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Explore Bravely: Wheeled-Legged Robots Traverse in Unknown Rough Environment

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Abstract— **This paper addressed a challenging problem of wheeled-legged robots with high degrees of freedom exploring in unknown rough environments. The proposed method works as a pipeline to achieve prioritized exploration comprising three primary modules: traversability analysis, frontier-based exploration and hybrid locomotion planning. Traversability analysis provides robots an evaluation about surrounding terrain according to various criteria (roughness, slope etc.) and other semantic information (small step, stair, bridge etc.), while novel gravity point frontier-based exploration algorithm can effectively decide which direction to go even in unknown environments based on robots' current pose and desired one. Given all these information, hybrid locomotion planner will generate a path with motion mode (driving or walking) encoded by optimizing among different objectives and constraints. Lastly, our approach was well verified in both simulation and experiment on a wheeled quadrupedal robot Pholus.**

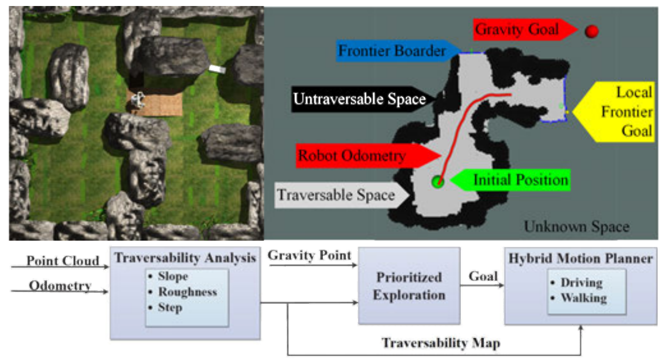

Fig. 1: Proposed framework implemented on Pholus robot for gravity point frontier exploration in a simulated environment

I. Introduction

Autonomous mobile robots are in urgent need for inaccessible and unsafe scenarios, such as construction sites, disaster rescue, scouting in other planets, etc. However, unknown tough terrain makes it very challenging for robots nowadays to traverse through. Recently, powerful yet malleable robots have been examined [1], [2]. Inspired by the capability of such robots, we developed motion control strategies for wheeled-legged robots exploring around unknown rough environments, in which online planning is performed based on terrain analysis and frontier-based exploration technology.

A. Related Work

One critical aspect of autonomous navigation is the traversability analysis of terrain. [3] proposed a probabilistic traversability map generated by fusing 3D LiDAR and camera, which demonstrated the possibility of ground vehicle doing road detection through terrain analysis. Some other work [4], [5] also tried to combine image (camera, ir camera etc.) and point cloud (stereo camera, kinect, LiDAR etc.) inputs to have better representation of the environment. However, general terrain geometric proprieties are usually extracted from 3D point cloud because of its advantage over surface modeling [6]–[8], and this technology is also adopted in our terrain analysis module.

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Recently, an autonomous exploration algorithm was presented based on traversability analysis [9] which makes use of terrain slope and roughness information. Additionally, it includes chassis collision and robots' body posture to have better understanding on the environment. Compared with wheeled robots, legged robots possess better traversing capability which allows them to tackle complex environments with even large obstacles and show up as an more promising alternative in rough terrain. [8] proposed a navigation method for legged robot, DLR-Crawler, which utilized stereo camera to identify geometrical information such as slope, roughness and steps from rough terrain and thereafter estimate reachable places. Similarly, besides the aforementioned geometric extraction and traversability analysis, quadruped robot StarlETH [6], navigated with a sampling-based RRT path planner. However, both work did not sufficiently represent environment regarding steps in traversability evaluation. These works assume step area if a certain region has a similar height which are not effective in sense of traversability since they can not identify step properties such as width and length to assess whether it is suitable for foot placement or not. Therefore, rather than iterating each grid cell for step evaluation, we proposed step segmentation method to identify walkable steps by extracting a step model (which consist of a center Cartesian point, width and length).

To conduct an effective search or rescue operation in scenarios with unknown terrain, robots need to plan search areas and explore wisely. Frontier-based approaches are quite popular which aim to maximize the search area in an unknown environment by providing robots with frontier targets. The concept of frontier is introduced by [10] which is defined as the boundaries between known and unknown spaces. Generally, frontier that is closest to the robot is preferred as it minimizes the motion expenditure and time [11], [12]. However, this overly simplified assumption may lead to poor coverage for big range exploration. Thus, the selection of frontier criteria should balance among travel distance, frontier size, magnitude of information gained and other factors which increase the explore coverage [13], [14].

Another key module to allow wheeled-legged robots to explore bravely in unknown-rough environments is hybrid locomotion planner. Researchers from ETH [15] installed additional wheels at the end of legs of their robot ANYmal. All the joints are fully torque-controlled including the wheels. Based on this, they developed several control algorithms to achieve hybrid locomotion. For instance, [16] presented a hierarchical control framework which adopts the trajectory optimization method and elaborates the kinematic rolling constraint of wheels. And [15] proposed another trajectory optimizer which can run online at 50Hz with linearized Zero Moment Point (ZMP) constraints. Meanwhile, [1] and [2] implemented a motion planner on a wheeled quadrupedal robot MOMARO with unified legged and wheeled modes considering slope and roughness (height variance) information of terrain. Their hybrid planner switches motion modes according to the distance between robot and detected steps. Moreover, they use only height information to climb through steps. Recently, [17] presents a walking excavator which controls body posture and foot placement over the rough terrain by using elevation map. The hybrid locomotion planner implemented in this paper is similar to previous work. Beyond that, it also considers the segmented steps along slope and roughness information when modelling the environment. A novel grid map named mode map is generated in order to efficiently switch between driving and walking instead of deciding based on how far the step is located while foot placements and motion sequences are determined according to extracted step model instead of height map. And the locomotion planner is ported to the gravity point frontier exploration module to navigate through unknown environment.

B. Contribution

Compared with existing works of wheeled-legged robots exploring in unknown rough environments, our work mainly contributes in three aspects as shown in Fig. 1:

1) traversability analysis considers not only terrain slope and roughness but also segment structured steps to further describe the environment semantically.
2) Frontier-based exploration is enhanced by giving gravity point which prioritizes searching areas with interest.
3) Proposed hybrid locomotion planner can switch modes (driving or walking) based on extracted information from traversability analysis to produce corresponding motion sequence.

In this paper, Section II introduced the implementation of traversability analysis and Section III presented the improved frontier exploration algorithm. Thereafter, Section IV elaborated on the proposed hybrid locomotion planner. The whole control framework is demonstrated and verified through simulation and experiment in Section V. At the end, Section VI concludes the work and gives an outlook on future research.

II. Traversability Analysis

Traversability analysis is to evaluate the surrounding environment and generate a map indicating the difficulty for each area to traverse with respect to robots' capabilities. It is utilized for conventional 2D planner for efficient and safe path generation. Existing mapping methods like ”gmapping” usually takes only occupation information (free, occupied or unknown) [18] into account resulting other important terrain characteristics are ignored. Traversability map is a digital representation of the environment and can be represented by either 2D grid cells [6] or triangulate cells [19]. Each cell stores an index value indicating the traversability of corresponding area.

In this section, traversability analysis based on laser scanning is introduced. Online LiDAR data is used to generate 3D point cloud and directly given as input. The 3D information is then converted to traversability index values and stored in a 2D grid map. The traversability analysis is based on rough environment (deviated slope, hills, etc.) and highly uneven environment (steps, stairs). Thus, the analysis represents geometric surfaces by calculating local roughness and slope. By using these two characteristics, we can differentiate between untraversable obstacles and traversable slopes. Moreover, it also represents uneven planar areas such as segmented stairs and its proprieties.

A. Local Roughness and Slope Calculation

As stated in [6], [8], before computing typical terrain characteristics (roughness and slope), elevation model is generated first due to its lower computational costs compared to raw 3D point cloud and rich-enough terrain properties.

Local roughness of terrain is defined as standard deviation of local heights within a given circle of elevation map. Hence, sudden changes on heights which are not suitable for walking can be easily detected and smooth areas can be separated from rough ones with thresholds.

On the other hand, local slope is defined for each cell as the angle between normal vector of local fitted plane and ground plane.

B. Semantic Step Segmentation

There are some existing works [6], [8] about step detection based on height variance in local terrain. Nonetheless, this approach is not suitable for our case as enough supporting area must be guaranteed for the foot placements of each step and the transition between neighbouring placements. [20] proposed a method to detect uneven planar steps from point cloud according to robots' foot size and then decide foot placement coordinates from the extracted step model.

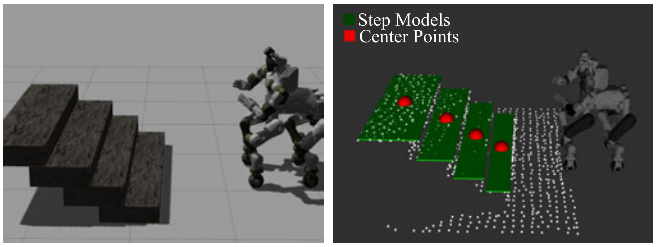

Fig. 2: Step Segmentation and Detection: (Left) a stair in simulation, (Right) representation of step models

Inspired by this work, a similar semantic step segmentation framework is developed which consists of three sections: point cloud based step segmentation, walkable step detection and a mode grid map generation.

In segmentation process, elevated environment model representing as a elevation map can directly store points parallel to ground. To segment the outliers, a common ground is detected assuming planar and within ± 5 cm range at the bottom of supporting feet. After removal of common plane, Point Cloud Library's region growing method [21] is used to cluster individual elevated points [22]. The region growing clustering parameters such as number of neighbouring points, smoothness, curvature threshold should be selected carefully since further processing depends on clustered points. Accurate clustering indicates desired object is individually separated from other objects. With assumption of having accurate clustered points, standard deviation of height is calculated for each cluster. If calculated deviation value is less than a fixed threshold, individual clusters are indicated as smooth planar and add step model as 2D polygonal shape.The step model with properties such as width, length and center pose is placed in the fixed world frame while its estimated center is averaged from clustered points.

In detection process, models are evaluated whether they are acceptable for walking or not according to predefined features such as maximum step height, minimum width and length. Additionally, detection algorithm checks if two steps are connected properly in order to identify a stair including multiple continuous steps. Figure 2 shows an example of stairs where multiple steps were detected with centres assigned through the proposed method. Thereafter, a 2D grid map named *mode map* is generated to determine the motion type for each cell. At the beginning, all the cells are set as driving mode, and cells will be reversed to walking mode when a step model is detected. Moreover, walkable grid cells are assigned with a fixed traversability score which will be used for the final traversability map generation.

One drawback of assigning fixed value to the cells of step model is the ignorance of direction in which robots cross. Here we simply assume the difficulty of robots crossing in different directions are the same. In addition, for step models with big area, setting corresponding cells as walkable mode may not be proper because robots can actually drive on it more efficiently. In this paper, only small step models will be detected to avoid this issue.

C. Traversability Map Generation

The aforementioned local roughness, slope and step segmentation can be unified into one traversability map representing as 2D grid cells and managed by map library [23]. It is formulated with logical operations that allows for flexibility to add more analysis in the future.

The pseudo code of traversability map generation is given in Algorithm 1, where i represents ID of grid map cells, N is the total number of cells in grid map, k is time stamp, S_k, R_k, M_k and T_k are respectively 2D grid map of slope, roughness, mode and traversability. Following [6], [8], the initial value of traversability map T_k is calculated by Eq. (1). s_{crit} and r_{crit} are the critical thresholds of slope and roughness which are determined by robots' own traversing capabilities. To normalize the traversability index into $[0, 1]$, each value is divided by its own critical value and multiplied by corresponding weight. w_s and w_r are the weights for slope and roughness and the sum of weights must equal to 1. For the resulting traversability index, 1 indicates highly traversable while 0 highly untraversable.

As mentioned in Section II-B, the score assigned on the mode map M_x is merged to traversability map by using logical operation. In the last step of Algorithm 1, current traversability values go through a low pass filter with α in between $[0, 1]$ aiming to damp out noise and disturbance.

$$T_k(i) = 1 - [w_s \frac{S_k(i)}{s_{crit}} + w_r \frac{R_k(i)}{r_{crit}}] \ , \ w_s + w_r = 1 \qquad (1)$$

Algorithm 1 Traversability Map Generation

for $i = 0, i \leq N, i$ +=1 **do**
  if $M(i)$ *is walking mode* **then**
    $T_k(i) \leftarrow$ *fixed traversability score*
  else
    $T_k(i) \leftarrow 1 - [w_s \frac{S_k(i)}{s_{crit}} + w_r \frac{R_k(i)}{r_{crit}}]$
  end if
  $T_k(i) \leftarrow \alpha T_{k-1}(i) + (1 - \alpha) T_k(i)$
end for

III. AUTONOMOUS EXPLORATION

Frontier-based exploration assumes that no prior knowledge of environments is provided. However, it can be very helpful and should be utilized if present. Existing methods ignore this information and their explorations are mostly based on clever manipulation on distance between frontiers and robot pose.

By making use of robots' initial pose and rough estimation of targeted area, the robot is able to perform search and exploration with higher possibility of discovering an interest target. The target can be given as a rough coordinate or a beacon which signals its own location. Here it is treated as gravity point since it attracts the robot to move toward itself.

A. A New Frontier Definition

As discussed in Section II, a traversibility map is generated and utilized for both localization and exploration which comprises of traversable, untraversable and unknown space. Commonly, frontier is defined as the boundaries between known and unknown spaces. In this paper, frontier is re-defined as the boundary which separates traversable region from unknown region in the map. The search for frontiers is carried out by the Wavefront Frontier Detector (WFD) algorithm [24] which returns a list of frontiers that is to be evaluated to produce the local frontier goal.

B. Evaluation of Frontier

The evaluation function is specially designed to evaluate not only the size of the frontiers and the distance between the frontier and the robot but also the distance between the gravity goal and the frontier.

The evaluation function can be written as:

$$E(f_i) = \omega_s \|f_i^s\| + \omega_{d_1} \|f_i^{d_1}\| + \omega_{d2} \|f_i^{d_2}\| \tag{2}$$

Where f_i^s, $f_i^{d_1}$ and $f_i^{d_2}$ are the size of i-th frontier, the Euclidean distance to the robot and the Euclidean distance to the gravity point respectively. ω_s, ω_{d_1} and ω_{d_2} are the weights of corresponding costs. To avoid any possible bias, all costs are normalized into a range $[0, 1]$ with respect to minimal and maximum limits.

Frontier with the lowest cost is denoted as f^* which can be obtained by minimizing Eq. (2):

$$f^* = \min_{f_i \in F} \Big(E(f_i) \Big) \tag{3}$$

where F denotes all the frontiers that have been found in the current traversability map.

Fig. 3 depicts the comparison between improved frontier-based approach [14] (left) and our proposed method (right). Both of the algorithms aim to discover the target point marked by a red sphere in the map, and our algorithm takes shorter way (shown in the red line trajectories from wheel odometry) and is much more efficient in terms of both time and motion expenditure.

By adding $f_i^{d_2}$ in the evaluation function, the robot can be guided toward the gravity point by choosing the frontier that is closest to the gravity point. However, when the structure of the unknown environment becomes very complex, the simple assumption of $f_i^{d_1}$ may not be accurate, as the direct measure between both points may be hindered by obstacles which are not accounted in the evaluation function. Since WFD is, essentially, based on Breadth-First Search (BFS), we can obtained path distance between robot and frontier with ease and have a more accurate representation of the cost.

To conclude, the intention behind the proposed exploration algorithm is to acquire as much new information as possible while traversing toward the gravity point.

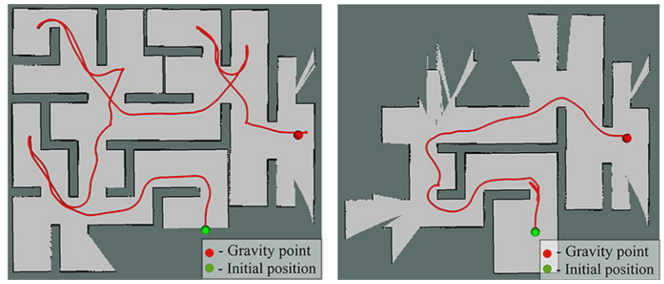

Fig. 3: Comparison of Explorations: (Left) frontier-based approach [14], (Right) proposed gravity point approach

IV. Hybrid Locomotion Planner

In order to move our wheeled quadrupedal robot Pholus to the desired frontier, a hybrid locomotion planner is proposed given the traversability map. Similar to [1], our planner consists of two main parts: a global-local path planner with respect to the generated traversability map and a walking planner to determine walking motion sequences on the extracted step models. Moreover, with the help of mode map in Section II-B, our planner is able to switch modes between ”driving” and ”walking” motions.

A. Global and Local Path Planners

The first part of the hybird locomotion planner is to generate a safe and efficient route, and a 2D planner is chosen here to avoid the complexity of a 3D planner. As this paper doesn’t focus on path planning, an off-the-shelf library, ROS navigation stack, is adopted which allows selection of various path planning algorithms. ”NavfnROS” is selected as the global planner while ”Elastic band” for the local planner. The local planner aims to satisfy kino-dynamic constrains by adhering to the global path while avoiding collisions [25]. And the generated command velocity is exported to ”driving” mode. Finally, the costmap is extracted from traversability grid map which can be utilized by the planner.

B. Walking Planner

The second part is to design foot motion sequences for walking mode which can be divided into three phases:

- Determining rough foot placements
- Searching for feasible foot placements in local area
- Generating motion sequences between initial to goal foot placements

During the first phase, rough foot placements are calculated according to extracted oriented step models from Section II-B which consists pose for each step. After that, it is used as the center of the local area for second phase where feasible foot placements are searched further regarding to robots’ foot size and cost evaluation of each foot pose in local area. Both traversability index value (highest value in the local area) and non-stepping space are evaluated in the cost function. Thereafter, multiple foot placements are generated by pose gain controller for the motion sequence of each foot in order to achieve goal. Additionally, to avoid collision during walking, feet are lifted to create ground

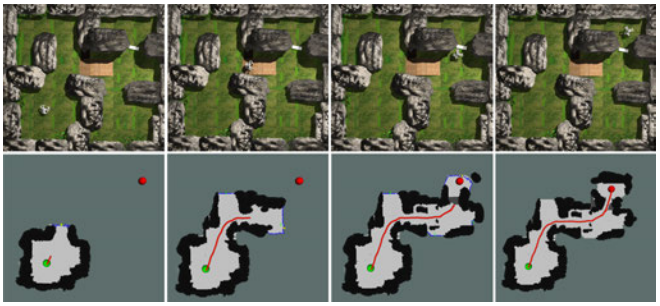

Fig. 4: The Snapshots of Simulation: (Left to right) Robot manoeuvres over slope and debris to search for gravity point.

clearness for swinging legs. And some fixed parameters such as shoulder length, initial homing pose, ground clearness, maximum step distance, stance duration should be given for motion sequence generation according to robots' capabilities. The produced motion sequences are executed by an optimal whole-body inverse kinematics controller referring to [26].

V. Results

The proposed control framework was verified and evaluated in both simulation and experiment as following.

The resolution of grid cell is set to 0.1 meter which is accurate enough to conclude traversability analysis and takes acceptable computational cost. And elevation map is computed by extracting highest height value of each grid cell. This may result in inaccuracy and inappropriateness if laser sensor tries to detect hanging objects or indoor ceilings. Thus, the laser sensor is deliberately tilted downward to perceive ground.

Moreover, critical roughness value r_{crit} is set to 0.04 to split smooth and rough area. For roughness calculation, choosing radius of local circles is tricky as it applies to all the cells when calculating standard deviation. Computational cost may be high if too big and insufficient accuracy if too small. Therefore, to balance between accuracy and computation cost, it is practical to set it slightly larger than the resolution of grid map. Here 0.1 meter is chosen. To differentiate between traversable and untraversable slopes, critical slope value should be decided by the robots' capabilities. For testing, s_{crit} is chosen as $15°$ for our robot.

The standard deviation threshold is set to 0.2 in semantic step segmentation process. This value may differ from surface and sensor noise. For detection, step model's minimum length, width are set to 1.5, 0.3 meter. Maximum height difference is 0.3 meter for both simulation and experimental tests. Fixed traversability score for step is chosen intuitively as 0.5 according to robots' capabilities.

A. Simulation

To demonstrate the feasibility of the whole pipeline of our method, a simulation environment is set up modelling an outdoor rough unknown terrain which includes rocky walls, slopes and steps. Walls are placed to mimic a maze structure to test the searching ability of the exploration algorithm. The simulation runs in Gazebo and corresponding results are present in Rviz as four stages shown in Fig. 4. In the first stage, the robot starts to explore unknown environment and approach the lowest-cost frontier.In the second stage, traversability analysis concludes the observed slope to be traversable area and this allows the robot to traverse over the wooden bridge. The third stage illustrates the ability of the hybrid planner to switch between driving mode and walking mode. The final stage depicts the robot successfully reaching the given gravity point in the unknown environment. Robot's Rviz visualization is labeled as 1.

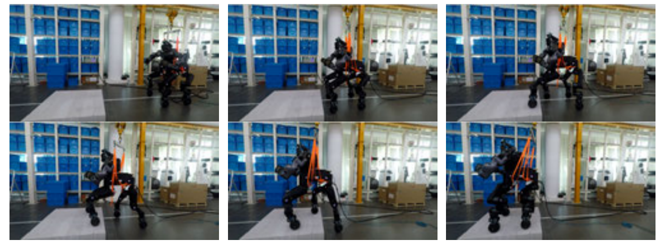

Fig. 5: The Snapshots of Experiment: (top to bottom) driving and walking motions of Pholus

B. Experiment

The indoor experiment is set up purposefully to validate both the traversability analysis and hybrid locomotion planner. Our robot, Pholus, is attached with a 3D LiDAR which is tilted down roughly $45°$ and also wheel encoders and IMU for localization. Due to hardware limitation, a pre-registered 3D point cloud is implemented for traversability analysis instead of an online cloud.

Fig. 5 illustrates the different stages of unified wheeled and legged motions in real world. First, the traversability analysis and hybrid locomotion planner framework was being initiated. Then step segmentation module which is in traversability analysis generated a step model according to Pholus known pose. As shown in Fig. 6, the step model is represented as a blue plane and the red dot is its estimated center. And the traversability analysis result is also present in which green and red markers stand for traversable and untraverable areas individually. The step area is indicated as brownish since it is traversable but not highly recommended. It is larger than the real step due to safety inflation.

Next, the hybrid locomotion planner generated a path to the given goal which includes both driving and walking modes according to traversability analysis. The planning result is shown in Fig. 7 where the global and stepping paths are marked as green and red respectively and foot placements are depicted as colored arrows.

The experiment results show that our algorithm is able to identify the step and traversable areas. Clearly, by using hybrid planner, the robot is able to switch between driving mode and walking mode while following global path and execute walking motion sequences according to segmented step model. However, due to safety consideration and hardware restrictions, more challenging experiments such as traversing in outdoor uneven areas haven't been done so far.

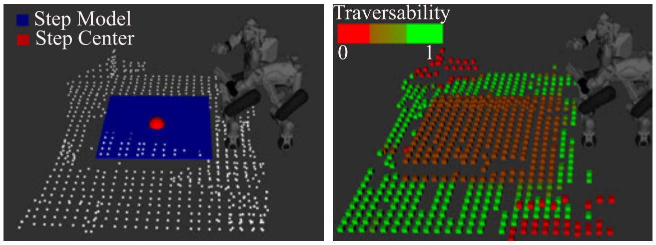

Fig. 6: Traversability analysis result: (Left) step model, (Right) traversability map.

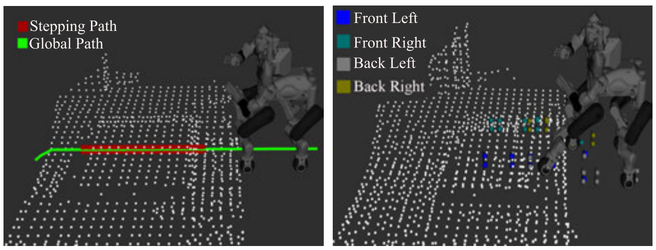

Fig. 7: Hybrid locomotion planner result: (Left) global and stepable path, (Right) foot placements

VI. Conclusion

This paper proposed a motion planing framework for wheeled-legged robots to explore in unknown and rough environments which is comprised of three primary modules: traversability analysis, frontier-based exploration and hybrid locomotion planning. Traversability analysis provides robots an evaluation about rough terrain according to various criteria (roughness, slope and segmented step), while the novel gravity point frontier-based exploration algorithm will decide which direction to go effectively in unknown environment based on robots' current pose and desired one. Based on the traversability analysis and desire frontier, hybrid locomotion planner will optimize a hybrid path with movement mode (driving or walking) encoded. At the end of this paper, our approach was well verified and demonstrated both in simulation and experiment on a wheeled quadrupedal robot - Pholus. Future research can be carried out on improving traversability analysis by detecting more features such as vegetation, water, mud, gap, etc. And the hybrid planner can be more efficient by adding driving motion in larger walkable areas. Moreover, deep reinforcement learning can be utilized to make the whole framework more adaptive and general.

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