Proceedings of the 4th International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/2026.38301

Planning Paths for All-Terrain Vehicles in Unknown Environments

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Abstract. Autonomous all-terrain vehicles (ATVs) must be able to generate paths and maintain stable, executable vehicle motion in the face of varying, unknown conditions in off-road environments. This paper provides an overview of recent advances in terrain-aware motion modeling and autonomous path planning for ATVs. The first part of the manuscript discusses how characteristics of terrain such as slope, roughness, loose surfaces, vegetation, and uncertainty will impact slip, steering, vibrations, stability, and control of a vehicle. More recent studies rely on learning-based approaches, and uncertainty and motion are integrated into models of the terrain–vehicle interaction. The second part of manuscript focuses on planning methods for unknown environments.It discusses graph search,sampling-based approaches,and hierarchical planner,while also showing how these methods connect route selection with vehicle motion.In many cases,factors such as stability,uncertainly,and traversability are considered directly during the planning process. The planning methods reviewed in the manuscript integrate perception and control, actively leveraging the interaction with the environment. Planning methods have moved toward closed-loop control and interaction-based navigation. The integration of planning methods across vehicles, terrain types, and sensing and operational conditions will be the focus of future research to reduce planning complexity while ensuring planning and control methods operate safely and efficiently. This integration is important because it allows autonomous vehicles to operate more safety and efficiently in off-road environments that are both unfamiliar and constantly changing.

Keywords: All-terrain vehicles, path planning, off-road vehicle

1. Introduction

Wheeled vehicles have difficulty crossing rugged terrain. All-terrain vehicles (ATVs) provide additional mobility on difficult terrain. But, these vehicles are still limited. Some areas where ATVs perform their tasks include use in search and rescue operations, agriculture, environment monitoring, and exploration. ATVs are used in environments that complicate the task of designing an autonomous vehicle. Some of the challenges that researchers in agriculture robotics face include sensing, localization, navigation, and guidance in outdoor environments [1]. RELLIS-3D, an off-road perception dataset, further demonstrates how these environments differ from driving in an

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DOI: 10.54254/2755-2721/2026.38301

urban environment [2]. There are classes of terrain such as soil complemented by the presence of vegetation, undulating landscapes and poor man-made elements that offer little or no road structure.

The challenging aspect of this problem is that terrain has more attributes than its mere geometry. Adverse conditions such as mud, wet soil, loose gravel, slope, and ditch can create a variety of conditions, including slippage, steering and vertical motion, and affect vehicle stability. Xiao et al. found that driving at high speeds over various terrain types amplify small differences. These differences can result in large errors in the planned trajectory. Lee et al. showed that the uncertainty in the interaction between the vehicle and the terrain should be captured in the planning cost and not assumed to be an unmodeled disturbance [3, 4]. The reason that a planned safe route can still be difficult to traverse by an ATV is because of the reasons given in these studies.

Unknown environments introduce problems. While information about known environments can be processed before an agent moves, in unknown environments, information about the environment becomes available as the agent moves. An agent must sense the environment, interpret what it means for the agent's new representation of the environment's state, and adapt its movement plan. This means the planning problem contains two coupled questions: how a moving agent interacts with the environment, and how the newly perceived environment affects the route and the agent's movement. The two sections of this paper address these two coupled questions. Section two reviews terrain-dependent vehicle motion and stability, whereas Section three reviews the problems of global/local path planning and the recent trend of coordinating path and motion planning. The focus is on the innovation logic of the recent methods: what problem they solve, the mechanism, and its relevance for real-time ATV planning in unknown environments.

2. Complex-terrain motion characteristics of all-terrain vehicles

2.1. Vehicle motion under varying terrain

An important development in recent off-road studies has been the transformation from an assumption of a fixed model of the vehicle to considering vehicle dynamics as terrain dependent. It is notable that the same steering or throttle control can impact the movement of the vehicle differently in grass, mud, gravel, compact soil, or even rough rock. TartanDrive demonstrates this by the existence of a large multimodal dataset collected on a Yamaha Viking ATV after some modifications. The dataset approximates 200,000 interactions and includes off-road driving over different terrain [5]. It combines different types of sensing across different terrains. This dataset does not only focus on size. It collects responses and actions of the vehicle, and supports models that learn to account for changes in environmental conditions and how those changes impact vehicle dynamics. This makes the dataset appropriate to use in understanding why a motion model based on a single nominal motion plan becomes inaccurate due to terrain changes.

Xiao et al. addressed this problem with an inverse kinodynamic model that uses onboard inertial sensors to capture how environmental conditions affect vehicle motion [3]. Instead of assuming that the same desired velocity and curvature will always produce the same low-level control commands, the model learns this relationship from data. Their experiments showed that this approach improved plan-execution success during high-speed operation compared with methods that did not account for environmental effects.Thus, the innovation is "using machine learning" alone. The critical aspect is to incorporate learning at the conversion of the planner's desired motion to physical control. In unstructured terrain, errors can be introduced by effects that are difficult to model, such as local traction or compliance. For ATV path planning, this means a planned route should be evaluated along with the confidence of performing the required motion on the current surface.

DOI: 10.54254/2755-2721/2026.38301

Lee et al. applied the same reasoning to motion execution and traversability assessment [4]. Their method uses the uncertainty in terrain triggered by prior driving experience. This uncertainty is included directly in the path cost, which changes how "good terrain" is evaluated. Geometry and slope are no longer the only factors that matter. The planner also considers how predictable the terrain is and how the vehicle is expected to respond. As a result, a route that looks acceptable may still receive a higher cost if previous interaction data suggests unstable or uncertain motion. This is especially useful in unknown environments, where perception is often incomplete. Instead of treating the terrain model as perfectly accurate, the planner can account for uncertainty and choose a longer but more predictable route.

Terrain conditions alter the importance of speed. For example, loose gravel causes sideways sliding during aggressive turns. Rough terrain can cause vertical vibration and sudden changes in tire load. CAHSOR formalizes this problem with a learned six-degree-of-freedom forward kinodynamic model in SE(3) [6]. The model is built using both visual and inertial data and is used to analyze potential sliding, rolling, and vertical instability. In physical experiments, CAHSOR successfully reduced vehicle instability while retaining the vehicle's average speed. Innovation comes from a shift from a planar assumption to a competence awareness: the planner is able to analyze both where the vehicle can go as well as what the vehicle can potentially do at that speed and over that specific terrain.

Classical studies of vehicle dynamics in agriculture arrive at the same conclusion through a different lens. Cui et al. built a dynamics model that incorporated both road curvature and topographic slope because a geometric path does not address slip and roll risks [7]. Their simulations studied how the responses of the vehicle were impacted by speed and curvature, as well as slope. This type of research is useful to the planning problem as it relates physical constraints to the planning problem. A short, steep path may be Jack-of-all-trades, but fast speeds and sharp curves may severely impact stability. Conversely, a longer path over more gradual terrain may support higher speeds and allow for relaxing steering.

These studies show that describing terrain as simply a label is inadequate. What is important is the vehicle-terrain interaction brought about by the surface condition and geometry, as well as the commanded motion and the state of the vehicle. The primary advancement is the preference of modeling motion when considering the terrain, as opposed to fixed motion models, so planners are able to distinguish between open geometries that can be driven and those that are reliably driven by an ATV.

2.2. Vehicle stability and motion adjustments in complex terrain

The second motion-related challenge is not only anticipating the motion of a vehicle, but determining how motion can be adjusted to sustain stability and optimize efficiency. Traditional planners largely separate the problem of route planning from the problem of speed adjustment. First, a geometric route is selected. After that, a controller is designed to follow that route. This separation falls apart off-road, as the shape of a route, speed, and stability are tightly intertwined with the terrain. A route with a sharp turn may be safe at a certain speed and unsafe at another, while a ditch may be impassable at a low speed, but passable with some degree of forward momentum. In contrast to the older methods, these planning concepts represent action-related distinctions.

CAHSOR learns a six-degree-of-freedom model to predict the results of dangerous off-road maneuvers. This six-degree-of-freedom model is useful for predicting rollover and lateral slides. A 2D planner can find a path that avoids collisions; however, it cannot predict the vertical and rotational responses of the vehicle to the irregular terrain. CAHSOR uses inertial signals and

DOI: 10.54254/2755-2721/2026.38301

estimates a broad response for terrain and chooses a motion within the limits of the vehicle's capabilities. Therewith, planning becomes about speed and steering maneuvers; it is not about planning and then adjusting for a lesser speed as a correction.

Motion-Aware Traversability (MAT) extends this idea by developing terrain cost functions that are velocity dependent [8]. Instead of giving each terrain cell a single traversability value, MAT defines the cost of a region of terrain as a function of motion. This is a significant advance, as it does not require a slower speed as a safe motion. For some obstacles, the correct action is a slower motion; for others, the vehicle may need to increase speed to become unstuck. The planner then can evaluate different motions for the same region of terrain. The authors report that their methods significantly reduce detours while improving safety, thus demonstrating that the assessment of terrain becomes more valuable when the action required to traverse the terrain is involved.

Cui et al. also used model based control for autonomous agricultural machinery. Their model combines global path generation, local obstacle avoidance, and a vehicle dynamics model that accounts for curvature and inclination. The novelty of this work is the connection of road geometry and the adjustment of motion. When the lateral deviation, yaw response, and roll tendency increase with speed and slope, a planner should not evaluate path length separately from motion constraints. This gives a physical explanation of why the off-road routing costs include penalties for slope, curvature, and/or expected slip.

The use of learning-based approaches complements this work well because stability limits are difficult to define using fixed thresholds. Xiao et al. demonstrated that learned inverse kinodynamics improve execution of the vehicle due to effects of the unobserved terrain. Lee et al. represent uncertain interactions as a planning cost, which results in the system being conservative in regions where vehicle response cannot be predicted. These approaches do not eliminate the use of physical models, but they reduce the burden and the need to define every single parameter in a terrain dependent manner.

According to the literature, there are three ways motion can be adjusted to aid practical ATV navigation. For one, the vehicle can gradually change its operating speed to keep itself on the same line of travel. This option is useful on a slippery terrain that offers resistance to speed. Secondly, the geometry of the path can be altered to ease the demands on the vehicle's lateral stabilization. Lastly, the vehicle can decide to completely avoid the area if the terrain is still too difficult, or the situation remains too unpredictable. It would be ideal to have a planner that contains all the responses listed, rather than choosing whether or not the path is completely "free".

The significance of this research is how it alters stability as a control issue that happens later, to being a planning factor. In the past, the question of geometric planning was if a collision free path was possible. With terrain-based motion planning, the question is if the vehicle can execute the path with an adequate motion response. With motion-based planning, the question is if a motion and speed that match the terrain are possible. This is crucial in uncharted areas since it cannot be known how well the terrain can be modeled. With the use of learned interaction models and motion conditioned control combined with uncertainty, the vehicle can change its stability assessment as new data becomes available. This offers a feedback mechanism for motion adjustment throughout the navigation process.

DOI: 10.54254/2755-2721/2026.38301

3. Autonomous planning for ATVs in unknown environments

3.1. Global and local path planning

Terrain effects are incorporated, and the planner must rapidly convert environmental data into a route for use in real-world scenarios. Classical graph search is a solid foundation of the technology. The use of heuristics in A* makes it the most compelling of the options. A* has an interpretable cost function that can easily incorporate many more values than just distance [9]. In an off-road map, cells or edges can be penalized based on slope, roughness, and uncertainty or estimated traversability. A* can be extended by Samptial Search. This logic can be applied to a state space that maintains continuous vehicle motion and kinematic constraints; the practical formulation described by Dolgov et al. was created for vehicles that use online obstacle detection [10]. Sampling-based planning methods, namely RRT and RRT*, will provide solid foundations if configuration spaces become large and/or more constrained. Karaman and Frazzoli have shown that RRT* and similar planning methods achieve asymptotic optimality while preserving the efficiency benefits of sampling-based planning [11].

The problems associated with the use of these methods in unknown off-road terrains are not the discovery of paths. The main problems are maintaining both the environmental representation and the search problem sufficiently small enough to enable repeated updates. Jerome et al. address this problem in particular with an intermediate-map method for off-road planning even without complete OSM data [12]. This method converts geographic features into a planning map and decomposes the task into plan generation, graph search, checking if a solution is kinematically feasible, and smoothing. In addition, they use a dynamic map slicing technique to avoid processing the entire map in each step. In their experiments, they claimed to find feasible paths on large off-road environments in several seconds. The main contribution is computational selectivity. Instead of providing the map at the finest resolution in all regions, the system processes only the region and the information that is required for planning.

Planning over long distances also brings a representation problem because near the vehicle local sensors provide only detailed data. Trailblazer solves this problem by learning off-road cost maps from many sources including overhead photos, LiDAR, elevation, and map data [13]. The learned cost map provides a global description and facilitates the selection of a path even over distances beyond the local sensor range. The main contribution is the transformation of diverse geospatial data into a cost representation and planning. This eliminates cost tuning and enables the global planner to think about the terrain outside the bounds of the binary occupancy map.

When a dense metric map of an unknown forest isn't needed or cost effective, another approach is to create a topological map. Tremblay et al. model the environment as panoramic observations and use edges that carry traversability information to connect the observations [14]. They have a system that includes both long-range planning, exploration, and low-level vision and GPS based navigation. This key innovation is that the map does not store all the geometric details, but instead contains information on how navigational connectivity is stored. This is useful in forest areas that are geometrically complex but can still be traversed, such as off-trail areas. A topological representation can thus be used to reduce map size without losing information required to reach a far away goal.

Global and local planning also need to interoperate, instead of following one another, in unknown environments. While a global route may give the direction for the goal, new local observations may be found that prevent a route from reaching the goal or make it unsafe. The local planner needs to respond in the short term without losing sight of the long term. This need is clearly demonstrated in dynamic agricultural scenarios. Ahmadi et al. represent a varying field as a graph with direct edges

DOI: 10.54254/2755-2721/2026.38301

and associated costs that are modified based on the observations of UAVs to varying obstacles and terrain [15]. Their contribution is not just obstacle avoidance, it is ongoing cost updates to make sure that the current path is valid in the current environment and not based on a map that was created prior to operation.

These approaches are used to control a trade-off common to many methods that is between the level of detail in the terrain and the cost of computation. Dense maps have been shown to help with local evaluation, but are costly with respect to sensing, memory, and search whereas sparse representations can lead to a lack of information for precise motion. A practical ATV architecture is thus hierarchical, consisting of a global layer which determines which corridor to take based on information of a lower resolution or learned through an experience layer, and a lower layer level which evaluates the detailed traversability using current sensors. The primary novelty is that instead of constructing a single map for a single plan, a representation is maintained of a plan which evolves through time, and only the regions of the map which change as a result of new observations are updated. This facilitates multiple replanning without building a rich world model that is not needed.

3.2. Path and vehicle motion coordination

Finally, the route that the planner chooses must be linked with the actual route that the ATV can accomplish. Here is where recent research is the most evident in going beyond traditional obstacle avoidance. This purely geometric planner determines the path and the speed and slip of the vehicle and the terrain response is handled by the controller. However, with coordinated planning the route cost can be modified based on the terrain perception and vehicle state. The resulting path does not have to be shortest, it is the best combination of shortness, traversability, uncertainty, and executable motion.

A direct example is given by Lee et al. who add learned uncertainty from terrain to traversability costs [4]. The planner may choose a marginally longer path if it is known that the direct path has very uncertain vehicle response. CAHSOR applies the same concept to aggressive vehicle behavior, the six degree of freedom consequences and competence limits [6]. Combined these techniques create an important point of planning, the terrain cost is not a terrain property. It's a terrain (and motion) interaction thing!

This principle will also alter the design of environmental perception. Geometric perception is not always enough since visually or geometrically non-simple areas like high grass can still have a physically simple path [16]. BADGR is able to learn navigation-relevant affordances from self-supervised data and can autonomously collect data. The novelty is that it uses the outcome of the robot's own interactions for supervising perception, in addition to the use of human semantic labels. This is directly relevant to the planning of ATVs as the perception output is not necessarily "what is this object?" but rather "what will happen if I drive here?".

SALON follows this trend and provides quick adaptation online of traversability and speed estimates [17]. It leverages its own experience to continually adapt risk-aware cost and speed maps in new environments with minimal human supervision. It was the innovation during deployment that was important. The domain shift can be observed when the surface appearance, season, lighting or soil properties change, when a fixed model is trained in one environment. While the planning system is running, the cost map is updated by SALON with the latest interaction data to ensure the planning system becomes more aligned to the current environment. This is useful for the ATV entering an unknown area as the system does not assume that all terrain classes will have been present at training.

DOI: 10.54254/2755-2721/2026.38301

For scenes that the vision-language model is not familiar with from a particular perspective, AnyTraverse uses selective human assistance [18]. The framework can recognize navigable areas with the help of prompts and ask for operator input if it doesn't know the situation it is currently seeing or if it is facing unknown classes. Selective intervention and not complete manual control is the innovation here. It concedes that the zero-shot semantic reasoning can be useful in expanding the knowledge about the environment, but acknowledges that it might not be enough for uncertain cases and a human decision could be beneficial. This represents a potential window for transition between autonomous learning and reliable supervision, for high consequence off-road applications.

The same coordination can be extended to longer distances as seen in Trailblazer and topological mapping. Trailblazer, on the other hand, transforms multimodal environmental data into off-road cost maps for long-range planning and Tremblay et al. label topological relations in unknown forest terrain with traversability information. These methods are useful as they require a global context to the local motion constraints. A local planner may not have to go through a bad area, however if it has to do it again, it will end up in a bad long-range route. Global traversability-aware representation gives the direction and local planning, based on motion awareness, determines how to traverse or avoid the terrain that become visible.

What is still a challenge is integration under real time limits. Semantics, geometry, uncertainty and traversability can be inferred from perception, motion models can estimate slip, stability and/or speed related costs. It's not possible to process all this at full resolution. Dynamic map slicing further decreases the number of map cells for which planning is active, SALON only modifies the cost and speed information online, and the information for agricultural environments can simply be updated by changing the graph weights and avoids the need to rebuild the entire problem.

Therefore, coordinated ATV planning should work as a closed loop: the sensor observes the terrain, the perception transforms it into costs and uncertainty that are relevant for navigation, and the planner decides on a global level how to proceed and how the terrain under the robot is to be traversed at a local level, and then the motion-aware model checks whether it is possible to execute the planned route at the current speed. Then the system changes its path or speed as soon as the predicted response is too unsafe. This interaction aware loop is the most important step after the geometric search and independent control.

4. Conclusion

Autonomous ATV (aTV) navigation in unknown unstructured terrain has been studied and has demonstrated that two problems are inseparably coupled: the understanding of the effect of the terrain on aTV motion and the application of this knowledge in the aTV path planning. Slip, steering, vibrations, trajectory tracking and stability are affected by the complexity of the terrain; the shortest collision-free path is not necessarily the safest and most efficient path. Recent approaches are thus abandoning the notion of fixed motion assumptions and instead using learned vehicle-terrain interaction models, uncertainty estimates, six degree of freedom competence models, and speed-dependent traversability.

The same transition can be seen in the environmental representation, at the planning level. A dense map is often not required and computation intensive, and an occupancy map is not sufficiently descriptive of a natural terrain. Intermediate maps, learned cost maps, topological representations and hierarchical global/local planning are four approaches to retaining navigation relevant information and reducing computation. The vehicle can also update its knowledge online and using a self-supervised learning approach, it can update its knowledge when it encounters terrain different from the training data.

DOI: 10.54254/2755-2721/2026.38301

Future ATV navigation should connect perception, path planning, and motion control rather than treating them as separate steps. A practical system needs to keep track of long-range goals while also updating local terrain information and checking uncertainty and stability. It should also be able to adjust both the route and vehicle speed without repeating unnecessary calculations. The main challenge is making this closed-loop system work reliably across different vehicles and terrain conditions while still responding in real time. Achieving this would make autonomous navigation safer and more efficient in truly unknown environments.

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