Road Traversability Analysis Using Network Properties of Roadmaps*

Muhammad Mudassir Khan¹, Haider Ali², Karsten Berns³ and Abubakr Muhammad¹

Abstract—Traversability analysis is an important aspect of autonomous navigation in robotics. In this paper, we relate the idea of traversability to safety and ease of road usage by defining a novel sensor-data driven metric called Road Traversability Index (RTI). The RTI translates the geometric interaction of vehicle with road into a distance modulated index that can be used as advice for a human driver or an autonomous agent intending to traverse a particular road segment using a specific vehicle. We present a framework in which 3D sensor data is converted into a road model, which in turn is converted into a roadmap based motion planning graph to represent the underlying configuration space. The RTI is defined as a function of the roadmap by axiomatically satisfying all required properties of road traversability. We have tested our algorithmic framework on simulated scenarios to explore safety; and real-world data sets to discover aspects of traversability for vehicles of various types. Experimental results show that RTI is a practical tool that reveals information that may be hidden to human inspection or other methods of assessment that do not explicitly model a vehicle.

I. INTRODUCTION

To traverse a road, both autonomous vehicles and human drivers need to detect obstacles and find navigable paths in real-time. The driver proceeds with the belief that at least some feasible path will always be available to take the vehicle closer to its destination. If for some unforeseen reason, a road becomes non-traversable, the vehicle gets stuck on the road. To prepare for such situations, a more desirable approach can be to predict beforehand whether the road conditions allow passage for particular types of vehicles. And if so, what is the relative level of confidence in allowing a certain vehicle to go forward? Due to advances in perception and motion planning techniques, such an approach is not only relevant for standard road safety analysis but can also be extended to off-road scenarios, disaster situations and unpaved pathways.

To determine the traversability of a terrain, proprioceptive techniques have been used to analyze the internal state of the vehicle using on board sensors like vibration, IMU, wheel slip, etc. Brooks et al. [3] used vibration analysis to classify terrain into sand, gravel and clay. Leppanen et al. [9] determined the quality of terrain, while driving with a mobile robot. Problem with proprioceptive techniques is that the vehicle has to traverse a terrain in order to measure its traversability which is sometimes not possible. To avoid traversing the terrain to find its traversability, exoterceptive techniques use long range sensors like vision, laser, ultrasound etc. to measure traversability of a terrain. [6] and [1] used vision based features to classify terrain into a number of classes like grass, asphalt, gravel, etc. [10], [8] and [11] use LiDAR data for terrain classification into ground, rocks, and vegetation. One can also envision the collection of such data using aerial platforms, by which the issue of traversability of the scout vehicle becomes irrelevant [14].

Once a map has been obtained, determining traversability of the terrain is the next task. Many approaches like [2] use only terrain data to find local traversability. They find features like roughness, slope, discontinuity and hardness of the terrain and try to infer traversability from these features. They do not analyze whether a vehicle of certain size and kinematics can traverse the terrain or not. Other approaches like [14], [12] and [13] uses vehicle model along with terrain data for traversability analysis. They use explicit motion planning techniques to find a feasible path in a given scenario. However, to give answers to questions of road safety or general traversability posed above, one needs to capture exhaustively all possible paths to allow the choice of the driver in enumerating all possible scenarios while negotiating a particular terrain. Moreover, the linear structure of road like pathways requires a moving-window approach in which the notion of a continuous forward movement is captured. This may or may not coincide with typical notions of navigable space in terrain traversability.

Given the 3D geometric properties of a road patch captured by a perception system and those of a particular vehicle, we seek to verify in this paper whether the vehicle can traverse through it in the forward direction. If so, what is the difficulty level of the vehicle’s traversability? We propose a sensor data driven Road Traversability Index (RTI) which assigns a scalar value to each road patch along the length of the road. We deploy a scout vehicle to collect the sensor data on which the index is computed offline. Once the RTI is computed as a function of distance along a particular road segment, it can be shared with a driver or autonomous vehicle to make it aware of the relative difficulties of traversing a particular road. It can provide non-obvious answers to traversability questions. For example, a particular road segment may be traversable by only one type of vehicle and not by another. To appreciate this, consider the scenario depicted in Fig. 1, where an obstacle on the road (e.g. a pit) is so wide that a smaller vehicle may not be able to pass but a larger vehicle may be able to negotiate the obstacle by placing tires on opposite sides of the pit. In a disaster

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*This work has been supported by a LUMS Faculty Initiative Fund (FIF); research visit support provided to H. Ali under the PPQP Scheme of Govt. of Pakistan; and a grant awarded to TUKL and LUMS under a DAAD German-Pakistani exchange program.
scenario, a paved road segment once considered safe for all types of vehicles may now be usable for only certain types. In a developing world situation, a village semi-structured road may have deteriorated to the point that only certain types of vehicles can use it. Answers to such questions cannot be given by qualitative manual inspection of the road only.

The paper is organized as follows. We first define the notion of road traversability and motivate the need for an index in Section II. Next, we present the framework under which we compute this index in Section III. We show axiomatically, how our definition of a Road Traversability Index (RTI) defined on roadmap graphs satisfies the requirements of a good metric for our envisioned applications. In Section IV, we summarize results from application of our framework to various data-sets, both simulated and real. The paper is concluded by a discussion in Section V.

II. MEASURING ROAD TRAVERSABILITY

Traversability is a broadly used term and it is interpreted based on the context and application. Generally, it is defined as the safety of a vehicle traversing a terrain while obeying some constraints. Traversability is also referred by different names depending upon the context in which it is used [12]. In this paper, we define it as a measure of the free space available for a vehicle to traverse from one end of the road segment to the other. This may be captured by the freedom in choosing paths on the road joining start positions in one end to goal positions at the other end.

In order to elaborate on this concept, refer to Fig. 2. The left image shows a single representative path (traced by the center of a vehicle) from one end of the road segment to the other. The center image shows the collective image of all such paths. Now, if obstacles are introduced, the traversability of the vehicle on the road will decrease and will be captured by the narrow passage shown in right image. Note that all paths present in the right image are already present in the obstacle free scenario. Therefore, the presence of obstacles has limited the freedom in choosing the paths joining both ends. However, measuring this freedom is not straightforward. The range of possibilities manifested by vehicle kinematics and its geometric footprint forces us to work in the configuration space rather than the ambient space of the road plane. Moreover, dealing directly with the underlying continuous space makes the problem of path enumeration algorithmically intractable. We therefore take the following approach.

The road model is built by a 3D perception system that digitally captures the ambient space geometry in front of the scout vehicle. From this road model, standard roadmap based sampling techniques are used to get a dense graph theoretic representation of the underlying configuration space. Traversability can now be studied on this roadmap graph to infer the desired properties of the underlying configuration space. In Section III, we formally define a function \( \text{RTI} : G \rightarrow [0, 1] \) which takes the roadmap graph \( G \) extracted from the road model as an input and outputs a real value, with 0 indicating that the road is not traversable by the vehicle, 1 meaning the maximum possible traversability and a value in between meaning relative traversability. Note that such traversability has to be reported for each road segment inspected by the scout and therefore the RTI will be computed as a distance modulated function of each segment analyzed along the length of the road.

It is also important to comment on the current limitations of this approach. Note, that in this geometric model two aspects are still missing. First, there is no inclusion of a road contact model whereby a surface that may look geometrically traversable may not be so due to improper tire grip and...
other factors. This however is a limitation common to all exteroceptive methods. In our case, if such proprioceptive data is available, it can be easily incorporated into labelling the obstacles based on both geometry and surface type. Secondly, only geometric interaction of vehicle with terrain have been modelled in this paper. Traversability of many obstacles depend on vehicle kinematics and dynamics (e.g. at different speeds, weight etc.). Again, the current framework provides the framework whereby configurations can be upgraded to full dynamical states, when computing the roadmaps. We leave such extensions to a future work. In this paper, the focus is on geometric interaction of vehicle and road.

III. METHODOLOGY

The methodology as given in Fig. 3 is used to find the traversability of a road patch. First road 3D data is recorded using any range sensor and it is preprocessed to remove outliers, crop unwanted region and down sample the data to reduce computation time. Terrain surface in the 3D data is find using a terrain model. Using terrain model and vehicle parameters, a number of different vehicle configurations \( Q_i \) are generated on the road surface. Each configuration is assigned a valid flag which is true if the configuration is collision free and false otherwise. A roadmap graph \( G = (V, E) \) is generated using these configurations, where each node \( v_i \in V \) is configuration \( q_i \in Q \) and each edge \( e(v_i, v_j) \in E \) means there is a collision free path from \( v_i \) to \( v_j \). By studying the properties of this roadmap graph, we can find interesting information about the traversability of the road. Below we explain all the steps in details.

A. Data Recording and Preprocessing

3D data of the road surface recorded using any range sensor and converted to point cloud format is used for analysis purpose. We used a quadcopter model with a 3D laser sensor for data recording in simulation. A Velodyne laser scanner mounted on a ground vehicle was used in the publicly available data-set analyzed in Section IV. Some standard pre-filtering of this data (e.g. removal of outliers and dynamic obstacles) has also been done. We omit these details for succinctness.

B. Terrain Model

Since we are interested in assessing the traversability of the road, the first task is to extract the road surface from the recorded point cloud. The simplest and widely used approach is to consider the road as a planar surface and then use plane fitting to extract its parameters. RANSAC is used to extract coefficients \((a, b, c, d)\) in plane parametric equation \(a \cdot x + b \cdot y + c \cdot z + d = 0\).

Obstacles: Our traversability is based on the assumption of non-traversable static obstacles. Both negative obstacles (ditches and potholes) and positive obstacles (speed breakers, traffic signals, walls, footpaths etc.) are assumed to be present on the road.

C. Vehicle Model

A subset of geometry based approaches uses vehicle model in order to find its traversability. Vehicle model consist of a number of parameters that describe the shape and physical properties of the vehicle. The parameters of the vehicle are used to generate vehicle model and the model is used to find the interaction of the vehicle with terrain. The parameters of the vehicle used for traversability analysis are given in Table I. Holonomic and non-holonomics constraints are used while generating roadmap graph.

D. Configuration Space (C-Space)

The configuration space of our vehicle is \( Q = \{(x, y, \theta)\} \), where \((x, y)\) is the vehicle center on the road and \(\theta\) is vehicle’s yaw angle with the road also called its orientation. Given a vehicle configuration \( q \in Q \), one can check whether it collide with any obstacle or not. If any of the tires of the vehicle or the vehicle body itself collides with any obstacle, then the configuration \( q \) is considered as invalid, otherwise its a valid configuration

E. Collision Checking

Collision checking in direct pointclouds is an expensive task as hundreds of thousands points have to be checked for collision detection for each configuration of the vehicle. An alternative solution is to use Digital Elevation Maps which convert the space into discrete grid cells. The problem with

<table>
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<th>Parameters</th>
<th>Vehicle 1</th>
<th>Vehicle 2</th>
<th>Vehicle 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Width of the vehicle</td>
<td>0.67</td>
<td>1.58</td>
<td>2.3</td>
</tr>
<tr>
<td>Length of the vehicle</td>
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<td>3.3</td>
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<td>Wheelbase: distance between front and rear axle</td>
<td>0.544</td>
<td>1.78</td>
<td>3.25</td>
</tr>
<tr>
<td>Track: distance between center of rear tires</td>
<td>0.545</td>
<td>1.3</td>
<td>1.86</td>
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<td>Ground Clearance of Vehicle</td>
<td>0.13</td>
<td>0.25</td>
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<td>Width of wheels of the vehicle</td>
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<td>0.24</td>
<td>0.3</td>
</tr>
<tr>
<td>Holonomic</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

Fig. 3: Framework for road traversability analysis.

Fig. 4: Various vehicles used for traversability analysis.
standard DEM is that it only store one value for each cell i.e. the height of terrain at that point, which is not sufficient for cases where there could be over hanging obstacles like bridges, trees etc. To overcome this limitation, an enhanced version of the DEM is used for collision checking that stores multiple level of obstacle heights for each cell. For collision checking all DEM cells under vehicle are retrieved and processed for collision checking. Tires are checked for collision with negative obstacles while vehicle body is used for collision with positive obstacles.

\[ q \text{ is no obstacle on the road. The minimum value occurs} \]
\[ \text{between} \ G \text{maps roadmap} \]
\[ \text{that captures the high dimensional CSpaces. We generate a} \]
\[ \text{PRM graph} \ G = (V, E) \text{with uniform distribution where} \]
\[ V \text{is a set of configurations chosen from} \ Q. E \text{is a set} \]
\[ \text{of edges connecting configurations} \ q \in Q \text{such that} \]
\[ q_i \text{is directly reachable from} \ q_j \text{and there is no intermediate} \]
\[ \text{invalid configuration between them, then there exists an edge} \]
\[ e_{ij} \in E \text{connecting} \ q_i \text{to} \ q_j. \text{An invalid configuration can not} \]
\[ \text{have an edge to any other configuration. Adjacency matrix} \]
\[ A \text{stores information of roadmap graph} \ G. \text{Each element} \]
\[ A_{ij} = 1 \text{if} \ q_j \text{is reachable from} \ q_i \text{and all sub-sampled} \]
\[ \text{configurations are also valid;} \text{and zero otherwise.} \]

\[ \text{G. RTI (Road Traversability Index)} \]

As the dimensions of CSpace grows, explicit representation of \( Q \) becomes expensive. PRM [4] constructs a roadmap which is represented by an undirected graph \( G = (V, E) \) that captures the high dimensional CSpaces. We generate a PRM graph \( G = (V, E) \) with uniform distribution where \( V \) is a set of configurations chosen from \( Q \). \( E \) is a set of edges connecting configurations \( q \in Q \) such that if \( q_i \) is directly reachable from \( q_j \) and there is no intermediate invalid configuration between them, then there exists an edge \( e_{ij} \in E \) connecting \( q_i \) to \( q_j \). An invalid configuration can not have an edge to any other configuration. Adjacency matrix \( A \) stores information of roadmap graph \( G \). Each element \( A_{ij} = 1 \) if \( q_j \) is reachable from \( q_i \) and all sub-sampled configurations are also valid; and zero otherwise.

\[ \text{RTI (Road Traversability Index)} \]

Using graph concepts RTI can be defined as the number of unique paths\(^1\) on the road from start nodes to goal nodes. In order to map the traversability of the road for given roadmap graph \( G = (V, E) \), we have defined RTI (Road Traversability Index) \( \Gamma : G \to [0, 1] \). The function maps roadmap \( G \) of the vehicle on the road to a real value between 0 and 1. The maximum value is obtained when the vehicle has perfect traversability on the road i.e. there is no obstacle on the road. The minimum value occurs when the road is non-traversable by the vehicle. A value in between shows the relative traversability of the road as compared to the above scenarios. To calculate RTI from roadmap graph \( G = (V, E) \) for each road patch, we split the vertices \( V \in G = (V, E) \) into start \( S \), intermediate \( I \) and goal \( F \) configurations such that \( V = S \cup I \cup F \) as shown in a toy example Fig. 5. We find all the connected components \( \{G_i\} \) where \( G_i \subset G = (V, E) \) and \( \bigcup_i G_i = G \). A connected component of a graph is subset of \( G \) such that all nodes are reachable from one another. We then calculate Maxflow/MinCut (minimum number of vertices whose removal will disconnect start and goal configurations) for each connected component to find \( \Gamma \). We require \( \Gamma \) to have following properties.

1) \( \Gamma(G) \geq 0 \) for all \( G \).
2) \( \Gamma(G) = 0 \), if no path exist between start configurations \( S \) and goal configurations \( F \). Hence the vehicle can not traverse from any start configuration to any goal configuration.
3) \( \Gamma(G) = 1 \), if all start configurations \( S \), intermediate configurations \( I \) and goal configurations \( F \) are in a single connected component of \( G \).
4) A connected component \( G_i = (V_i, E_i) \) with no start configurations \( S \) or no goal configurations \( F \) does not contribute to \( \Gamma(G) \).
5) RTI of a roadmap \( G \) is the sum of RTI of all its connected components \( G_i \).
6) \( \Gamma(G_i) \propto \mu(G_i) \) where \( \mu(G_i) \) is the Maxflow/MinCut from start configurations to the goal configurations in the connected component \( G_i \). \( \mu(G_i) \) can also be defined as the number of unique paths from start to goal configurations on the road. From graph theoretic perspective, it is the minimum number of vertices that need to be removed in order to disconnect start configurations from goal configurations.
7) For two roadmap graphs \( G \) and \( H \), \( \Gamma(G) > \Gamma(H) \), if number of unique paths connecting \( S \) and \( F \) in \( G \) is greater than \( H \) i.e. \( \mu(G) > \mu(H) \).
8) \( \Gamma(G_i) \propto \omega \), where \( \omega \) is the ratio of the width of the current road patch \( w_r \) and nominal road width \( w_N \).

\[ \omega = \min\{\frac{w_r}{w_N}, 1\}. \]

Using the above properties of \( \Gamma \), we derived the following (1) for RTI of a connected component \( \Gamma(G_i) \).

\[ \Gamma(G_i) = \omega \cdot \mathbb{I}(G_i) \cdot \frac{\mu(G_i)}{\mu_N}, \]

\[ \mathbb{I}(G_i) : (G_i, S, F) \to \{0, 1\} \text{ is an indicator function that returns 0} \]
\[ \text{if there is no start or goal configuration in} \ G_i = (V_i, E_i) \text{ or 1 otherwise as given in (2).} \]
\[ \mu_N \text{ is the Maxflow/MinCut of the nominal road with no obstacle} \]
\[ \text{and is used to normalize} \Gamma(G_i). \]

\[ \mathbb{I}(G_i) = \begin{cases} 
0 & \text{if } V_i \cap S = \phi \text{ or } V_i \cap F = \phi, \\
1 & \text{otherwise.} 
\end{cases} \]
Putting everything together, we get:
\[
\Gamma(G) = \frac{\omega}{\mu_N} \sum_i \mathbb{I}(G_i) \mu(G_i),
\]
(3)
where \(\frac{\omega}{\mu_N}\) remains constant for fixed width road.

IV. EXPERIMENTAL RESULTS

To validate our framework we used two different simulated scenarios and a publicly available dataset and tested it with three different vehicles. Fig. 4 shows the vehicle we have used for testing and Table I shows the vehicle parameters.

A. Simulated Scenarios

Using simulation environment V-REP [5], two scenes each depicting a different problem scenario were generated and tested for traversability analysis. The data was recorded using a Quadcopter flying above road surface with a 3D laser sensor. Each frame consist of 38400 points with a width of around 6 meters and length of about 8 meters. Below we explain the traversability analysis of each scenario.

1) Safest Route: The first scenario shown in Fig. 6 is to find the safest route from point A to point B in a road network. There are two routes from point A to B, we call them Route1 (green) and Route2 (blue). Route1 has more obstacles than Route2 and a traditional traversability analysis would term Route2 as safer than Route1. In Fig. 7 we show the RTI of the two routes using three different vehicles from Table I. The RTI graphs suggest that Route1 is more safer than Route2 for all vehicles. A quick look at the scenario would also reveal that there is more space for vehicles to travel on Route1 than on Route2 due to obstacles blocking majority of the road. Hence RTI is a practical tool for finding safer routes in road networks.

Fig. 6: Simulation scenario to find safest route from point A to another point B on a road network with two options.

2) Effect of Negative Obstacles: In the second scenario we simulated the situation discussed in Section I and shown in Fig. 1. The scene is a straight road with two negative obstacles; one in the middle of the road and another at the side of the road. Looking at the RTI of the this scenario in Fig. 8, we can see that Vehicle1 has no problem traversing both obstacles due to its small size but Vehicle2 and Vehicle3 each has problem with the same obstacle being placed at different position of the road. So for the negative obstacle at the center of the road (Frame 7 — 11), Vehicle3 can traverse it by placing its tires on the sides of the obstacles but Vehicle2 can not. For the negative obstacle to the side of the road (Frame 23 — 26), the situation is reversed and now Vehicle2 can traverse the road but Vehicle3 can not.

Fig. 7: RTI of safest route scenario: Route1 (Green) Vs. Route2 (Blue).

Fig. 8: Effect of negative obstacles on traversability.

B. Real World Data

For validating our framework on real world data, we used a publicly available data-set (KITTI) [7], which has been recorded using a Velodyne installed on top of a car. Velodyne records data for all 360 degree around the sensor. We crop a frontal patch of 6 × 8 meter² point cloud and processed it using our framework. The results of the KITTI dataset is shown in Fig. 10, and looking at the results we can infer that there must be obstacles at frame 60, 90 and 120. Fig. 9 shows the corresponding frontal RGB images. We observe the following:

1) In frame 60, there is no road in front of the vehicle. This is where the vehicle takes a tight turn.
2) In frame 90, there is a road block that restricts larger vehicles to pass through but smaller vehicles can traverse with relative ease. When the corresponding roadmap graph was studied, we found that the height of the road barrier was more than the height of (small) Vehicle1, hence it could traverse the road by passing under the obstacle. This explains the higher RTI.
3) In frame 120, vehicle is oriented towards the car parking and no road surface was captured in the cropped point cloud. Hence we see small RTI values for all vehicles.

Notice the utility of the framework. While Frames 60 and 120 should not not have been reported as completely non-traversable (the scout vehicle was actually turning and we
discarded all non-frontal data), the framework was able to flag the road segments where the vehicle faced the most difficulty (tight turns). In Frame 90, we were able to discover unexpected features (such as the traversability of the smaller vehicle under the road barrier). Much of this is not possible in framework that measures road conditions without referring to a particular vehicle. Video includes pointcloud and RGB images along with RTI for each frame.

Fig. 10: RTI of KITTI dataset.

V. DISCUSSION AND CONCLUSIONS

We have established a framework under which road traversability questions can be answered for a given type of vehicle and exact road conditions. We use standard robot motion planning techniques to generate a graphical representation (roadmaps) for the vehicle configuration space. We then use network properties of roadmaps for traversability analysis of a vehicle on a road surface. With vehicle parameters like width, length, height, wheelbase, track and tire width exactly specified, we can analyze road traversability for that vehicle and find how safe it would be for the vehicle to drive on that road. We have used Maxflow/Mincut and connected component analysis to develop a metric which provides acceptable results to find the narrow passages in road. The results of simulated and experiments on acquired real data indicate that our RTI can really predict the traversability of any road surface for any vehicle with given parameters.

An advantage of using RTI is that we can find the traversability of any vehicle using 3D point cloud of any road. With the rise of autonomous vehicles, it is easier than ever to get 3D maps of the roads. Once a 3D map is available, we can perform traversability analysis to get RTI of the road surface and use it for various tasks. As shown, only the number of obstacles or the area obstructed by obstacle is not enough to determine whether it is less safer than the another road with less obstacles. RTI could help us find safest routes for vehicles to travel on. An important aspect of our framework is the use of Configuration Space instead of the more conventional ambient space for traversability analysis. This allows for extension to more complicated scenarios in which higher dimensional state-space based traversability can be explored, where by state we mean the incorporation of vehicle kinematics (e.g. speed) and road surface conditions (e.g. roughness) on top of geometric approach.

REFERENCES


