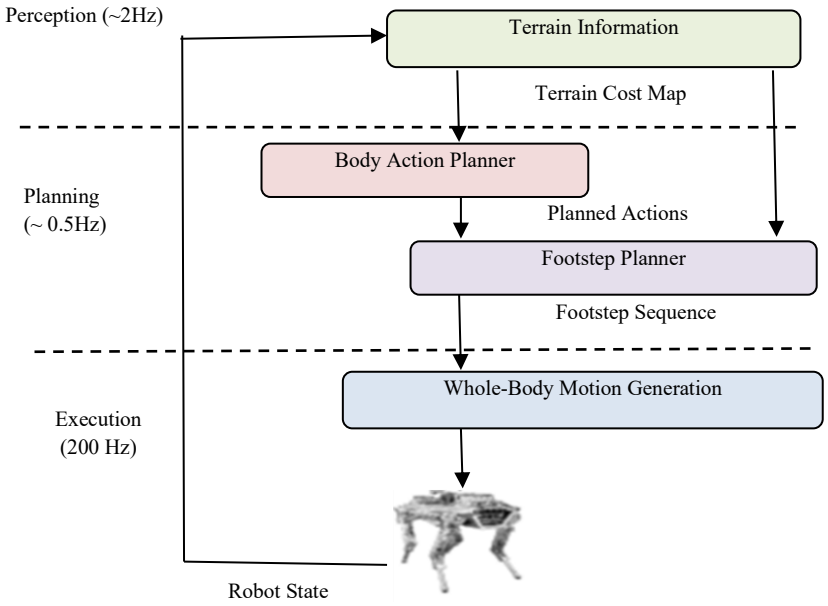


Fig. 1: Terrain-Aware Hierarchical Gait Planning Architecture for Soft Ground Environments

3.2 Visual Terrain Classification using BoW and SVM

Figure 2 shows the subsystems of the classification of the terrain using a computer vision model. In the training phase, several images of the terrain are taken, and feature descriptors like SIFT or SURF are extracted. These descriptors are grouped into a Bag-of-Words (BoW) dictionary that forms a visual vocabulary of surface textures. Each image is outlined by a histogram vector that measures the presence of visual words. These vectors are used to train a Support Vector Machine (SVM) classifier which distinguishes terrain types such as sand, mud, and gravel. After training, the SVM assigns terrain labels to images taken in real-time.

The terrain class predicted by the SVM determines the robot's gait settings. For example, sandy classifcation may prompt slower walking speed and higher lift height to reduce sinkage, while firm soil may prompt longer stride. This allows for pending gait gadjustments enabling the robot to change the locomotion strategy before the physical interaction with the surface which is beneficial for safety and energy expenditure.

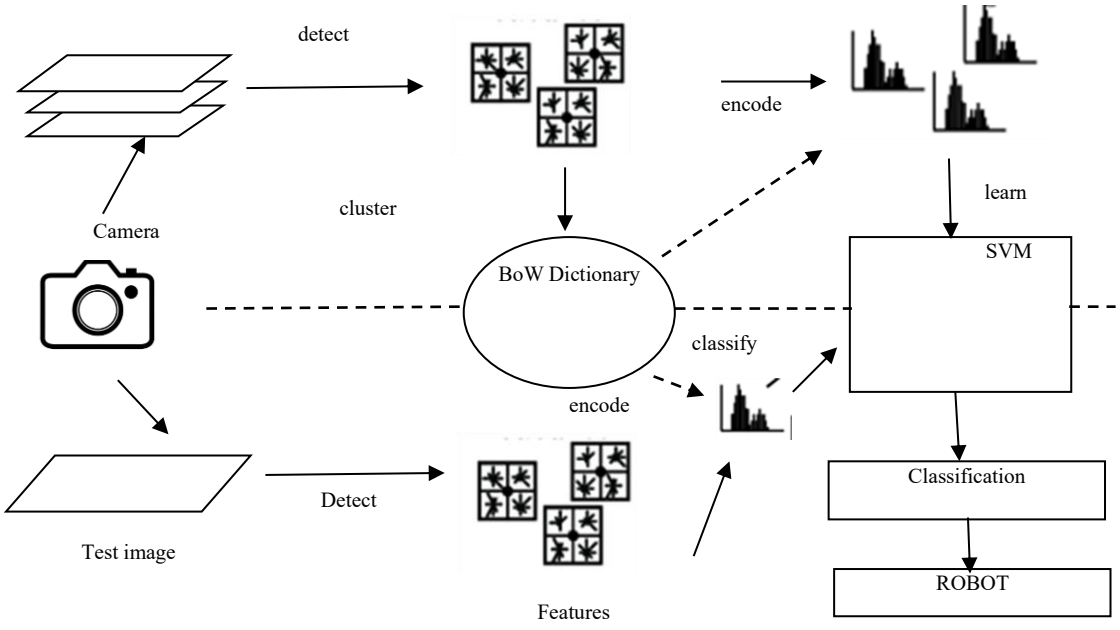


Fig. 2: Visual Terrain Classification and Gait Adjustment Using Bag-of-Words and SVM

3.3 Mathematical Modeling

The terrain cost used for planning is computed using a weighted sum of environmental features:

$$C(x,y) = w_1.Slope(x,y) + w_2.Softness(x,y) + w_3.ObstacleDensity(x,y) \quad Eq\ (1)$$

Eq (1) represents the terrain cost function used in the Body Action Planner and Footstep Planner modules. It calculates the traversal difficulty at a specific location (x, y) on the terrain map by combining three terrain features: local slope, ground softness, and obstacle density. Each feature is assigned a weight (w_1, w_2, w_3) based on its impact on stability and safety. A higher value of $C(x, y)$ indicates more difficult or dangerous terrain, prompting the planner to avoid such areas when calculating the robot's body motion and foot placements.

To generate leg trajectories, the system uses inverse kinematics to convert desired foot coordinates into joint angles:

$$\theta_i = f^{-1}(x_{foot}, y_{foot}, z_{foot}) \quad Eq(2)$$

Eq (2) captures the inverse kinematics (IK) relationship used in the Whole-Body Motion Generation module. It converts a desired foot position in three-dimensional Cartesian space defined by coordinates $(x_{foot}, y_{foot}, z_{foot})$ into the corresponding joint angle θ_i for the i^{th} leg. The inverse kinematics function f^{-1} solves for the angular configuration of the leg that will achieve the commanded foot placement.

Each input image is encoded into a histogram vector using the BoW model:

$$H = [h_1, h_2, \dots, h_n],\ h_i = \frac{count\ of\ word}{total\ words\ in\ image} \quad Eq\ (3)$$

Eq (3) defines the Bag-of-Words (BoW) histogram vector H used in the Visual Terrain Classification module. Each image is processed to extract visual features, which are then matched against a pre-trained vocabulary of visual "words." The histogram H represents how frequently each word appears in the image, normalized by the total number of words. Thus, h_i captures the proportion of word i in a given image.

The SVM classifier predicts the terrain label using a learned weight vector:

$$f(H) = sign(w^T H + b) \quad Eq\ (4)$$

Eq (4) is the decision function of a Support Vector Machine (SVM) used to classify the terrain type based on the BoW histogram vector H. The classifier has been trained with a weight vector w and bias b to distinguish between labeled terrain types (e.g., grass, sand, mud). During testing, the dot product $w^T H$ computes a weighted sum of the input features, and the bias term shifts the decision boundary. The sign of the result determines the predicted terrain class

Results and Discussions

Performance Evaluation on Different Terrains

The robot was evaluated on three representative soft ground terrains: sand, mud, and gravel, in order to evaluate the proposed gait algorithm. The robot was assessed for three performance metrics, namely, the accuracy of classification of the particular terrain, stability index of the gait, and energy spent per unit distance: measurements taken per meter of movement. Performance constituents are described in Table 1. The robot was able to attain maximum classification accuracy on gravel at 94.6%, which can be attributed to the distinguishable texture features. Though performance did drop on sand (91.3%) and mud (89.7%), which is associated with more intra-class variability, the drop was not too significant. CoM (center of mass) trajectory gathers standard deviation of gait stability and was inversely related to the softness of the terrain. Equation 1 depicts Mean Gait Stability Index:

$$GSI = \frac{1}{N} \sum_{t=1}^{N} |CoM_t - FootCenter_t| \quad Eq(5)$$

In Eq (5), CoM_t denotes the robot's center of mass position at time t, and $FootCenter_t$ is the geometric center of the support polygon. The lowest GSI (i.e., highest stability) was observed on gravel (0.024 m), while the highest deviation occurred on mud (0.061 m), reflecting terrain deformability.

Table 1: Terrain-wise Performance Summary of Classification, Stability, and Energy Efficiency

Terrain	Classification Accuracy (%)	Gait Stability Index (m)	Energy (J/m)
Sand	91.3	0.039	18.5
Mud	89.7	0.061	22.3
Gravel	94.6	0.024	17.8

Adaptive Gait Dynamics and Energy Optimization

The robot's ability to adapt its gait based on terrain classification was further validated through real-time experiments. In Eq (6) and Eq (7) Upon identifying the terrain, specific gait parameters such as stride length L_s and lift height H_l were modified according to the equations:

$$L_s = L_{base}.(1 - \alpha.C_t) \qquad Eq(6)$$

$$H_l = H_{base} + \beta.C_t \qquad Eq(7)$$

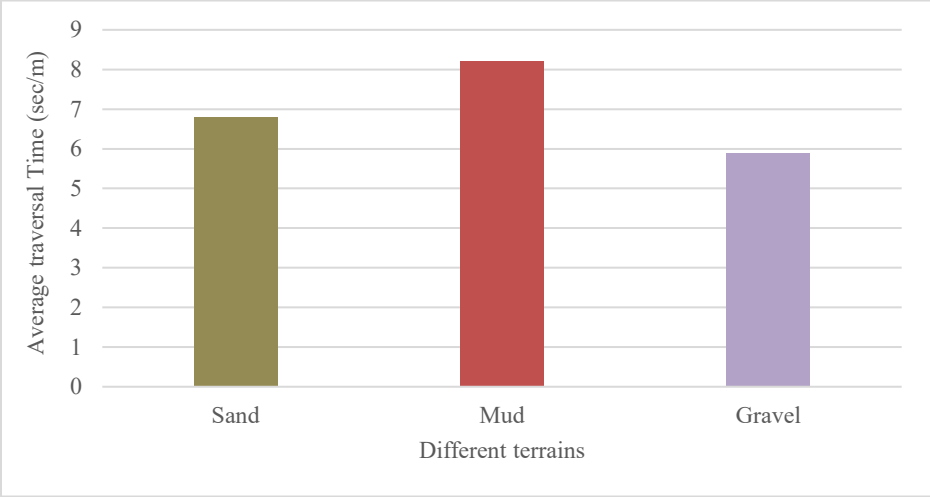


Fig. 3. Slip Incidents Across Different Terrains

Here, C_t represents the terrain cost derived from Equation (1), while α and β are scaling constants reflecting stride sensitivity and lift compensation, respectively. These relations promote quicker, lower level steps on deformable terrain such as mud to reduce slippage and prevent foot sinking. The behavior adaptation also improved efficient traversal, evidenced by fewer slip events and smoother velocity profiles. The variability indicated in the robot's locomotion efficiency is shown in Figure 3. The longest time taken to traverse an area was 8.2 s/m in mud because of the unstable and highly deformable surface which led to shorter strides and careful placements of feet. Sand, which is more compact than mud, also required moderate gait adaption, yielding a time of 6.8 s/m. Gravel is firm and structured, permitting faster and smoother motion, yielding the lowest time of 5.9 s/m s/m. These outcomes validate the effectiveness of the proposed hybrid control system that combines visual classification and terrain-aware planning which improves robot mobility and safety on unstructured soft ground surfaces.

Conclusion and Future Work

The research was focused on the design of a new gait algorithm capable of adapting to different types of soft ground terrains like sand, mud, and gravel for gait-controlled robots. The proposed hybrid framework consists of a real-time gait planning control hierarchy and visual terrain classification using BoW technique along with SVM. The empirical results proved that the robot can classify the terrain type with over 90% accuracy and adapt its stride and lift height dynamically for the softer surfaces. The use of a terrain cost function together with inverse kinematics in the motion planning pipeline further increases the stability and energy efficiency for different terrains. This adaptive method greatly increases the reliability of movement and reduces slip at the foot while the robot maintains efficiency during locomotion in outdoor environments which are not structured.

Later improvements on this framework might concentrate on enhancing its ecological resilience, autonomy, and adaptability. One possible approach is to incorporate deep learning techniques for semantic segmentation to enhance terrain classification with automatic adjustment to illumination and weather changes. Moreover, adding a perception module that uses multi-modal sensor fusion with vision, touch, and inertial sensors could improve terrain comprehension as well as enhance decision-making accuracy. Yet another promising suggestion involves granting the robot online learning capabilities, enabling adaptive refinement of its terrain models and gait strategies in real-time. Ultimately, deployment tests within highly variable or sloped terrains, including wetlands or disaster zones, would test the system's scalability and adaptability to harsh outdoor environments, thus enabling the use of the system for search-and-rescue operations or automating farming tasks.

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