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Real-Time Remodeling of Granular Terrain for Robot Locomotion

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Terrain irregularities in natural environments present mobility challenges for autonomous robots and vehicles. Loosely consolidated sandy slopes flow unpredictably when perturbed, often leading to locomotion failure. Systematic experiments with various robot morphologies on flowable terrains feature open-loop quasistatic gait strategies that remodel the terrain to aid locomotor kinematics. On a sloped terrain of granular media near the critical angle, a laboratory-scale rover robot induces a flow via a localized fluidization gait to remodel local terrain and succeed in locomotion. A Bayesian optimization machine learning approach that modulates this gait strategy then finds a pattern of selectively fluidizing and solidifying terrain to climb slopes rapidly. In a biped walker robot, a cleated foot design dynamically manipulates the stress fields of flowable slopes. The deeply submerged cleats remodel the shear response of the material by creating jammed regions behind them which then improve forward progression by reducing slip when compared to a flat foot. The "robophysics" approach of systematic experiments exploring terrain reconfiguration combined with future machine learning models of flowable terrain evolution can augment gait discovery for future robots.

1. Introduction

Much of the dry landmass on both Earth and extraterrestrial worlds remains impassible to most wheeled and tracked machines. Natural environments can have highly irregular terrain profiles, terrain deformation and flow, surfaces of variable friction, and buried obstacles. These provide challenges to locomoting robots that cannot sense and manipulate their local environments successfully. Autonomous robots and vehicles must occasionally recover from locomotion failure,[1] especially in challenging, unpredictable terrains like loosely consolidated, flowable substrates. Exteroceptive sensors such as LIDAR cannot describe physical properties of such terrain such as friction, compliance, and failure thresholds, so stress sensors must account for resistive forces of the terrain via physical contact.[2] Planetary science and exploration missions continually increase their requirements for autonomous mobility, with priority missions now planning to traverse as far as 2000 km.[3] Exploratory rovers frequently experience adverse terrain profiles that can unpredictably fail, flow, and avalanche down slopes[4] in response to an intruding body or appendage, impacting the mission and even leading to total failure.[5]

Over the years, our group has investigated an approach where active reconfiguration of the terrain via the robots' intruding appendages becomes key to successful locomotion.[6–11] The terrain response to robot movement is controlled via reconfiguring the kinematic or mechanical features of the underlying substrate, which we refer to as "remodeling." Granular material incorporates solid- and fluid-like properties, as it exhibits solid-like stress/shear response at typical densities and also functions as a frictional fluid.[12] Thus, our remodeling approach utilizes the multiphase feature of the flowable terrain by either exploiting the fluid-like response to create local mounds (kinematic) or employing the solid-like response to generate jammed regions with a strengthened shear response (mechanical). By combining both robust locomotion and terrain manipulation strategies in robots with active appendages, a paradigm of "locomoting via remodeling" can achieve a unified robot and terrain control. With the proper contact strategy and robot morphology, various robots could control the terrain's response during these contact events for the purpose of locomotion.

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With the convergence of new technologies, like additive manufacturing and improved servomotors, we have explored experimental "robophysics" approaches to robot design and locomotion in the past decade. The conveniences and relatively low costs of 3D printing allow for the rapid manufacturing of a diversity of robot morphologies, and low cost but powerful microcontrollers aid in generation of novel behaviors. This allows us to investigate new and emergent physical phenomena with atypical robotic forms. Following our adage: "The robot is the experiment,[13]" we observe interesting mechanisms in robots and their interaction with the environment, which inform us of novel physical phenomena that is leveraged to aid future designs. This approach has yielded laboratory-scale rover robots that actively remodel terrain to climb slopes,[6] snake sidewinding robots that ascend sandy slopes,[7] and self-propelling swimming quadriflagellates,[14] along with various robot swarms which can cooperatively link for locomotive advantage,[15] mimic active cohesive granular matter,[16] act as a larger robot,[17] or cooperatively excavate in confined tunnels like ants.[18]

When manipulating flowable terrain, an intuitive strategy for successful locomotion is maintaining a solid-like substrate response with minimal deformation. In flowable terrain, the effects of the locomotor on the terrain, along with environmental self-deformation during phenomena like avalanching, must be accounted for (**Figure 1**A). We discovered that some successful robotic and biological locomotors modulate gait behaviors to strategically induce solid- and fluid-like responses in their flowable substrates. For example, both sea turtles and a turtle-like robot from our lab (Figure 1B) would alternate between solid-like and frictional fluid-like responses during intrusion into granular media.[19] The sidewinding rattlesnake (Figure 1C) would increase its contact area when ascending sandy slopes to stay below the sand's yield stress, maintaining a solid-like response; this strategy proved useful in enabling a limbless robot to ascend such slopes.[7] In contrast, the sandfish lizard (Figure 1D) uses fluidizing gaits in level sand beds to self-bury and achieve buried locomotion.[20]

In this piece, we present a pair of robophysical studies that build on previous projects of bipedal robot walking[22] and rover locomotion[6] in flowable, granular terrain. These studies are representative of a broader class of interaction with flowable systems, where the locomotor or vehicle becomes coupled to its environment as a unified body, such that the locomotor actively remodels its environment to succeed. Many studies attempt to make robots robustly function despite their environment via methods like fault-tolerant[23] and compliant control,[24] effective motion planning,[25] and learned gaits.[26] We aim to collaborate with the environment via active manipulations.

2. Fluid-Like Remodeling

Recent studies of robot movement in flowable granular media (inspired by difficulties faced by extraterrestrial rovers) reveal a coupled locomotor/substrate effect where the robot spontaneously remodels its environment,[6] selectively inducing a creative fluid-like response. This strong coupling occurs in certain limb/wheel movement patterns and results in a localized granular flow allowing the robot to effectively "swim" up highly flowable slopes. This was enabled by a selective fluidization of

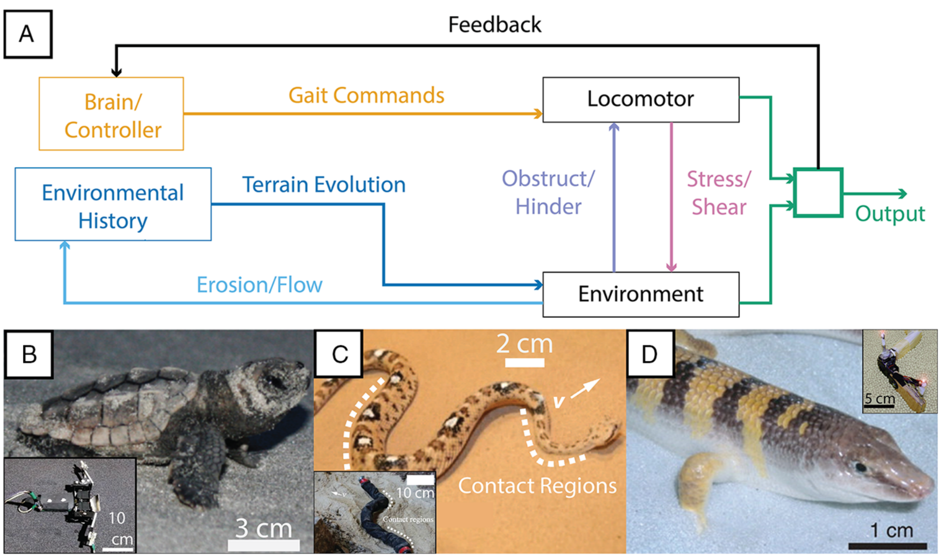

Figure 1. Robot and animal locomotion on flowable terrain. A) Conceptual framework detailing the necessary remodeling paths in flowable ground robot locomotion. Motion commands input into the locomotor will apply stress and shear to flowable substrates, deforming it via material flow. Along with external forces (e.g., aeolian processes), this flow will change the environment over time, which in turn can hinder or aid the locomotor. Examples of robotic and biological locomotors on flowable terrain that deal with this include: B) hatchling loggerhead sea turtle (*Caretta caretta*) and a sea turtle-inspired robot (inset), FlipperBot, which locomotes on granular media via selective solidification. Adapted with permission.[19] C) A sidewinding rattlesnake (*Crotalus cerastes*) and a modular snake robot (inset) moving on sandy slopes of 20° inclination via selective solidification. Adapted with permission.[7] D) The desert sandfish (*Scincus scincus*) moves within dry sand via localized fluidization. (Inset) A three-link swimmer robot resting on a bed of plastic spheres that can swim in granular media when submerged. Adapted with permission.[20,21] Each locomotor example has a different strategy for controlling their "Erosion/Flow" pathway in subfigure (A).

material via the rover robot spinning its wheeled appendages while executing its gaits. This selective fluidization is an open-loop quasistatic gait strategy that disturbs grains into avalanching toward the robot's actively pushing wheels. However, these gait strategies were discovered via trial and error by human operators.

Inspired by recent progress in robot learning, we applied Bayesian optimization to discover effective gaits in flowable frictional media from real-world physical interactions. Bayesian optimization is a black box numerical optimization algorithm that does not require any assumptions on objective functions or gradients, which is often sample-efficient for low-dimensional problems. As the objective function is unknown, the Bayesian approach treats it as a random function and assigns it a prior probability distribution via a Gaussian process, and then queries the function at a point (in our case, a gait trial). Over multiple iterations, the function evaluation result then updates the priors to form a posterior distribution, which generates a set of acquisition functions that decide the next query point, until the queries reach the maximum of the unknown objective function.[27] The black box nature of Bayesian optimization gives us significant advantages for our scenarios because the robot and the terrain show nontrivial, nonlinear dynamics and prevent us from obtaining closed-form solutions. In addition, its efficiency allows us to learn the gait from real-world experience, which has been proven effective for complex real-world robot interactions.[28–31]

We set the objective function as the total traveled distance during the fixed duration of the episodes and searched the gait parameters around those of the previously studied gait called Rear Rotator Pedaling.[6] Our experimental testbed for the rover was the SCATTER (Systematic Creation of Arbitrary Terrain and Testing of Exploratory Robots) system,[8,32] which is a tilting rectangular bed full of granular substrate (1 mm diameter poppy seeds) which is air fluidized at a level slope after each trial to reset the media to a loosely packed state (**Figure 2**A). The poppy seeds constitute a model for flowable terrain,[33] enabling a uniform, loosely packed test surface for systematic experiments. The SCATTER testbed allows for controlled resets of granular terrain to a consistent initial state via fluidization,[34] providing a physical model for real-world loosely consolidated terrains. We performed Bayesian optimization in the SCATTER setup as shown in

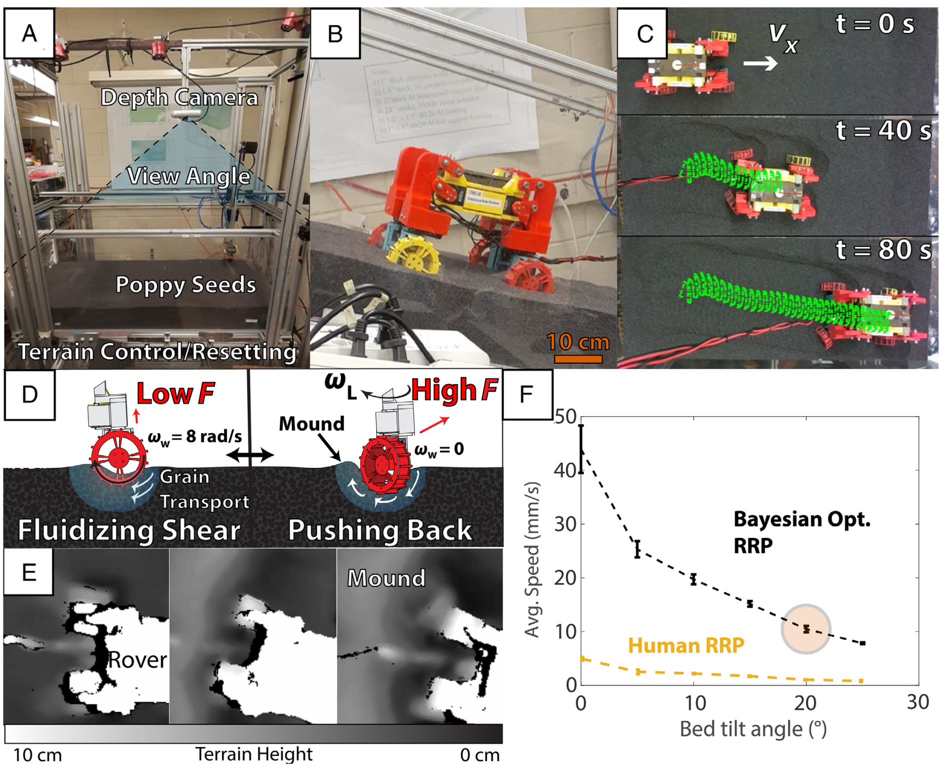

Figure 2. Fluid-like remodeling with the mini rover. A) Side view of the SCATTER testbed system:[8,32] a tilting rectangular bed full of granular substrate (1 mm diameter poppy seeds) which allows for controlled tilting and substrate (poppy seeds) resetting via fluidization. An Intel D435 Depth Camera provides a top-down spatiotemporal view of both the robot and the terrain deformation. B) Side view of the mini rover robot at rest in the SCATTER system. C) Top-down views of the mini rover in the SCATTER system executing a Bayesian optimized Rear Rotator Pedaling gait[6] at a 15° slope. The green line marks the tracked trajectory of the robot's center. D) Behavior of the Bayesian optimized Rear Rotator Pedaling gait for the two rear wheels. The Bayesian optimization converged on a strategy of alternating two phases: activating wheel spin ($\omega_w = 8$ rad s^{-1}) to create fluidizing shear when resetting an appendage forward to generate a low reaction force F rearward, and disabling wheel spin ($\omega_w = 0$ rad s^{-1}) to maintain a solid mound when pushing back to generate a high reaction force forward. E) Depth buffer of the terrain surface at a 25° tilt, after 0, 4, and 8 cycles of the Bayesian optimized Rear Rotator Pedaling gait. F) Mean ± SD of average speed versus bed tilt for human-tuned[6] versus Bayesian optimized Rear Rotator Pedaling gaits (BO RRP). Both gait trials were executed on the same robot. The Bayesian optimized Rear Rotator Pedaling was trained on a 20° slope (circled) and then applied blindly to each other slope. ($N = 5$ for each slope.).

Figure 2B for 30 experiment episodes on a 20° granular slope and selected the best gait parameter set. The Bayesian optimized modulation converged to alternating between a "fluidizing shear" phase, where wheel spin and low applied pressure sustained granular transport, and a "pushing back" phase, where wheel spin stopped to shear grains rearward at high pressure as a solid mass (Figure 2D). The depth camera tracking the terrain deformation showed that the rover robot selectively avalanches grains to quickly form an initial mound structure behind its rear wheels (Figure 2E).

We applied the 20° Bayesian optimized Rear Rotator Pedaling gait to a range of bed inclines and found that the machine-learned gait outperformed the previous human-tuned gaits for all slopes in terms of speed (Figure 2F). We then used the human-tuned Rear Rotator Pedaling gait from Shrivastava and Karsai et al.[6] as a comparative baseline for the Bayesian optimization trials. In Shrivastava and Karsai et al., the human-tuned Rear Rotator Pedaling had five points per gait cycle where the sweeping servomotors would jitter due to a programming error when sending gait commands. We recreated this Rear Rotator Pedaling gait on the updated rover robot, eliminated the code error causing jitter, and executed locomotion trials (Figure 2F). Compared to Shrivastava and Karsai et al., eliminating the jitter also reduced the locomotion speed of human-tuned Rear Rotator Pedaling by about a factor of 2, surprisingly suggesting jittering motions are helpful in such gaits.

A key factor the Bayesian optimization discovered was disabling the wheel spin during the pushing back phase, as maintaining a solid-like mound resulted in much higher locomotive torque. Without sensory feedback, the Bayesian optimization converged on this open-loop gait strategy of modulating the properties of its local terrain through wheel spinning. The Bayesian optimized gait also minimized the initial sliding backward at steep slopes observed in the human-tuned gait via its manipulated solid mound. The human-tuned gait could slide the rover rearward up to half a robot body length,[6] whereas the Bayesian optimized gait did not. Our results demonstrated that the Bayesian optimization scheme could improve performance without knowledge of the terrain flow, showing that "blind" learning can be effective. For this approach, a gait with some locomotion viability should initialize the learning process. Some progress toward the objective function is essential such that the robot avoids a local minimum in the performance space.

3. Solid-Like Stress Field Remodeling

As seen in the above example Legged systems can offer a significant advantage over their wheeled counterparts for locomotion on granular media by leveraging the redundant links and joints to generate diverse locomotion patterns.[35] This redundancy enables control over the robot's center of mass position and allows the robotic limbs to navigate complex media. The fluid-like remodeling approach exploits the advantage of using high degrees of freedom appendages as detailed in the previous section. In this section, we investigate the locomotion of a bipedal robot which can only locomote effectively by exploiting the solid-like response of granular slopes. Such systems emerge as suitable platforms for human collaboration, and object manipulation in constrained spaces.[36] We investigate the control of bipedal robotic walking on granular slopes using a tiltable air-fluidized bed of poppy seeds (see **Figure 3**A).

The legged robotics community mostly relies on dynamic and feedback control strategies to generate stable locomotion on rigid surfaces. This approach overlooks the locomotor–terrain interaction on deformable substrates and offers limited locomotion capabilities on flowable slopes.[37] This limitation might be partly due to limited understanding of the ground reaction forces on flowable substrates, hence restricting the use of feedback mechanisms. As an alternative, our approach relies on open-loop quasistatic gait strategies and systematic parameter variation of locomotor kinematics on deformable terrain. This approach enables robotic locomotion on such surfaces by promoting effective locomotor–terrain interaction to generate forward thrust and avoids needing control for the complex and unpredictable reaction forces which could lead to rapid sinking, slipping, and even catastrophic failure. As a result, effective robotic appendage designs along with successful gait patterns allow various locomotors to generate locomotion behavior on level and sloped flowable surfaces.[7,11,19]

The instability of bipedal systems on deformable slopes is detrimental to locomotion, because small terrain disturbances lead to locomotor failure due to substrate yielding and avalanching flow. Thus, we generate a gait scheme via adapting Zero Moment Point gait trajectories to terrain slopes. This allows the biped to maintain its stability during single-support phase, i.e., while taking a step, and translate its center of mass on deformable slopes during double-support phase. This gait adaptation eliminates unpredictable robot tilting and more importantly allows effective and predictable foot contact over deformable terrain. We tested the new Zero Moment Point gait[38] on the biped with flat feet (see the inset of Figure 3B) across granular slopes ranging from $\pm 20°$, where $-$ and $+$ represent downhill and uphill slopes, respectively. An ideal walking with no slipping would have an achieved/targeted distance ratio of 1 (black dashed line). As the robot starts slipping on increasing slopes, the performance diverges from an ideal scenario. The robot exhibits minimal slip locomotion up to terrain slopes of $\pm 10°$ with both flat and cleated foot configurations. However, the performance of the flat foot robot significantly deteriorates as the terrain slope approaches $\pm 20°$, beyond which it constantly slips. This is approximately the angle where the tangential component of the gravitational pull overcomes the frictional force between the flat foot bottom and the poppy seeds ($\theta = \tan^{-1}(\mu) \approx 19°$, for $\mu = 0.35$).

Although the slope-adapted Zero Moment Point gait allows climbing moderate granular slopes, its success is restricted by the flat foot–terrain interaction, i.e., robot slipping due to lack of traction, hindering the robot from climbing higher slopes. To facilitate locomotion on steeper slopes, we draw inspiration from turtle flippers[19] and principles of soil mechanics[4] that offer terrain solidification methods. This motivated us to design a new foot that would support the new Zero Moment Point gait with effective terrain engagement by creating tractive forces. The foot design consists of thin appendages protruding perpendicularly from the foot bottom, which we refer to as "cleats" and insert fully into the medium at a low intrusion force (see the inset

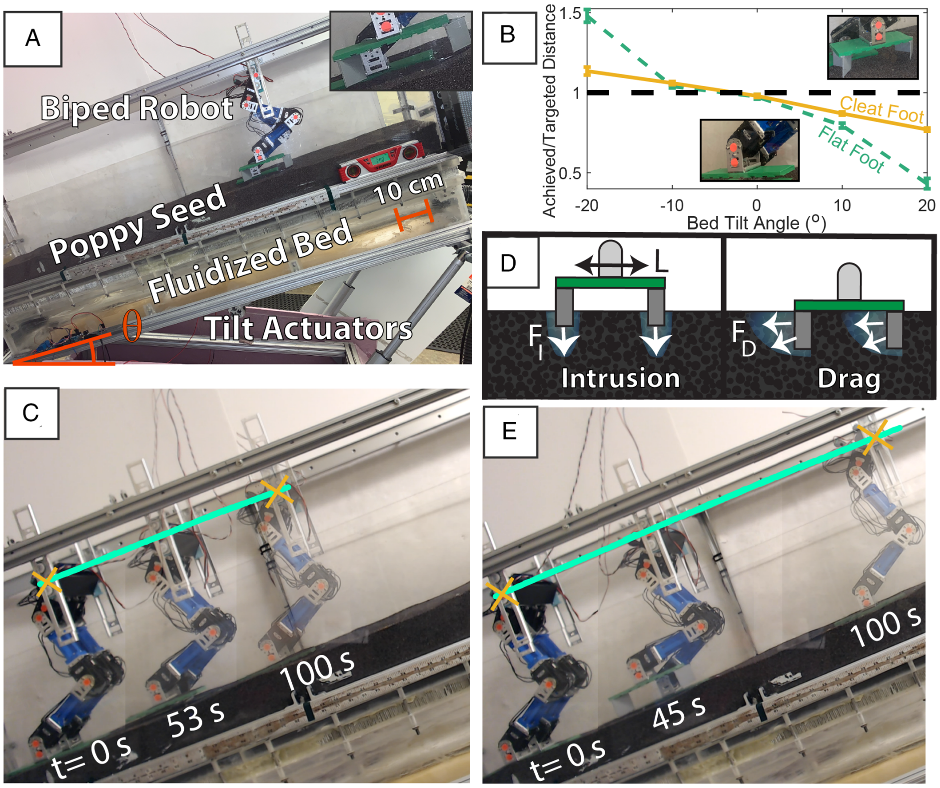

Figure 3. Solid-like remodeling with a biped robot. A) The biped robot and tiltable air-fluidized bed of poppy seeds. The robot takes a step with the cleats beneath the foot on a granular slope of 20°. The inset focuses on the foot and the cleats. B) Locomotion performance of the robot across a wide range of terrain slopes with flat and cleated foot configurations (see inset for visuals). Displacement tracking of the biped (cyan) with C) flat and E) cleated foot. The crosses represent the position of the markers at the initial and final instances of the experiment. D) An illustration of cleat intrusion and drag in poppy seeds. Thin blades cause minimal intrusion resistance, F_1, reducing downward flow of the material. Moreover, the spacing between cleats (L) is chosen such that the cones generated by the blades do not interact, limiting fluid-like response and downward flow. Consequently, the submerged cleats create traction force, F_D, by constructing jammed regions behind the blades which exploit the solid-like feature of the material and enable uphill ascent.

of Figure 3B). This allows the material to remain near or below its yield stress during the cleat-terrain engagement, preventing terrain failure and avalanching flow that increases locomotion difficulty. This is in direct contrast to the fluid-like modeling approach in the rover study. Here, we use direct mechanical stabilization via the foot's blades to constrain possible granular media flows. Our "remodeling" involves changing the stress state and yield surfaces of the local granular media, changing not the visible flow but the invisible stresses. The solid-like stress field remodeling is achieved via intruding thin but large-surface-area cleats deep into the media. The separation between cleats is chosen in such a way that there would be no or limited interaction between blades during intrusion, which reduces overall intrusion forces while avoiding a fluid-like response. Consequently, the submerged cleats create tractive forces and boost solid-like response of the flowable material to a set of intruding bodies during locomoting.

We experimented with a cleated foot incorporating two V-shaped intruder geometries placed at the heel and toe (see the inset of Figure 3B). The robot significantly benefits from the cleats enabling minimal slip locomotion on steep granular slopes of ±20°. The cleats penetrate deep into the material with minimal terrain deformation and create maximal traction force that supports the robot mass on granular slopes by shear strengthening of the material. To illustrate the effect of cleats on the locomotor, we applied motion tracking on the locomotion videos, as shown in Figure 3C,D. We tracked the position of the marker located on the planarizer rail and superimposed the images taken at the onset, midway, and termination of locomotion on a 20° slope. The tracking results show that the flat foot slips significantly due to lack of traction support (Figure 3C). However, once the same gait is applied to the robot after an adjustment of foot placement to avoid cleat scuffing, the resultant slipping is significantly reduced with cleats, achieving 80% success on the same slope.

4. Conclusion and Future Work

Our robophysics approach has demonstrated utility in detailing both how robots move in the complex real world and the principles of selectively solidifying and fluidizing terrain. Varying both robot morphologies and gait strategies in systematic experiments lets us observe how the robot and its environment evolve and manipulate each other during locomotion. Our studies have shown how different terrain remodeling mechanisms can affect robot movement in nontrivial ways. However, the extensive parameter space of most locomotion and terrain scenarios creates bottlenecks in practical study. Augmenting robophysics with machine learning will reduce these constraints, as evidenced by previous studies which achieved optimal control in a 1D jumping robot by iteratively adapting to deformable terrain dynamics.[39]

Beyond blind learning and Bayesian optimization approaches, future studies will use a neural network-based machine learning scheme to characterize the gait and terrain interactions for both the rover and biped robots. We will capture the robots' kinematics and the surrounding terrain deformation using external depth cameras (Figure 2A) and train a machine learning model to describe the coupling of the robot/terrain system. To calibrate the machine learning model without the robot occluding the scope of view, plate drag experiments just below the surface can act as a simple perturbation to generate input force/output flow relations.[40] Robot occlusion of the top-down terrain view can also be solved by syncing multiple depth cameras to cover most blind spots. The machine learning method approach for characterizing substrate flow can offer an approximate numerical model of the environment. This circumvents the need for approximate numerical models or computationally costly and potentially inaccurate continuum models for frictional material, and offers an approximate numerical model that learns from terrain data. A neural network trained with sufficient spatiotemporal terrain data could predict granular flow with high accuracy and generality, augmenting gait learning with knowledge of the environment's evolution during movement. Due to the highly hysteretic nature of granular flowable terrains, the environmental history also has to be considered in gait design and locomotion planning.

The robophysical experiments augmented with high resolution depth cameras and neural network training may offer insights into the physics of locomotion within such media. This scheme may also lead to insights into effective substrate remodeling schemes that improve robot mobility in situ for real-world environments by offering adaptability to flowable terrain via rapid learning. As suggested by our Bayesian optimization results, a rover-like robot could learn unintuitive techniques to execute arbitrary commands on loosely consolidated hills. Bipedal robots could learn more robust gait schemes for atypical foot morphologies. Enlarging the fragile stability basin of bipedal systems on loosely consolidated surfaces may also reveal new robust gaits for many degrees of freedom systems. By combining our robophysics approach of observation on systematic experiments with a sufficiently powerful terrain model, new principles for effective robot locomotion within flowable terrains could be discovered.

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Conflict of Interest

The authors declare no conflict of interest.

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flowable terrains, granular media, machine learning, robophysics, robot locomotion

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