# Ground vehicle path planning on Uneven terrain Using UAV Measurement point clouds

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## **ABSTRACT:**

The objective of this study is to develop a system to support rapid ground vehicle activities by planning safe travel routes for ground vehicles from point clouds of wide-area uneven terrain environments measured using UAVs. However, fast path planning is difficult in complex environments such as large, uneven terrain environments. Therefore, this paper proposes a new RRT method based on the RRT algorithm that can perform fast path planning, even in complex environments. In the proposed method, narrow areas that are difficult to be explored by ordinary RRTs are first identified in advance, and nodes are placed in these areas to guide the search. When searching with RRTs, the tree is extended via these guide nodes to efficiently traverse the narrow area. In the validation of the proposed method, a comparison was made with RRT and RRT-Connect in two environments, including narrow areas. The results show that the proposed method has a higher route discovery capability, at least two times fewer search nodes and five times faster path planning capability than other RRTs.

# 1. INTRODUCTION

Japan is one of the world's most prone to natural disasters such as earthquakes and torrential rainfall, and landslides caused by these natural disasters often disrupt traffic networks. In fact, the Noto Peninsula Earthquake of 1 January 2024 caused landslides in several locations, destroying roads and other traffic networks. After the occurrence of such a disaster, rescue and recovery work and the transport of supplies to the affected area are required. The transport vehicles, construction machinery and rescue robots used to carry out these tasks need to travel over uneven terrain caused by landslides and other disasters. However, unlike the normal environment, the post-disaster environment contains many large obstacles such as undulating terrain and fallen trees. In such an environment, the visibility of ground vehicles is obstructed by the obstacles, which significantly reduces the range of visibility. This makes it difficult to obtain terrain information over a wide area, and the only way to travel to a destination is to determine a travel route based on information within the sight range. This makes efficient travel difficult.

We have therefore carried out studies aimed at guiding ground vehicles in uneven terrain environments. In previous research, 3D point clouds of the terrain were generated from continuous images acquired by Unmanned Aerial Vehicles (UAVs) using Structure from Motion / Multi View Stereo (SfM/MVS) to determine areas where ground vehicles can travel and to plan routes. There are various path planning methods for ground vehicles (Liu et al. 2023), among which the Rapidly-exploring Random Tree (RRT) algorithm, a sampling-based algorithm, is widely used for fast path planning. An example of similar research is, for example, (Fedorenko et al. 2018), who measured point clouds of an uneven terrain environment by aerial photogrammetry with a UAV and used the RRT algorithm to calculate a travel path that satisfies the Unmanned Ground Vehicle's (UGV) performance on uneven terrain. However, although the RRT algorithm is capable of fast path computation, its search efficiency decreases when there are narrow areas in the search space. This makes it difficult to compute fast paths in complex environments such as uneven terrain environments, as search efficiency is reduced.

To address these issues faced by conventional RRT, a new RRT method with improved search efficiency in uneven terrain, including narrow areas, is proposed and its effectiveness is described in detail through comparison tests between conventional RRT and RRT-Connect.

#### 2. RELATED WORKS

Numerous studies have been conducted on UAVs to provide wide-area visibility and navigation to ground vehicles. (Vasić et al. 2020) and (Katikaridis et al. 2022) use UAVs to capture aerial images and identify passable areas and obstacles from the images for ground vehicle navigation. (Wang et al. 2023), the point cloud of the wide area measured by the 2-D laser on board the UAV is matched with the point cloud of the surrounding environment measured by the LiDAR on board the UGV to produce a risk map and to plan the path of the UGV. (Miki et al.2019) proposed a method that not only navigates UGVs from point clouds of terrain obtained by laser measurements with UAVs, but also improves the UGV's running performance with UAVs. These coordinated systems between UAVs and ground vehicles provide ground vehicles with a wide field of view and increase the range of their activities. On the other hand, the challenge is that the time of activity of the ground vehicle is limited by the energy-constrained UAVs in the coordinated system.

On the other hand, there are also methods of path planning for ground vehicles based on environmental information measured by UAVs in advance, rather than by a coordinated system. (Guastella et al. 2017), a Digital Elevation Model (DEM) is created from pre-measured aerial photographs to plan routes according to the performance of the ground vehicles.

Next, the path planning methods for ground vehicles are introduced. Grid-based and sampling-based algorithm methods are commonly used for global path planning for ground vehicles (Thoresen et al. 2021). Grid-based algorithms can find the optimal path as long as a path to the goal exists and optimality is guaranteed. However, path planning can be time-consuming, as the number of search grids increases exponentially with increasing search map size and grid resolution (Yin and Zhang, 2023).

RRT (LaValle, 1998) is a sampling-based algorithm that can compute pathways faster with less memory consumption than grid-based algorithms in large environments. There are many variants of RRTs with improved search efficiency. RRT-Connect (J. J. Kuffner and LaValle, 2000) is one of the RRT variants, which efficiently searches free space by extending the tree alternately from both the start and goal sides. However, sampling-based algorithms, including RRTs, have the problem of reduced search efficiency when narrow areas exist within the search area (Elbanhawi and Simic, 2014).

Several studies have been carried out to solve this problem. LGM-BRRT\* (Shu et al. 2019) uses bridge-test to identify narrow areas in advance and creates local trees in the narrow areas to search narrow areas efficiently. As this method identifies narrow areas by random sampling, it takes time to identify all narrow areas when there are many narrow areas. RRT-NPR (Zhou et al. 2023), the tree is partitioned in a hypersphere domain as it expands, and when the tree expansion in the hypersphere stalls, the sampling density of the narrow area is increased by Gaussian sampling. This increases the number of narrow area samplings and thus facilitates tree expansion. The challenge with this method is that it requires a time lapse to confirm the stagnation of the tree. RRV (Tahirovic and Ferizbegovic et al. 2018), if the tree expansion fails due to an obstacle, the shape of the surrounding passable area is calculated using principal component analysis (PCA) and the tree is expanded in the direction along the obstacle. This allows it to avoid obstacles, such as vines, and facilitates passage through narrow areas. However, the computational cost is high because PCA is performed every time the tree expansion fails.

The RRT proposed in this study identifies narrow areas as a preprocessing step in the search. Narrow areas are determined by a thinning process and PCA, and nodes that guide the tree expansion of the RRT are placed in the narrow areas. When expanding the tree, the search tree is expanded via the guide node to easily pass through the narrow area without additional calculations.

#### 3. PROPOSED METHOD

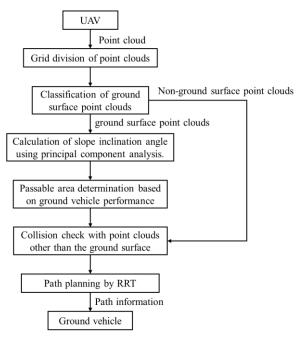
#### 3.1 Estimation of passable areas

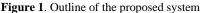
The system measures three-dimensional point clouds of uneven terrain by aerial survey using UAVs and SfM and determines the passage of ground vehicles from the point clouds. The system then plans a travel route based on the traffic decision. An overview of the proposed system is shown in Figure 1.

The first step in determining the passable area is to estimate the slope inclination angle from the point cloud. The point cloud is divided into an x- and y-axis grid of 0.25 m squares, and PCA is performed on the point clouds within the grid. the slope angle of the grid is estimated from the angle between the surface normal vector and the z-axis obtained by PCA. At this time, the grid

contains a mixture of point clouds on the ground surface and point clouds other than the ground surface, such as tree branches. If PCA is performed including point clouds other than the ground surface, the slope inclination angle cannot be calculated correctly. For this reason, the ground surface point cloud is classified as a pre-processing step before the slope inclination angle is estimated. The point cloud classification method is shown in Figure 2. First, a group of points in the grid is projected onto the z-axis. The point with the smallest value on the z-axis is then defined as the ground surface point. If the difference in height is within a pre-defined threshold, the next point is also considered to be a surface point. If the difference in height exceeds the threshold value, all points with a higher zaxis value are considered to be non-ground surface points.

After the slope inclination angle has been estimated, the passable area is determined based on the inclination angle of each grid and the size and hill climbing ability of the ground vehicle. First, the grid to be occupied by the ground vehicle on each grid is determined. If there is a grid within the occupied grid with an inclination angle that exceeds the hill-climbing ability of the ground vehicle, the grid is determined to be an impassable area. The system also determines collisions with point groups other than the ground surface classified earlier, and if there is a collision, it determines the area to be impassable.





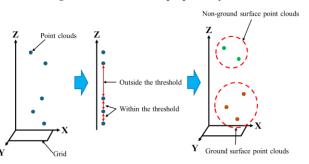


Figure 2. Ground surface point cloud classification process

# 3.2 Path planning using RRT

## 3.2.1 Rapidly-exploring Random Tree

In this method, we propose an improved version of the RRT algorithm. The basic operation of RRT is shown in Figure 3. the search process of RRT is as follows.

1) Define a start point  $Q_{\text{start}}$  and a goal point  $Q_{\text{goal}}$  in the search area.

2) Place the sampling point Qrand at random coordinates within the search area.

3) Find the point Q<sub>near</sub> closest to Q<sub>rand</sub>.

4) Extend the search tree from  $Q_{near}$  to  $Q_{rand}$  by a certain step size and add Qnew to the search tree.

5) The above process is repeated until Qnew and  $Q_{\text{goal}}$  are connected.

After reaching  $Q_{\text{goal}}$ , the path to  $Q_{\text{start}}$  is calculated by traversing the parent nodes.

As mentioned in the Introduction and related studies, RRTs lose their search efficiency when narrow areas exist within the search area. A new RRT method to solve this problem is described next.

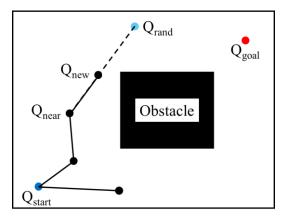


Figure 3. Basic operation of the RRT algorithm

#### **3.2.2** Identification of narrow areas

In the proposed RRT, nodes are placed in the narrow area to guide the search by RRT. Therefore, the narrow area is identified before the search by RRT is carried out.

In the identification of narrow areas, the search area is first converted into a binary image with passable areas in white and impassable areas in black. Next, the centreline of the passable area is obtained from the binary image by means of a thinning process. The point that becomes the centreline is the candidate point for the guide node. On each candidate point, a grid of passable areas unobstructed by obstacles within a certain radius is then obtained by ray casting. PCA is performed based on the coordinates of the acquired surrounding grid, and if the contribution of the first principal component is greater than a predefined threshold, the area is judged to be a narrow area that extends only in a specific direction. The candidate points are then used as guide nodes in the narrow area. If there are no obstacles within the ray casting area, it is clear that the space is wide and open, so PCA is not performed to reduce the computational complexity. This allows a more efficient narrow area decision to be made, focusing on the area around obstacles.

#### 3.2.3 Tree expansion in narrow area

Once the narrow area has been identified, path planning is carried out by RRT using guiding nodes. The proposed RRT performs tree expansion based on uniform sampling, similar to a basic RRT, as long as it searches open areas. However, when the search tree approaches a narrow area, it first performs a connection check between the tree and the guide nodes. If a connection is possible, the guide node is added to the search tree and the algorithm moves on to narrow area search. Narrow area search searches for other guide nodes that exist within a step size from the current node. If guide nodes exist, the search tree is connected to the nearest guide node among them. In addition, once a guide node is connected to the tree, it is deleted so that the connection is not made again. This process is repeated as long as there are guide nodes around. The guide node is the centreline of the passable area obtained by the thinning process, so the tree can pass through the narrow area along the centreline.

## 4. VERIFICATION

#### 4.1 Analysis of areas accessible to ground vehicles

To verify the effectiveness of the proposed method, experiments were conducted in an uneven terrain environment on a university campus. The UAV was flown at an altitude of 75 m, and 240 aerial photographs were acquired. The overhead view of the uneven terrain environment is shown in Figure 4, and the result of the SfM reconstruction is shown in Figure 5. Next, to estimate the passable area from the point cloud, the slope inclination angle was estimated for the point cloud of uneven terrain as a pre-processing step. The visualization of the results is shown in Figure 6. Obstacles such as sheds and slopes are colour-coded, indicating that the slope angle calculations have been carried out correctly.

Next, based on the slope inclination angle estimation results, the passable area for ground vehicles was determined. Figure 7 shows the passable area for ground vehicles when the slope climbing ability is set to  $10^\circ$ ,  $20^\circ$  and  $30^\circ$  respectively. It can be seen that the passable area widens as the passable slope angle increases.



Figure 4. Aerial images of uneven terrain environments.



Figure 5. Point cloud obtained by SfM

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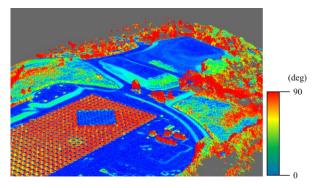
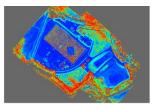


Figure 6. Inclination angle visualisation results.





(a) Inclination angle visualisation.



(d) Passable inclination angle of 30°

(c) Passable inclination angle of 20°
 (d) Passable inclination
 □ : passable area
 ■ : Impassable area

Figure 7. Passable area determination result

## 4.2 Validation of the proposed RRT method

In this section, to verify the effectiveness of RRT, path planning was verified in two different environments: a virtual map with narrow corridors constructed virtually and a map of the real environment analyzed in section 4.1.

The map of the virtual environment is shown in Figure 8, and the map of the real environment is shown in Figure 9. The start and goal positions are shown in the figures. In both environments, there are multiple narrow areas between the initial position and the goal, which are difficult to search for using general RRT.

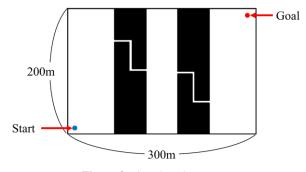


Figure 8. virtual environment.

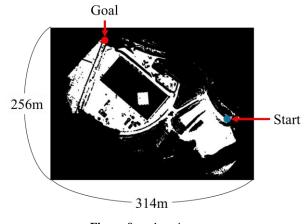


Figure 9. real environment

#### 4.2.1 Finding a Narrow Area

The proposed RRT identifies narrow areas within the search area as a pre-processing step. The results of the narrow area identification process in virtual and real environments are shown in Figure 10 and Figure 11 respectively. The red dots in the diagrams show the areas identified as bridge areas. In both environments, the narrow areas appear to have been calculated correctly. However, in the real environment, areas that are only close to obstacles are also partly identified as narrow areas.

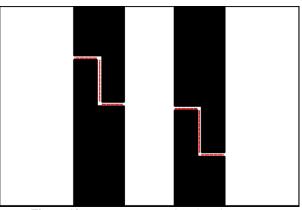


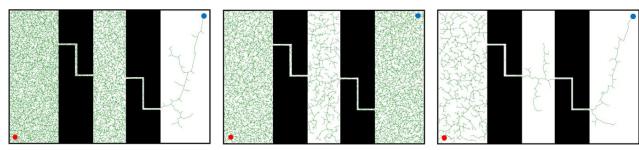
Figure 10. Narrow areas on virtual environments



Figure 11. Narrow areas in the real environment

#### 4.2.2 Comparison of several RRT methods

To verify the performance of the proposed RRT, we compared it with a general RRT and RRT-Connect. 5.0 m was set as the step size for tree expansion, and the number of search nodes



(a) RRT n=15266

(b) RRT-Connect n=13291

Figure 12. RRT trees in virtual environments

(a) RRT n=20000

(b) RRT-Connect n=14608 Figure 13. RRT trees in real environments

(c) Proposed RRT n=4921

(c) Proposed RRT n=1125

was limited to 20,000. The validation was performed on a computer with an Intel Core i7-10750H and 64GB RAM, and the program was implemented in Python3.

Three items were compared: the total number of search nodes required to complete path planning, success rate of route discovery, and execution time. Since RRT is a random algorithm, each method was run 30 times, and the comparison was based on the average of these runs.

First, Table 1 shows the results of the test using a map of the virtual environment. Focusing on the route discovery rate, the proposed RRT discovered routes with a probability of 100%, while both RRT and RRT-Connect had a low success rate of around 65%. Next, we discuss the comparison results of the total number of search nodes. The proposed RRT was able to discover a route with significantly fewer nodes, approximately seven times fewer than RRT and RRT-Connect. The proposed method also takes much less time to execute. Figure 12 shows the search tree at the end of the search for each method in the virtual environment. n shows the number of nodes it took to complete the search. It can be seen that RRT and RRT-Connect perform many tree extensions to traverse narrow areas. On the other hand, the proposed RRT. n passes through the narrow area with a small number of tree extensions.

Next, Table 2 shows the results of a similar test conducted in a real environment. The results show the same trend as in the virtual environment. A comparison of path discovery rates is shown below. The conventional RRT failed to discover a single route, and even with RRT-Connect, the route discovery rate was as low as 50%. On the other hand, the proposed RRT was able to discover a route 100% of the time, just as in the virtual environment. Next, we compare the number of search nodes: the difference between RRT and RRT-Connect and the proposed RRT is not as large as in the virtual environment, and the number of nodes is about 2.3 times smaller. The execution

time was significantly improved as in the virtual environment. In the real environment, the execution time of RRT-Connect was longer than that of the normal RRT. This is due to many failures in the expansion of the tree on the goal side of RRT-Connect, caused by the very narrow traffic area near the goal. Figure 13 shows the search tree at the end of the search for each method in a real environment. It can be seen that in RRT and RRT-Connect, the area delimited by the narrow area at the top of the map is not explored, while in the proposed RRT the search tree extends to the area at the top of the map.

	RRT	RRT-Connect	Proposed RRT
Success rate	0.66	0.63	1.00
Nodes number	16,751	17,166	2,242
Path planning time (sec)	48.80	34.33	5.00

Table 1. Virtual environment results

	RRT	RRT-Connect	Proposed RRT
Success rate	0.00	0.50	1.00
Nodes number	20,000	17,037	7,267
Path planning time (sec)	63.99	87.87	16.11

 Table 2. real environment results

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## 5. CONCLUSION

In this study, a new RRT method is proposed for fast global path planning of ground vehicles in complex environments such as uneven terrain.

The proposed method finds narrow areas that are difficult to search by ordinary RRTs using a thinning process and PCA, and efficiently extends the tree using guide nodes.

The performance of the proposed method is compared with the widely used RRT and RRT-Connect, showing a high path planning success rate. The total number of search nodes and execution time were also improved by at least a factor of two.

These results show that the proposed method can perform fast and efficient path planning even in uneven terrain environments. This makes it possible to apply the proposed method to systems for rapid navigation of ground vehicles in time-sensitive situations, such as disaster response.

On the other hand, some issues were discovered during the validation. In the narrow area identification process, some open areas that were simply close to obstacles were judged as narrow areas. As these areas may be subject to unnecessary search, it is necessary to improve the method for determining narrow areas in future research.

In addition, as mentioned in related research, many studies have been carried out on path planning methods for ground vehicles, and future work is intended to compare these methods and path planning with those carried out by humans.

#### REFERENCES

A. Tahirovic and M. Ferizbegovic, "Rapidly-Exploring Random Vines (RRV) for Motion Planning in Configuration Spaces with Narrow Passages," 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD, Australia, 2018, pp. 7055-7062, doi: 10.1109/ICRA.2018.8460186.

Guastella D., Cantelli L., Melita C. and Muscato G. A Global Path Planning Strategy for a UGV from Aerial Elevation Maps for Disaster Response.

In Proceedings of the 9th International Conference on Agents and Artificial Intelligence (ICAART 2017), pages 335-342 DOI: 10.5220/0006298303350342

H. Yin and L. Zhang, "Path Planning Algorithm Based on RRT-A\* in 3D Terrain," 2023 IEEE International Conference on Mechatronics and Automation (ICMA), Harbin, Heilongjiang, China, 2023, pp. 2315-2319, doi: 10.1109/ICMA57826.2023.10215843.

J. J. Kuffner and S. M. LaValle, "RRT-connect: An efficient approach to single-query path planning," Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065), San Francisco, CA, USA, 2000, pp. 995-1001 vol.2, doi: 10.1109/ROBOT.2000.844730.

Katikaridis, D.; Moysiadis, V.; Tsolakis, N.; Busato, P.; Kateris, D.; Pearson, S.; Sørensen, C.G.; Bochtis, D. UAV-Supported Route Planning for UGVs in Semi-Deterministic Agricultural Environments. Agronomy 2022, 12, 1937. https://doi.org/10.3390/agronomy12081937

LaValle, Steven. "Rapidly-exploring random trees: A new tool for path planning." Research Report 9811 (1998).

Lixing Liu, Xu Wang, Xin Yang, Hongjie Liu, Jianping Li, Pengfei Wang,

Path planning techniques for mobile robots: Review and prospect,

Expert Systems with Applications, Volume 227, 2023, 120254, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2023.120254.

L. Zhou, J. Ding and X. Fan, "An Adaptive RRT Algorithm Based on Narrow Passage Recognition for Assembly Path Planning," 2023 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, Singapore, 2023, pp. 0203-0208, doi: 10.1109/IEEM58616.2023.10406335.

M. Elbanhawi and M. Simic, "Sampling-Based Robot Motion Planning: A Review," in IEEE Access, vol. 2, pp. 56-77, 2014, doi: 10.1109/ACCESS.2014.2302442.

M. K. Vasić et al., "Deep Semantic Image Segmentation for UAV-UGV Cooperative Path Planning: A Car Park Use Case," 2020 International Conference on Software, Telecommunications and Computer Networks (SoftCOM), Split, Croatia, 2020, pp. 1-6, doi: 10.23919/SoftCOM50211.2020.9238313.

M. Thoresen, N. H. Nielsen, K. Mathiassen and K. Y. Pettersen, "Path Planning for UGVs Based on Traversability Hybrid A\*," in IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 1216-1223, April 2021, doi: 10.1109/LRA.2021.3056028.

R. Fedorenko, A. Gabdullin and A. Fedorenko, "Global UGV Path Planning on Point Cloud Maps Created by UAV," 2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE), Singapore, 2018, pp. 253-258, doi: 10.1109/ICITE.2018.8492584.

R. Wang, K. Wang, W. Song and M. Fu, "Aerial-Ground Collaborative Continuous Risk Mapping for Autonomous Driving of Unmanned Ground Vehicle in Off-Road Environments," in IEEE Transactions on Aerospace and Electronic Systems, vol. 59, no. 6, pp. 9026-9041, Dec. 2023, doi: 10.1109/TAES.2023.3312627.

T. Miki, P. Khrapchenkov and K. Hori, "UAV/UGV Autonomous Cooperation: UAV assists UGV to climb a cliff by attaching a tether," 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 2019, pp. 8041-8047, doi: 10.1109/ICRA.2019.8794265.

X. Shu, F. Ni, Z. Zhou, Y. Liu, H. Liu and T. Zou, "Locally Guided Multiple Bi-RRT\* for Fast Path Planning in Narrow Passages," 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), Dali, China, 2019, pp. 2085-2091, doi: 10.1109/ROBIO49542.2019.8961757.