A comprehensive survey of unmanned ground vehicle terrain traversability for unstructured environments and sensor technology insights

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Review

A comprehensive survey of unmanned ground vehicle terrain traversability for unstructured environments and sensor technology insights

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A B S T R A C T

This article provides a detailed analysis of the assessment of unmanned ground vehicle terrain traversability. The analysis is categorized into terrain classification, terrain mapping, and cost-based traversability, with subcategories of appearance-based, geometry-based, and mixed-based methods. The article also explores the use of machine learning (ML), deep learning (DL) and reinforcement learning (RL) and other based end-to-end methods as crucial components for advanced terrain traversability analysis. The investigation indicates that a mixed approach, incorporating both exteroceptive and proprioceptive sensors, is more effective, optimized, and reliable for traversability analysis. Additionally, the article discusses the vehicle platforms and sensor technologies used in traversability analysis, making it a valuable resource for researchers in the field. Overall, this paper contributes significantly to the current understanding of traversability analysis in unstructured environments and provides insights for future sensor-based research on advanced traversability analysis.

Contents

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1. Introduction

1.1. Preamble

Studies in autonomous vehicles gained momentum in the last couple of decades. This has been further enabled by the advances of Machine Learning techniques, as well as sensor technology development facilitating the data for situational awareness and perception of robotic vehicle platforms. Research within the remit of autonomous vehicles (AV) covers a variety of topics, e.g. ground vehicles, aerial vehicles, sensor suites, novel vehicle platform concepts, Positioning Navigation Timing (PNT), advanced navigation for unmanned ground/aerial vehicles etc.

Autonomous navigation is one of the most common topics found amongst the studies in the literature and is normally grouped under two main terrain categories, i.e. *navigation in structured* and *navigation in unstructured environments*. Many publications exist in the literature on the former category, i.e. structured environment (on-road). Researchers have presented a variety of algorithmic solutions that perform several tasks such as path planning and/or vehicle lateral and longitudinal control. For on-road autonomous vehicles, navigation includes vehicle ego and environmental maps. Path planning and control problems can be addressed via an internal map facilitated by the available sensors. Hence, many well-known algorithms such as SLAM and decision matrix algorithms can be followed.

Furthermore, navigation in unstructured (or demanding) environments, i.e. off-road terrains, poses more challenges and complex tasks to perform compared to on-road scenarios. In fact, terrain uncertainty and terrain variability levels greatly impact the driving (or *going*) ability of the vehicle. Uncertainty in demanding terrains comprises *surface friction*, *a variety of terrain slopes*, *different obstacles*, *uneven terrain levels*, *terrain with various slip characteristics*, and other, that can impact autonomous vehicle navigation considerably. Hence, exploring terrain traversability prior to creating a navigation map for safe and/or optimized going is of particular importance.

Moreover, terrain traversability analysis (TTA) is a challenging task for autonomous vehicles both on Earth and in space applications (e.g.on the Moon or Mars). Recently, many projects have been overwhelmed by space vehicle platforms and their landing (used in space exploration). Namely, six vehicle platforms, Sojourner (1997), Opportunity (2004), Spirit (2004), Curiosity (2012), and Perseverance (2021) managed by NASA and Zhurong (2021) managed by the China National Space Administration, performed various navigation tasks on Mars as of June 2021. For the safe travel of these vehicles, it is necessary that the terrain characteristics and the traversability of the terrain are properly investigated/evaluated.

1.2. Objectives, contribution and structure of the paper

This rigorous and comprehensive survey paper follows an extensive review of terrain traversability analysis methods, in a systematic way, and aims to facilitate the pathway to future research on sensor-based advanced traversability work. The intended research objectives are:

- to give an overview of existing solutions
- to discuss advantages and disadvantages of methods to date (state-of-the-art)
- to critically present current terrain traversability challenges and seeking of solutions.

We rigorously review traversability analysis in unstructured/demanding environments covering: *terrain classification*, *terrain mapping and cost-based traversability* and *hybrid approach*. Each method is split up into three parts that are appearance-based, geometric based and mixed-based for appropriate presentation and comparison of the works. Also, *end-to-end methods* is classified according to the learning algorithms used in the study. End-to-end methods that cover traversability analysis and control steps for navigation. Hence, it is not explicitly classified under TTA. Schematically, this can be seen in Figs. 1 and 2.

We note that some review papers related to traversability analysis and end-to-end methods already exist, i.e. the authors in [102] present a brief review regarding steering angle estimation, and the article [25] provides an extensive survey specifically on deep learning-based steering angle estimation methods. 3D point cloud segmentation has been discussed in [47]. Moreover, terrain traversability analysis methods for planetary robotic platforms are reviewed in [125] and a rigorous survey for unmanned ground vehicles (UGV) is given in [104]. One sees that mainly studies up to 2013 are discussed in these review papers. However, various approaches have emerged since the time the aforementioned reviews (surveys) were published and newer developments are not examined. A very recent review on vehicle traversability in unstructured environments was presented in [45], albeit exposes only a learning-based method and is different to what is addressed in this proposed survey paper.

Another recent survey [14] discusses the significance of terrain traversability analysis in the context of autonomous ground vehicles before providing an overview of the associated methods, sensors, and challenges. The authors discuss cameras, Lidar, and radar, among other sensors that are commonly used for traversability analysis. In addition, they describe various traversability analysis methods, such as feature-based approaches, machine learning-based approaches, and hybrid methods that incorporate multiple methods. In addition, the paper discusses the difficulties associated with traversability analysis, such as coping with complex terrain, addressing uncertainty, and integrating multiple sensors. The authors provide a summary of benchmark datasets that have been created to evaluate traversability analysis algorithms. The main difference of our paper is that it focuses on the traversability analysis and scrutinises studies in the domain from this specific point of view. In addition, we consider different approaches' limitations and potential drawbacks, thus adding a missing part to the puzzle.

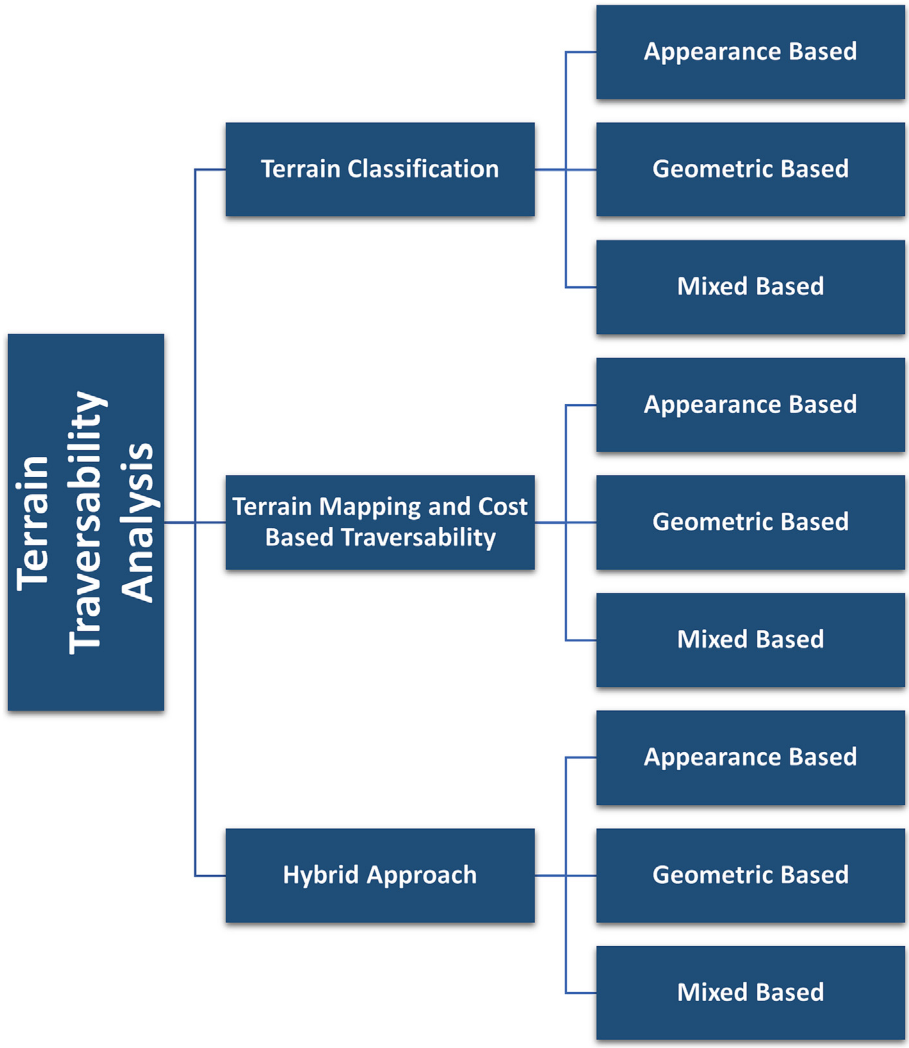

Fig. 1. Proposed Architecture for Categorization of Terrain Traversability Analysis.

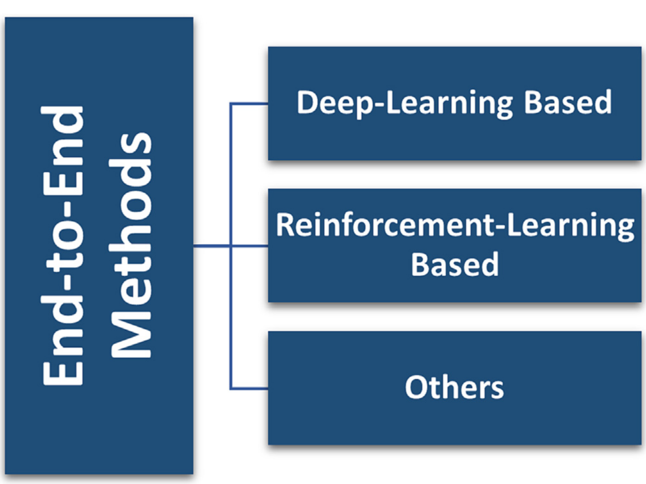

Fig. 2. Proposed Architecture for Categorization of End-to-End Methods.

This survey paper covers, in a rigorous manner, both *learning-based* and *analytic-based* approaches (such as creating cost functions from terrain and vehicle information without any learning approaches) in recent years. These investigated studies are classified under several relevant titles for ease of access by the interested reader in terms of feature types such as geometric-based, appearance-based or hybrid based, and in terms of traversability methods such as classification, mapping or cost-based. In addition, the reviewed studies are examined and tabulated according to a variety of characteristics such as: *the types of methods used in the studies*, *the vehicle platform utilised where applicable*, *the environment* and *the relevant dataset(s)*.

The main contributions of this research review paper are as follows:

- Provide an extensive review of terrain traversability analysis studies (emphasis on recent developments since 2013)
- Provide an analysis of the current studies, their advantages, and disadvantages, identify gaps and provide fresh conclusions for improvement of the methods
- Present rigorous comparison of the main traversability-related methods via comprehensive classification both in discussion and tabular mode
- Investigate sensor types used in studies of terrain traversability analysis according to their practical consideration, i.e. technologies, usability in different weather conditions, size, resolution, maintenance, cost, effectiveness, etc.

- Present a comparison of the types of sensors and vehicle platforms utilised in relevant studies.

An important point of this paper, from a practical listing viewpoint, is a structured listing of available studies according to points such as platforms and sensors used in the studies.

The remainder of this review article is structured as follows. A comprehensive discussion on terrain traversability analysis methods is presented in Section 2. Section 3 presents the vehicle platforms used in traversability studies and a rigorous discussion on sensors/datasets. Section 4 discusses and evaluates the traversability-related methods and approaches in this review paper with particular emphasis on the pros and cons. The paper concludes with Section 5 which also exposes the authors' position towards the future research epochs in traversability studies.

2. Terrain Traversability Analysis (TTA)

Terrain traversability is the analysis of a terrain whereby a vehicle can move and travel safely [104]. To enable useful categorisation for the interested reader, in this paper, terrain traversability methods are classified into four main sections: *terrain classification*, *terrain mapping and cost-based traversability*, *hybrid approaches* and *end-to-end methods*. We also classify traversability analysis methods (other than end-to-end methods) as follows: *appearance-based, geometric-based* and *mixed-based methods*. In this context, mixed-based methods involve integrating the visual and geometric characteristics of terrain or vehicle. In addition, geometric-based methods process Proprioceptive-based algorithms that seek to provide information about the terrain's characteristics and suitability for a particular vehicle or automaton. In the case of end-to-end methods, we opt to study these under *deep learning-based* and *reinforcement learning-based* and *others* ones as can be seen Fig. 1.

2.1. Terrain classification

Autonomous navigation in unstructured (demanding) terrains, i.e. typically off-road terrain types including grass areas, sand, and rocky areas, is more challenging compared to on-road due to the variability and uncertainty of the terrain characteristics. Perceiving and processing data about such an environment for safe driving can be a demanding task. Hence, the classification of such types of terrains is useful to obtain reliable information to enable safer vehicle-going (traversability) tasks. In this context, appearance-based and geometric-based classification methods have been widely used to segment and classify terrain types.

2.1.1. Appearance-based terrain classification

In appearance-based classification, camera (vision) images and/or Lidar feature maps have been used to classify the terrain for on-road and off-road environments. A variety of methods/algorithms have been applied for this task. Below, we present an important set of these methods.

The researchers in [149] have proposed a classification method for on-road and off-road environments whereby RGB images are normalized by using linearization techniques to decrease gamma (γ) correction effects (the latter proposed in [95]). The approach enables image features such as contrast and colour space to be calculated, hence facilitating better terrain classification due to (the claimed) easy processing of image information. Supervised learning and Multi-Layer Perception (MLP) classifier methods have been used to predict terrain classification, while the model provided 93% accuracy rate overall. It is worth mentioning that the off-road environment results obtained were better than the on-road ones, according to the authors this was due to denser information in the on-road environment. .

An off-road detection method based on mechanical traversability, human selection, and far-field capability, was proposed in [87]. A monocular camera was used to identify the traversability together with a road-type inference algorithm classifier. The classifier predicted the road type using the information of road model estimation from the learning algorithm and the information of the candidate-predicted region.

The authors in [17] proposed a Virtual Autonomous Navigation Environment (VANE). In this study, decision tree classification methods were used for material classification and a labelling toolbox for the segmentation of images for the creation of datasets. Both real-environment and simulated data were utilised for testing.

It was mentioned that traversability in off-road type terrains is more challenging than on-road ones given the uncertain features of the former. This is extended by considering obstacle features in off-road terrains. When it comes to obstacles in the terrain, these have been classified by learning methods using semantic segmentation. Still, under appearance-based methods, several studies have addressed this aspect and we list important ones below.

Cinaroglu and Bastanlar [23] used an image retrieval-based visual localization strategy in which database pictures are preserved with GPS coordinates and the location of the returned database image serves as the position estimate of the query image in a city-scale driving scenario. They used the weakly supervised CNN model for localization with triplet ranking loss after picture semantic label extraction. The suggested hybrid technique improved the localization performance of the classic RGB image-based approach by 7.7 percent.

An important study appeared in [154], a significant finding was the generation of a foothold projection on a 2D map using the foothold position of a legged robot, the camera trajectory, and the value of labels using the force torque signal from a 6-axis framework. The data was fused to perform labelling of the data. A large dataset was obtained with this basic labelling progress based on weakly supervised semantic segmentation (for terrain class) and a (so-called) ground reaction score. To increase the size of the dataset, the same data augmentation methods were implemented in both RGB images and labelled images with a footpath used as input for the learning algorithm. The method was validated using an ANYmal quadruped robot [58] in an unstructured environment including terrain types such as asphalt, dirt, sand, and grass, and under different weather and light conditions. However, the method was tested and verified only using a legged robot.

Another study of interest, i.e. [145], proposed a multi-modal semantic segmentation method using the AdapNet++ architecture and the dataset of Cityscapes [24], Synthia [122], SUN RGB-D [136], ScanNet [27], and Freiburg Forest [146] to train their model. In this study, a number of data augmentation methods such as cropping, rotation, and scaling were implemented to increase the size of the dataset. The study outcome was verified using the Forest dataset including various off-road terrain characteristics and the authors concluded that improved results have been achieved in terms of classification accuracy and time compared to alternative methods existing at the time of publication (seen in Fig. 3) [145].

In addition, there are several studies for classification problems, some of which utilised semantic segmentation methods [147,26].

2.1.2. Geometry-based terrain classification

While appearance-based methods in the traversability analysis gain high interest from the research community given the more vision-based nature of the information obtained for the environment, another way of classifying terrains is according to terrain and/or vehicle geometric information such as slope, slip, vibration,

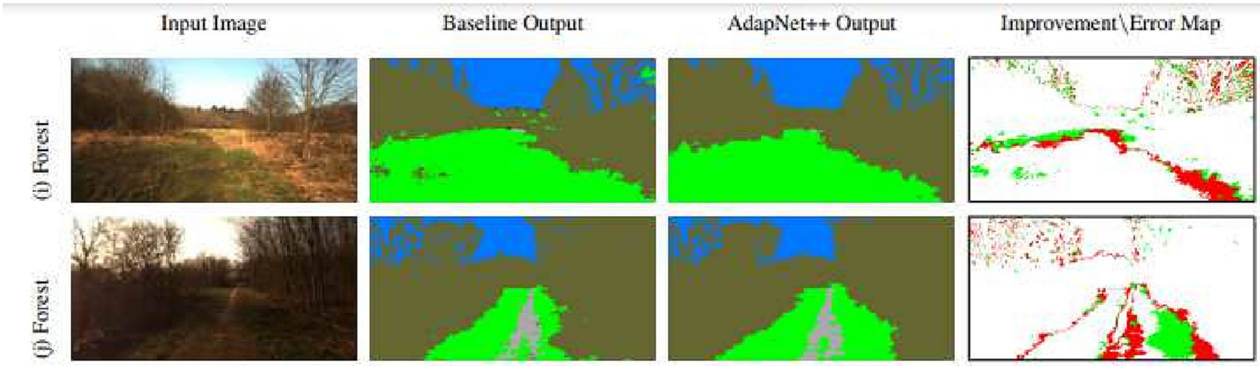

Fig. 3. Semantic Segmentation Results for the Forest Dataset [145].

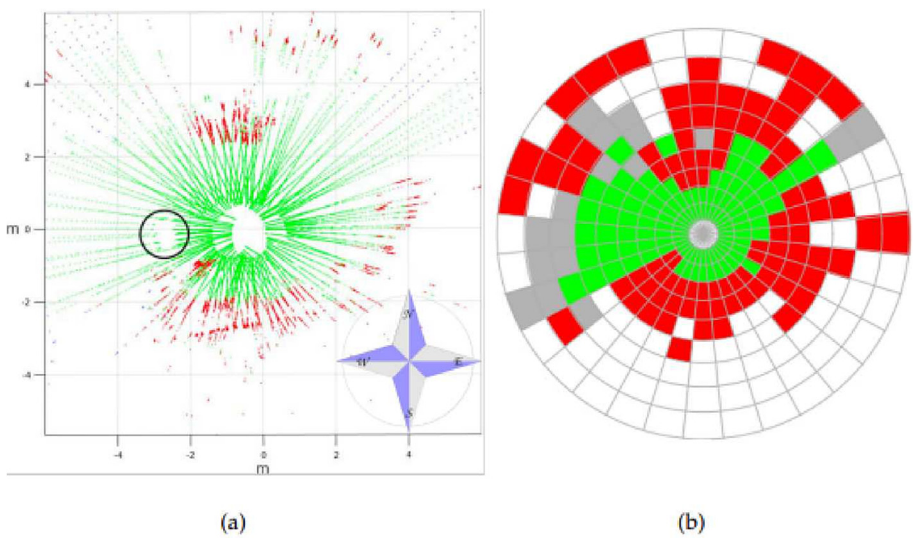

Fig. 4. Top View of 3D Point Cloud (a), Traversability Map (b) [84].

roughness, and terrain friction. An important set of recent papers that appeared in the literature is analyzed below.

In this context, a recent study by Martinez et al. [85] introduced the supervised learning method, which uses labelled data for training quantifying part of terrains such as ground, grass (of height below 5 cm), and the side-walk portion to label it as traversable area via the use of Lidar sensing. Later, the parts of terrain with slope amount greater than 20% have been labelled as untraversable areas. The labelled dataset was obtained to enable the training of the various learning algorithms. The study was performed both in Gazebo simulation and using the real environment with an Andabata vehicle platform having a 3D Lidar sensor. The terrain was classified into just two categories, i.e. traversable and untraversable areas. It is noted that such classification is not sufficient for off-road navigation tasks and major improvements can be looked at such as identifying fast-speed, low-speed or semi-traversable, untraversable areas.

Reina and Galati [114] propose a novel method for estimating the condition of the terrain using a skid-steer vehicle. The authors propose using slip-based estimation methods to estimate the vehicle's slip ratio, which can then be used to compute the terrain conditions, including terrain roughness and traction. The approach is evaluated using data acquired from a skid-steer vehicle equipped with a commercial slip sensor. The results indicate that the proposed approach can accurately estimate slip ratio and terrain conditions across a variety of terrains. Slip-based terrain estimation can provide an effective and low-cost method for terrain assessment in off-road vehicles and can be used in a variety of applications, including precision agriculture, forestry, and mining.

Ugenti et al. [143] present a method for increasing the precision of terrain classification algorithms used by robotics for planetary exploration. The authors propose a method for selecting informative features and signals that can enhance the precision and efficacy of terrain classification. They apply this method to data collected by a Mars rover and demonstrate that it can substantially enhance the accuracy of terrain classification in comparison to conventional methods. The significance of feature and signal selection in enhancing the performance of machine learning algorithms used for terrain classification, which is crucial for the success of planetary exploration missions, is emphasised in this paper. The implications of this study's findings for the development of autonomous navigation systems for future planetary exploration missions are substantial.

The same, main set of, authors in [84] used a 2D terrain traversability map created by calculating traversable scores based on a 3D Lidar, as seen in Fig. 4. The authors presented a study that offered better terrain scan appreciation and more accurate labelling with regarding small objects.

Within the review of recent traversability-related literature, [124] proposed an automatic labelling method as a part of unsupervised learning that learns samples from unlabelled data using 2D maps obtained from the Gazebo environment and converted to a 3D point cloud. Each point is labelled colour-based automatically using Matlab software. The method in the paper classified several objects and terrain types and forms a useful solution for labelling. The study was verified in the Gazebo simulator, but its effects on real traversability assignments were not detailed. Regardless of the simulation-based work, this study is important in terms of the concept they address.

Radar and camera sensing plays a useful role to support determining traversable areas. Work in [116] investigated such an aspect with this set of sensors, in particular, a 3D point cloud was generated a the stereo camera and employed to obtain geometric features for traversability. The 3D point cloud, in this study, was subdivided into $0.4\text{m}\times0.4\text{m}$ parts, and geometric features of each part were calculated according to a function that integrated the terrain slope and "fit goodness", calculated as the mean-squared deviation of the points, height difference and main height of the point data range. Based on the scoring via this approach, the terrain was labelled as "ground" and "not-ground". Moreover, obstacles were labelled using radar as well, and this labelled data has been combined with the sub-cloud generated by the 3D point cloud to obtain the features of the terrain. Hence, two methods, i.e. stereo data only, and combined stereo and radar data, were proposed and validated in an off-road environment. Both methods provided efficient results from the evidence included, however, the exact results and comparison of the two methods were not detailed in the work.

Kaleci, Turgut and Dutagaci [68] used 2D laser data to classify mobile robot positions as rooms, corridors, and doorways. 2DLaserNet uses the ordered connection between consecutive points in the point cloud from 2D laser readings, unlike point-based deep learning methods, and was able to learn laser scan geometry for room, corridor, and doorway classes. They tested the suggested technique using the publicly accessible Freiburg 79 dataset.

A self-learning classification method has been studied to analyse the terrain without manual labelling by [117]. The geometric properties of the terrain i.e. terrain slope, the goodness of fit, height difference and mean height of point range data were obtained from the point clouds generated via Lidar and stereo cameras. According to these geometric features, a self-learning algorithm was applied to identify traversable and untraversable areas. The data was labelled automatically, and the classification method was updated with the next scanned data. The stereo-based classification and Lidar-based classification were implemented independently and then fused. The methods based on the stereo, Lidar, and combined stereo-Lidar were validated utilising real environment information. The authors demonstrated that the mixed method performed best, i.e. obtaining a 96.5%prediction accuracy compared to the stereo-only and the Lidar-only approach (their accuracies amounted to $95.1\%, 95.5\%$, respectively).

From an inertial-measurement traversability analysis viewpoint, an IMU sensor was utilised to provide vehicle acceleration data for terrain traversability analysis in the paper [98]. The authors utilised the Pioneer P3-AT platform for the data collection on a variety of terrain types. The terrain dataset was labelled according to vibration information. The fairly simple approach presented in the work achieved an average of 80% accuracy. In the case of features such as road curb detection, the authors in [46] used an approach based on ground segmentation. In the solution, a 3D Lidar was used to detect the curbs such as road-sidewalk, island, and parking entry. It is highlighted that this work referred to an on-road environment rather than an off-road one (however we believe the information on identifying road curb features is important for informing the interested reader of the traversability topic).

2.1.3. Mixed-based (combined appearance-/geometric-) terrain classification

Without a doubt fusion of information, approaches have attracted the interest of many researchers in many different application domains, i.e. image processing, computer vision, condition monitoring, control, etc. [48]. This is true in traversability analysis as well, fusing both geometric- and appearance-based classification methods to improve terrain classification reliability.

In the paper of Kurup et al., [74], pitch angle, roll angle, and accelerations that present terrain roughness have been calculated and transferred to the feature vector with the corresponding terrain type. The images from the visual sensor have been labelled manually using classification score-based algorithms of k-means clustering. These images and labelling data have been used as inputs for the traditional machine learning algorithm to predict terrain types with supervised learning and physical features with unsupervised learning. Then, new data obtained from the environment has been used to update the classification method for adapting to new terrains and enabling online learning. The study has been performed in various terrain types and weather conditions using a Clearpath Husky UGV and the authors presented a method that offered sufficiently high accuracy for the classification of terrains. According to their results, the prediction accuracy of terrain classification and properties of terrain are 92% and 76%, respectively.

Another supervised learning-based terrain classification approach has been studied by the authors in [161]. Here, a Microsoft Kinect V2 visual sensor able to supply infrared (IR), colour and depth stream features was used to predict terrain types categorised into five groups, i.e. gravel, sand, pavement, grass and litterfall & straw. After manual labelling and pre-processing, IR, colour and depth features were combined for the terrain recognition model with a Support Vector Machine (SVM) classifier. Also, transformation algorithms have been implemented to RGB images and IR features such as converting RGB images to Lab colour space features and texture description methodology. The proposed method has been verified and tested in a real environment. The authors note that the depth features of the terrain did not improve the prediction accuracy of terrain classification. The IR and colour features have been used in the main model, and just this model was tested using a Pioneer 3-AT vehicle platform. The IR-only-based model had 92.57% accuracy, while the combination of IR and colour-based model offered a mere 95.4% accuracy result.

Reina, Milella, and Galati [115] present a new approach for evaluating terrain for precision agriculture based on vehicle dynamic modelling. The authors suggest using a simulation model of a vehicle traversing a field to estimate the vehicle's vertical acceleration, which can then be used to compute the terrain roughness index (TRI) and the root mean square slope (RMSS). These terrain indices can be utilised to identify regions of a field that may require additional care or management, such as soil compaction, irrigation, or fertiliser application. The authors demonstrate that their method can reliably estimate TRI and RMSS using field data collected from a commercial tractor equipped with a triaxial accelerometer. The paper concludes that vehicle dynamic modelling can provide a cost-effective and efficient method for terrain evaluation in precision agriculture applications.

The authors in [11] have suggested a method for recognizing terrain traversability and understanding terrain conditions from a 3D point cloud generated with two 2D cameras. The authors address a space description-based problem. The authors present the importance of covariance features, geometric-based features and appearance-based. RGB intensity and hue that describe dark and light features of colour have been calculated as appearance-based features. The authors highlight the importance of using Artificial Intelligence approaches for the analysis, and in fact, they use

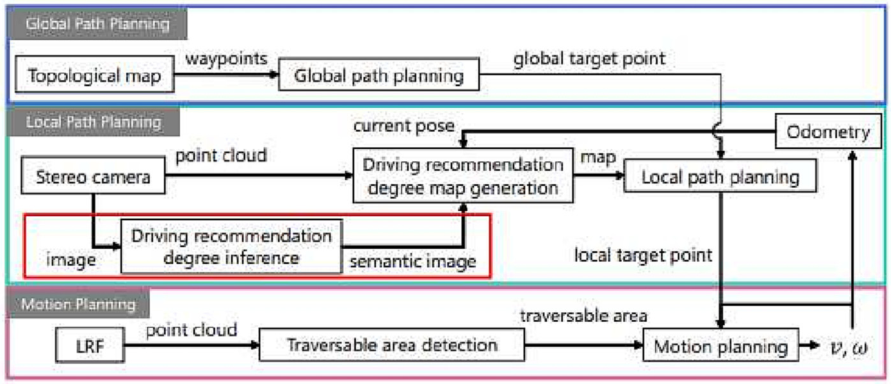

Fig. 5. Onozuka et al. Framework on Weakly Supervised Learning Traversability [101].

the (SVM) algorithm to detect the traversability of terrain. While their method provides useful results, it has been proposed for an on-road environment.

Vulpi et al. [151] investigate the use of deep neural networks, specifically recurrent and convolutional neural networks, for autonomous robot terrain classification. Using these neural networks, the authors propose a method for classifying terrain based on features extracted from terrain height maps. They demonstrate that the proposed approach obtains high classification accuracy by applying it to a dataset of terrain height maps acquired from a real-world rover mission. The conclusion of the paper is that recurrent and convolutional neural networks can provide an effective method for autonomous robotics to classify deep terrain, thereby enabling enhanced autonomous navigation and exploration in challenging environments.

Milella et al. [91] propose a new method for segmenting the visual ground using radar data in order to enhance the precision of ground detection. The authors propose using a radar sensor to measure the distance between the rover and the surface and to distinguish the surface from other objects based on the radar data. The proposed method is evaluated using data collected by a Mars rover, and the results demonstrate that it can accurately partition the ground from other objects and enhance the accuracy of ground detection in comparison to conventional methods. Using radar data for visual ground segmentation can provide an effective method for terrain assessment by autonomous robotics, which is crucial for the success of planetary exploration missions, according to the paper's conclusion.

More recently, [141] proposed a segmentation method that is using automatic labelling. Lidar sensing was used for generating a global map, and a camera for segmentation. The vehicle is used for multiple operations for collecting data for labelling. The proposed model was tested on a few different datasets. A large number of labelled datasets can be created via this approach, but automatic labelling can be difficult in rough terrain.

Also, IMU-obtained vibration data can be utilised for the classification of terrain. A study in [75], proposed a traversability score based on translational accelerations of min, norm, autocorrelation, variance, RMS, mean and max, and R, G, B image channels. SVM algorithms were used to classify the terrain (SVM being a supervised learning method used for classification and regression with a decision boundary line for class separation). The overall method has shown an 87% accuracy using just camera data and 90% using both camera and IMU data. This is an example that geometric feature information provides partial improvements in traversability analysis (and can be considered in cases of need for more precise traversability investigation).

Weakly supervised learning techniques have been studied by several researchers. In particular, Onozuka et al. in [101] have proposed a traversability method based on the aforementioned technique. In this paper, three steps were involved global path planning, local path planning, and motion planning, the schematic diagram is seen in Fig. 5. The first step, i.e. global path planning, is based on a topological map that has provided concise information about the environment. A driving recommendation degree system has been used for local path planning as the second step of the system. The method has included two-step that is the offline training step with labelled images and the online semantic segmentation step. In this way, the path planning has been updated and the accuracy of prediction has been increased. The last step of the overall system is motion planning which has determined the combination of all systems to predict the navigation parameters such as velocity and steering angle. In the study, the automatic labelling system has been proposed using human-driven knowledge. The labelling progress used two progress that is offline training with trained images and online process with semantic segmentation. Also, the data augmentation and the loss weighting method have been used as a part of the learning step and some pre-processing algorithms have been implemented such as cropping. After creating global and local path planning and detecting traversable areas using semantic segmentation, motion planning has been predicted. The study has been verified in the real environment with a vehicle in the structured terrain. The environment has included some roads with no edges, but the study has not been validated in the off-road conditions, and various terrain or weather condition. Although the effectiveness of the method is not demonstrated in off-road conditions, it looks promising for semi-structured terrains and can be further modified and tested for unstructured conditions.

The authors in [10] also proposed a weakly supervised segmentation to predict traversable paths for urban roads under various weather and traffic conditions. The data has been labelled as per the proposed path, unknown area, and obstacle. Lidar was used to detect the 3D location of untraversable objects and stereo visual odometry to predict vehicle motion. This was progressed as part of weakly-supervised segmentation without manual labelling. Then, the labelled data was used to classify the terrain in SegNet deep segmentation learning algorithms [7] as input. A histogram graph has been used to identify the data distribution and balance the dataset with various turning angles. Then, the KITTI [36] and Oxford RobotCar [81] datasets have been used to verify the proposed method. The results show that the method has given acceptable prediction accuracy of the proposed/traversable path. But, the method has not been tested in a real environment with a real car,

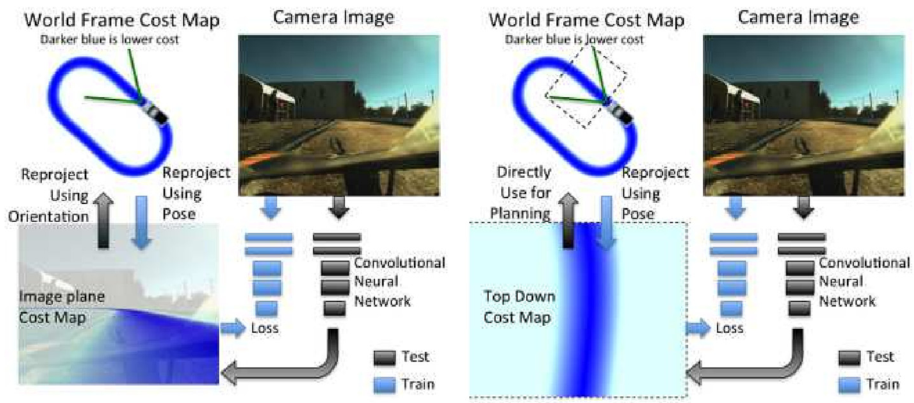

Fig. 6. The Framework of Automatic Labelling and Generating Cost Map [31].

and the proposed classes (path, unknown area, and obstacle) are not sufficient for reliable terrain classification.

Howard and Seraji, [57], have presented a novel terrain classification method that utilised visual sensing providing terrain information of roughness, slope, discontinuity and hardness and fusing these into a Fuzzy traversability metric using a fuzzy logic framework (Artificial Neural Networks). In terms of the process utilised, firstly the horizon line was identified for the terrain and then the tasks of edge identification, obstacle recognition and ground signature extraction were performed to identify target objects. The terrain roughness was determined according to the following features: smooth, bumpy, rocky and rough. The terrain slope was predicted using two cameras, and a learning algorithm, with inputs being x, y pixel coordinates for each camera image. Also, terrain types, sand, gravel and compacted soil, were predicted to determine terrain hardness. Lastly, terrain discontinuity between different terrain features or undefined areas was also identified. Hence, their fuzzy-based solution predicted the traversability of the terrain in terms of four groups, i.e. *passable*, *moderately passable*, *impassable* and *moderately impassable*. In addition, the authors validated the proposed method experimentally.

2.2. Terrain mapping & cost based traversability

Cost function and/or cost map that represents terrain traversability features can be generated from terrain and vehicle information using various sensors such as Lidar, Camera, IMU, GPS and Wheel Odometry. This gave rise to another set of methods for traversability, i.e. so-called terrain mapping and cost-based traversability. To maintain the reader-friendly pattern of the methods, we again present these methods under *appearance-based*, *geometry-based* and *mixed-based* versions below.

2.2.1. Appearance-based terrain mapping & cost based traversability

Although geometry-based or mixed-based methods have been used for creating traversability maps or cost functions, there are some studies solely based on appearance information.

Within this remit, a vision and learning-based model predictive control (MPC) algorithm was studied for real-time scene understanding within a high-speed environment. The camera images were converted to an image-based cost map via a convolutional neural network (CNN) algorithm (Fig. 6), and this cost map was used for MPC to plan vehicle paths directly without any preprocessing. The method has been validated in a real environment using an AutoRally platform [40]. The results have shown that the approach is suitable for high-speed navigation tasks using deep learning (DL) structure, and different traversability maps were created, such as a bird's eye view, that gave the most reliable and accurate results [31].

Older research studies have proved useful in paving the paths to advancing traversability analysis, such as the work in [37] that proposed a method looking at the slope, roughness, smoothed and interpolated height as part of a cost function investigation. The predictions of travelled distance, a slope that is two-dimensional and roughness from three-dimensional data were used in this cost function. Also, error propagation was implemented in their proposed algorithms to predict the accuracy of calculated values. Then a parallel search algorithm was implemented to obtain reliable/safe path planning. The aerial images, images from vehicles, and overhead view data, generated in simulating planetary environments, were used for experimental studies.

2.2.2. Geometry-based terrain mapping & cost based traversability

From a data fusion perspective, the Kalman filter has been a rather robust and popular estimator to use. The trend followed in traversability studies using Kalman Filters for the estimation of terrain characteristics. In particular, work in [105] favoured an extended Kalman filtering method for creating a 2.5-D traversability map. In the study, IMU and internal sensors were used to predict the vehicle state via the Kalman Filter process, and laser range finders for representing the terrain map. Fusing the two, the 2.5-D map, updated simultaneously, presented the mean value and variance of the terrain height (elevation) in each cell. The proposed method which is performed in a real environment shows that the quality of terrain maps and accuracy of height prediction is increased when the vehicle traverses at low to medium speed. Also, the study illustrated using map elevation to enable more accurate traversability mapping.

Another recent study, by Chen et al. [19], proposed a relative probabilistic mapping (RPM) algorithm. The authors In their method divided the environment map into grids, and various features such as different types of grid elevations, their variance and the number of points falling in the grid, were gathered in each grid to avoid the wrong classification. Kalman filtering was used to update the measurement of these features (highest and lowest elevation measurements) and also the Gaussian Mixture algorithm (average elevation measurements). The traversability assessment was performed via an algorithm that takes into account these updated measurements, and the terrain has been classified using three labels: *obstacle*, *traversable patch* and *unknown patch*. The method was verified in an unstructured real environment using a Sport Utility Vehicle (SUV) platform and sensors: Lidar (for the perception of the environment), IMU and GPS for state estimation. The

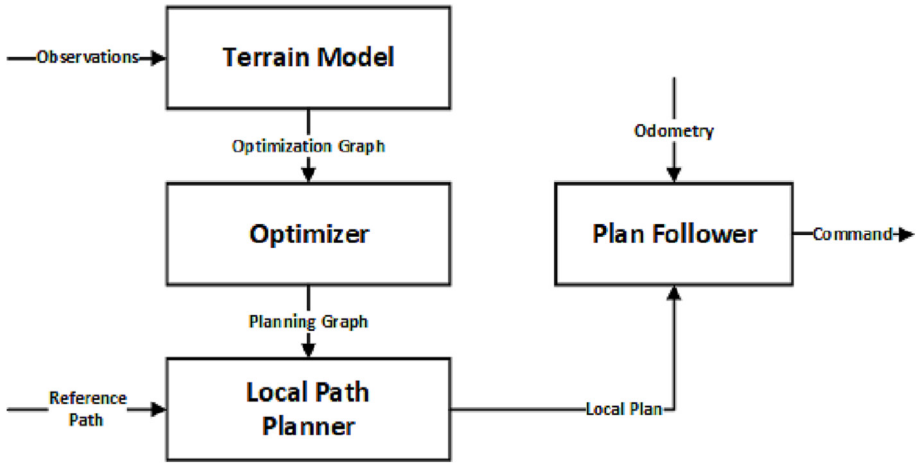

Fig. 7. The Schematic Diagram of the Optimization-based Terrain Modelling and Path Planning in Graf et al.[41].

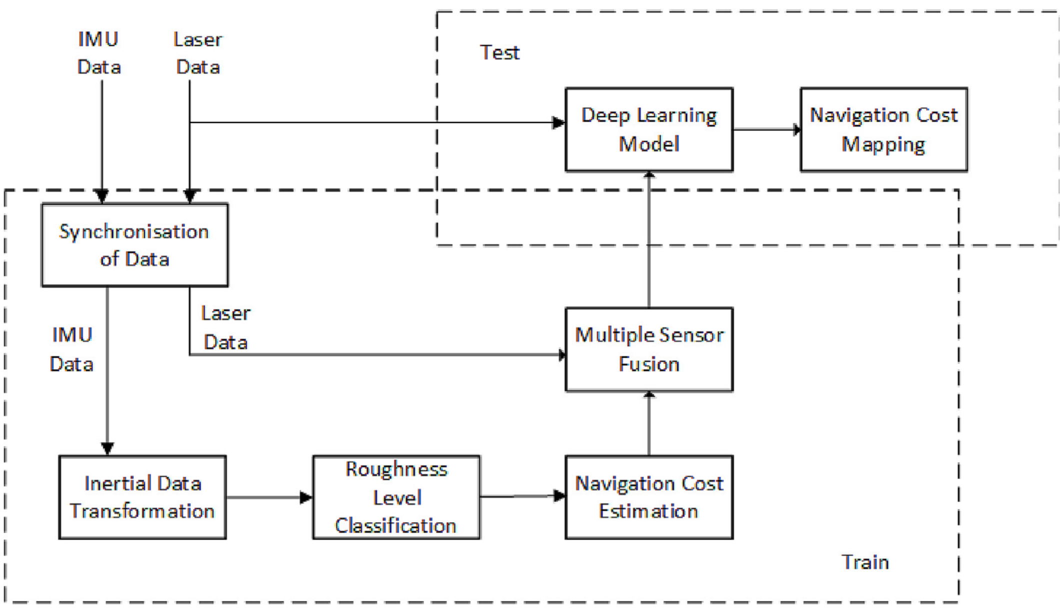

Fig. 8. The Overall Layout of the Three-Dimensional Mapping Method by Oliveira et al. [97].

method is shown to provide a reliable and accurate perception of the environment and effective detection of obstacles.

A further geometric-based method is on vehicle vibration data. An interesting study has been performed by authors in [156]. In this study, the vehicle vibration information was employed for the prediction of vehicle state and a Time-of-Flight (ToF) camera was used to create a 3D point cloud of the terrain. The terrain input was generated via this 3-D Point cloud and used together with a vehicle mathematical model to obtain relevant vehicle parameters, e.g. acceleration. The proposed solution was tested in a real environment which included features of grass, gravel, pavement and root terrain using a high-speed Loc8 UGV platform. The authors concluded that the terrain input affects the estimation result significantly and a better terrain input estimation method should be developed. Also, the study was merely based on the use of vertical acceleration (and not including pitch and roll directions).

Continuing with inertial-based studies (vehicle vibration information), researchers in [169], utilised vehicle pose via a mathematical model of the vehicle suspension system and 3D Point Clouds created by Lidar sensing. Also, terrain roughness and the height (terrain elevation) difference were computed using a point cloud. The traversability score according to vehicle roll, pitch, roughness or height difference of terrain, was computed. The trajectory planning algorithm was implemented based on the aforementioned traversability score. The authors tested their solution in both real and simulated environments. The results show that the accuracy of pose estimation is increased using a vehicle suspension model, and the proposed traversability model is useful for unstructured terrain types. However, their method did not refer to any appearance-based information and hence mixing such information can improve results further.

There are also some optimization-based methods to calculate cost maps or create traversability maps. Authors in [41] have proposed a method that analyses terrain traversability via mapping and optimization pipeline. The terrain model takes environmental observations as input and populates an underlying data structure. The optimizer modifies the model's parameters to discover the optimal fit given the observations. The local path planner tries to discover a path on an optimised terrain model (specifically, a graph representation of the underlying tree) towards a reference path or waypoint provided by a global planner. Their proposed method is summarised in the schematic diagram of Fig. 7. The authors presented a novel graph-based, multi-resolution terrain model suited for real-time optimization. The study was verified in a real structured and unstructured environment.

Another research [155] has proposed a traversability method for the legged robots. In the study, the 2D elevation map has been generated with height and variance information of each grid via a Hokuyo UTM-30LX laser scanner and cameras, and these data have been updated with the new measurements. The traversability map has been generated using the features of the local step height, slope and terrain roughness predictions. Then, the robot footprint traversability features have been implemented in the methodology to improve the effectiveness of the algorithm for the path planning task. Then a path planning algorithm based on the cost functions has been performed. The proposed method has been tested in both simulation and the real environment with the quadruped robot StarlETH. Also, a similar traversability methodology has been used for navigation tasks, obstacle avoidance and path planning in the paper of [61].

In [97], Oliveira et al. proposed a 3D map creation to represent the environment with the C-SLAM approach ([52]) and the C-LOC techniques ([107]) using data from MicroStrain 3DM-CV5-25 IMU and Velodyne VLP-16 Lidar sensors. A navigation cost function was proposed by the authors using roll and pitch orientations (these have been used to obtain terrain slope) and the roughness level as inputs. With the cost function (after post-processing) and Lidar data, the navigation cost was mapped to predict the traversability of terrain. In this way, a 3D augmented terrain map was obtained to navigate the platform in a reliable and safe manner. The detailed framework of the method can be seen in Fig. 8. Also, the method was tested under different real environments using the Pioneer P3-AT and John Deere Gator platforms.

There are also some further studies on this topic followed in the literature i.e. [77,118,62,137]. The two former papers concentrate on LADAR-based terrain classification, while the two latter papers (very recent works in the literature) target aspects of reliability-based terrain mission planning and online learning unmanned tracked vehicle dynamics enabling optimised path planning, respectively.

2.2.3. Mixed-based terrain mapping and cost-based traversability

Behaviour-based methods can be seen in geometric or appearance-based methods for traversability analysis. Such an approach uses cost functions that can include driving behaviour and different scenery. Hence, the nature of this section in this review paper is to cover such approaches.

Authors in [171] proposed a traversability map created via a fully convolutional network (FCN) based method whereby a feature map generated using Lidar has been used as input to the FCN. Also, trajectory planning has been implemented using Inverse Reinforcement Learning (IRL), and different methods under various scenes have been analysed. The results show that the proposed method is a valid solution to be explored by researchers in the field, however, the dataset and terrain used in the study for the testing were limited.

Work in [139] presented an algorithm that utilised height difference, measurements remission, roughness, and slope values to create a traversability map. The dataset was gathered by manually driving two different vehicle platforms and the data was trained a semi-supervised learning method. Positive Naive Bayes (PNB) based and Learning Classifiers from Only Positive and Unlabeled Data (POS) based classifiers were used to predict the traversable area of the terrain. The study has been verified on both on-road and off-road environments, the latter including forest and grass terrain. The results have shown not using slope and roughness values in the traversability map, precision decreased by about 15%, and decreased further by 30% when the remission values were not used. This indicates that a better traversability model can be created by using a variety of vehicle and terrain features.

In [106], a method that is suitable for extreme environments such as rough and steep terrain and for a tethered rover has been investigated taking into account terrain-tether interaction, the rover stability and reachability. Also, reliable paths have been predicted with the combination of the values of yaw, roll, and path length. The traversability method has been developed with some logic checks such as whether there is a collision or not and after checking, the sample has been included on the map. Rover settling, that is the value of the difference between the surface point cloud and rover, and stability analysis has been determined to set the traversability analysis method. The study has been tested in both simulation and planetary analogue environments and the proposed method has achieved success according to these results.

Fig. 9 illustrates the approach proposed by the authors in [103] for mapping the unstructured environment. The local geometric map has been generated with local trajectory estimation from a SLAM algorithm and an environment model from a range sensor. The environment point model scanned by the range sensor was converted to global points. Then, a traversability assessment was performed using terrain slope and roughness for each grid. Also, a ray tracing algorithm has been performed to detect obstacles. Furthermore, this map has been transferred to another block for creating a global dense map, as seen in Fig. 9 that illustrates building global and local dense maps. The methodology referred to as

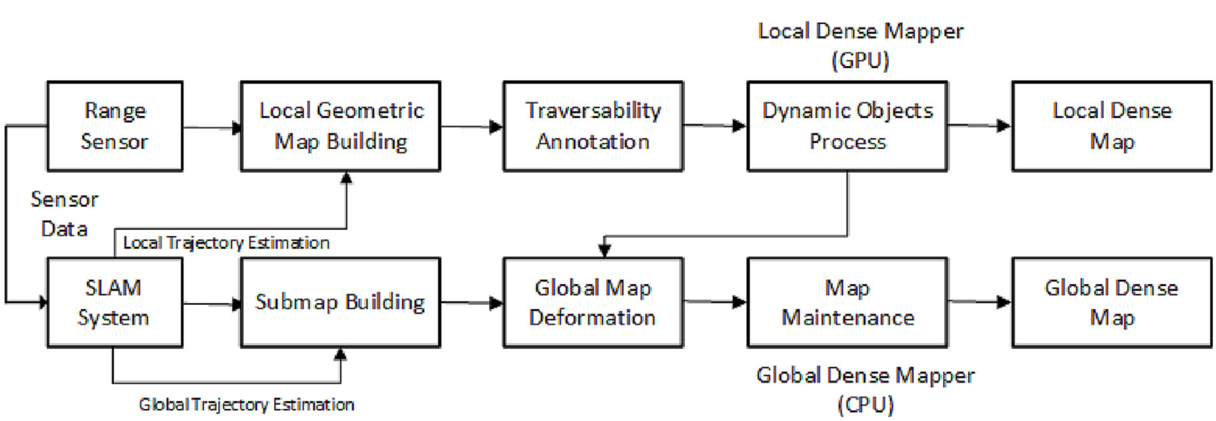

Fig. 9. Overview of the Proposed GEM Algorithm [103].

GEM has been implemented and tested in a simulation environment as well real environment for all systems.

The authors in [157] have investigated a behaviour-based navigation method whereby a 2.5D elevation grid map has been generated using height information from the terrain. Also, gap and height filters have been implemented to detect negative obstacles such as holes, and consider overhanging points, respectively. The features of contact points of the wheels and Euler spiral have been considered in the trajectory generation algorithm. Also, some limitations such as roll-over and collision have been taken into account in the method. The proposed approach has been verified in the simulation environment with a Finroc robot control framework [113] and V-Rep simulator [35] using Unimog U5023 virtual vehicle platform and in the real environment with a GatorX855D robot.

The paper [144] describes a method for learning and predicting the interaction between a vehicle and terrain using 3D vision data. Using a neural network, the proposed method discovers the relationship between the 3D visual features of the terrain and the resulting vehicle dynamics. Experiments on a dataset of vehicle-terrain interactions demonstrate the effectiveness of the authors' approach. Overall, the paper contributes to the development of intelligent systems for autonomous vehicles that can precisely perceive and react to various terrain types.

Lacaze, Mottern, and Brilhart [76] provide an overview of the difficulties and opportunities associated with developing autonomous mobility systems for off-road environments. The authors emphasise the unique characteristics of off-road environments, such as variable terrain, limited infrastructure, and unpredictability of obstacles, which present significant obstacles for autonomous vehicles. Advanced sensor systems, machine learning algorithms, and robust control systems are just a few of the approaches and technologies discussed in the paper that can be used to surmount these obstacles. In addition, the authors provide examples of ongoing research efforts and applications of autonomous off-road mobility, including agricultural automation, mining operations, and military logistics. Overall, the paper explores the potential benefits of off-road autonomous mobility and emphasises the need for sustained research and development in this area to address the unique challenges of off-road environments.

2.3. Hybrid approach

There are several papers and research that combine terrain classification and terrain mapping and cost-based traversability methods. These studies are gathered and discussed in this section. However, there are limited studies presenting an appearance-based hybrid approach, this seems to be due to these methods not being so reliable and safe to use for creating a cost map and method of terrain classification (that is, just from appearance information). Hence, in this review paper, the hybrid approaches are mainly discussed in the following sub-sections, i.e. geometry-based and mixed-based hybrid approaches.

2.3.1. Geometry-based hybrid approach

A classification method with an elevation grid map created with height features of terrain such as maximum, minimum, mean heights and height difference (min–max difference) from the transformed point-cloud data proposed in [88] can be classified as a geometry-based hybrid method. Then, the terrain has been classified using features of height, roughness and slope angle. The classified type of terrain has been determined according to these terrain features with a comparison approach. The study has been conducted using a 3D Lidar and concluded that the method was reliable for classifying the aforementioned terrain type. A more recent study in [142] demonstrated a navigation method for developing a point cloud-based traversability model for challenging environments. The multi-fidelity mapping has been generated with depth measurement from Lidar and poses estimation from different sensors. Traversability assessment has been predicted with this map, and the point cloud was segmented into two classes, i.e. ground and obstacle. Also, the platform was included with this point cloud map according to pose estimation. Then, the traversability matrix was calculated from the settled pose, the point cloud of the surface and its interaction. Furthermore, the cost maps were generated from this point cloud traversability map for planning algorithms. The proposed method has been tested on four different platforms, that is Clearpath Husky A200 (skid-steer platform), Telemax Pro (tracked vehicle), X-Maxx (Ackermann suspension) and Spot (Quadruped robot). Although the model is providing useful outcomes in general, it has not provided reliable results for detecting small, narrow and negative (such as holes) obstacles and some unexpected hazards such as puddle areas or mud. The architecture of the proposed method can be seen in Fig. 10.

A neural network-based traversability estimation has been proposed by [127]. In the study, roll and pitch features have been generated by the IMU and depth images by a Kinect camera. Then, the features have been extracted from the image dataset with the CNN learning algorithm. These features, roll and pitch angles have been fused with the dense layers to predict the traversability of the environment. The dataset has been obtained via a tracked vehicle in a $60x60$ m^2 simulation environment that was created in the V-REP simulator (Virtual Robotics Experimentation Platform). The proposed method was verified using both structured and unstructured environments. Results provided approximately 92% accuracy rate

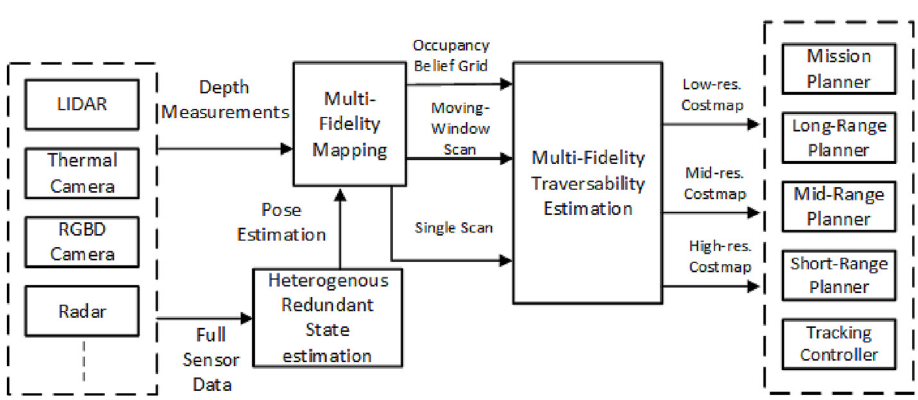

Fig. 10. Overall Layout of Resilient Multi-Fidelity (RMF) Method [142].

for estimating traversable area and 72% accuracy rate for untraversable area prediction.

2.3.2. Mixed hybrid approach

Within the mixed-based hybrid approaches, work in [158] presented a hybrid approach where the terrain has been segmented into portions such as sky, road, vegetation, grass, and obstacles. This enabled the classification of the terrain and estimation of the traversability of the path. In fact, the occupancy map has been used for the traversability assessment. The study has been implemented in a simulation environment named Unreal Engine 4 [34] and in the real environment with a real-size heavy vehicle i.e. Unimog U5023. The validation trials have shown the applicability of the methods. The shortcoming of the study is that the segmented class is not sufficient for off-road terrains.

In a further study, RGB images have been converted to semantic segmentation images based on supervised learning and these images were fused with a point cloud from the Lidar sensor to create the semantic mapping. Then, path planning algorithms have been conducted from this 2.5-D semantic map based on point cloud and segmented images and from traversability cost scores that present semantic classes. For semantic segmentation, DeepScene labelled six classes and Yamaha-CMU dataset [86] labelled eight classes for the training of the segmentation algorithm with the fully convolutional network (FCN) (used to label all pixels of data). Also, the researchers proposed a new learning segmentation algorithm to decrease training speed. It is worth noting that the dataset was labelled, and the geometric- and appearance-based traversability model considered both height difference and terrain class.

Slip prediction is a significant part of terrain traversability and several researchers have studied this topic. For example, work in [5] proposed a slip prediction method based on visual sensors using geometric and appearance information of terrain. The method was twofold, i.e. performing terrain classification and slip prediction. Firstly, all-terrain cells were classified into six parts: soil, asphalt, sand, woodchips, gravel, and grass, with texton-based methods. According to each terrain type, the slip was calculated using the information of terrain geometry from IMU and the 2D map created by the camera. Then a slip error was formed by feeding back the calculated slip and the measured slip from visual odometry and the encoder to predict the slip value. A learning algorithm was implemented to predict slip. Also, the research has shown that the slip value can be calculated just from visual information. This posed some challenges in achieving small errors in the outcomes, mainly due to terrain classification errors. The authors suggested another slip prediction method based on terrain geometry and terrain type for both fixed terrain and general case. After the terrain type has been identified, geometry-based slip prediction algorithms have been used to estimate the slip. Rocky8 and LAGR robots were used to collect datasets and test the proposed method [3].

The same authors extended their study to a learning slip prediction algorithm extracted from terrain slope and appearance information such as texture and colour. The slip value has been predicted with a combination of measured slip value from wheel encoders and visual odometry, the terrain slope obtained from IMU and the 2D cell map. The terrain types were classified into six classes, i.e. soil, gravel, sand, asphalt, grass and woodchips with a k-means algorithm. The learning algorithm was developed to predict slip with just visual information. The study has been tested with Rocky8 and LAGR rovers [4].

Another traversability analysis based on slip prediction was demonstrated in [52]. In the study, the goodness value was calculated with several parameters such as the pitch, roll, terrain roughness and step height for each map cell to create the goodness map. The terrain was classified as definitely traversable, definitely not traversable, and uncertain labelled from this map. Also, the slip value was calculated when the terrain is labelled traversable. For slip estimation, the attitude of the platform and camera image was used to create an environment elevation map, and the longitudinal and lateral slopes were obtained with this map. After classifying the terrain based on texture and colour features, the slip prediction algorithm has been implemented according to terrain class to get a 2D slip cost map. Moreover, this cost map and geometric goodness map have been fused to create a slip-augmented goodness map a path planning algorithm has been applied to this map. Another algorithm named High-Fidelity Traversability Analysis (HFTA) was used when the terrain is labelled "uncertain" from the terrain goodness map.

From a space-related application, authors in [123] proposed a method for MARS rover mission, orbital, and ground-based terrain classification, based on Soil Property and Object Classification (SPOC) that predicts terrain types and features. The study has included two significant steps/missions. The first is the landing site traversability analysis method to categorize the terrain. The method has been applied to 17 terrain types using the semantic segmentation method based on supervised learning. Then, a traversability class has been created with identified terrain classes. Data labelling progress has been completed via web labelling tools manually. Also, some pre-processing algorithms such as normalizing, darkening, and converting images to bird-eye images, cropping, and masking using RANSAC has been used to create a realistic Mars environment. The study has been verified in Columbia Hills that was deemed suitable by the researchers for the landing study of the rover. The method has predicted the terrain types such as smooth regolith, dense ridges, rock field, scarp, and deep sand with 90.2% accuracy overall. But, there was some misclassification especially for small rocks due to issues such as data distribution. The second step is the slip prediction method and the terrain classes predicted in the previous step have been fused with slope and wheel slip. Terrain slope has been predicted from the rover tilt and the slip and rover's position have been calculated with visual odometry. The result shows that the prediction of slip for rocks is acceptable. But, the results are not satisfactory for sand due to some geometric and appearance features such as terrain geometry and sand depth. Of course, this paper presented a more bespoke demanding environment, this of an extraterrestrial planet.

A method of fusing 3D cost maps and terrain classification has been proposed by [120]. Three main steps were followed, i.e. creating a 3D traversability cost map, terrain segmentation/classification and obtaining a segmented traversability map. The traversability map has been generated from the 3D point cloud and the cost score included a combination of terrain slope, cell elevation and obstacle. The cell-based terrain classification is created by a feature vector that included 14 properties of the image such as values of RGB channels and skewness, and entropy. Also, inverse perspective mapping (IPM) and tuned support vector machine algorisms have been used to eliminate the distribution of image views for better classification and try to find the best training parameters, respectively. The accuracy of the method has been calculated according to the combination of traversable and untraversable predictions. The last main step is that the 3D traversability cost map has been converted to a grey-scale image and then to a segmented traversability map. In this study, the cost value in every cell has been associated with the terrain class. Furthermore, the proposed approach has enabled the terrain to be classified successfully, and the method has been updated simultaneously using online learning. But it has classified the terrain using two classes i.e. traversable and untraversable (not in a more continuous form).

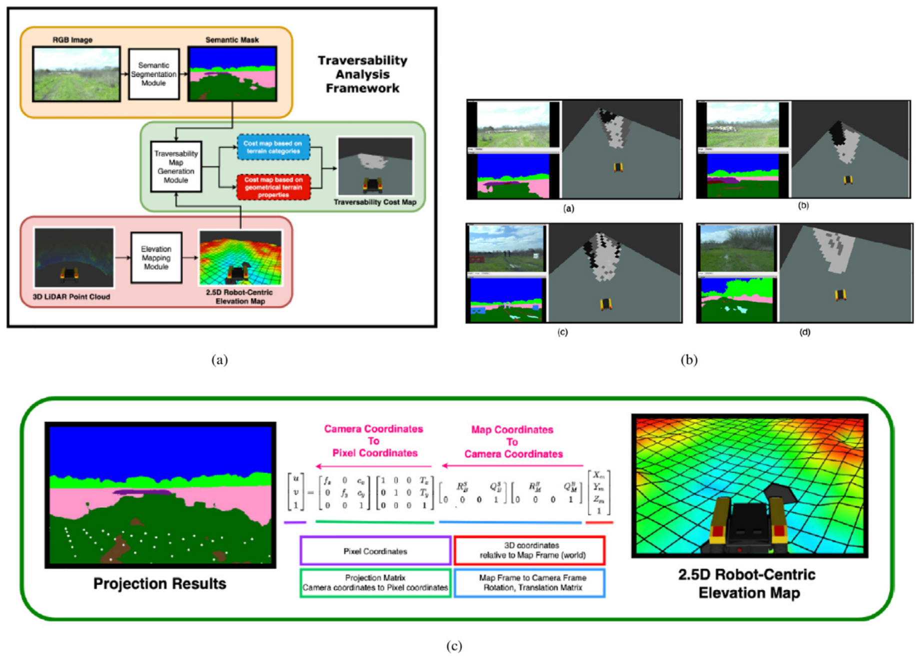

Fig. 11. Figure info: (a) the main framework, (b) Visualization of Traversability Cost Map (in each image the top-left is the main image, bottom-left is the semantic mask, and on the right is the terrain traversability cos map. Darker colour shade represents the less traversable area, (c) the Projection Process [79].

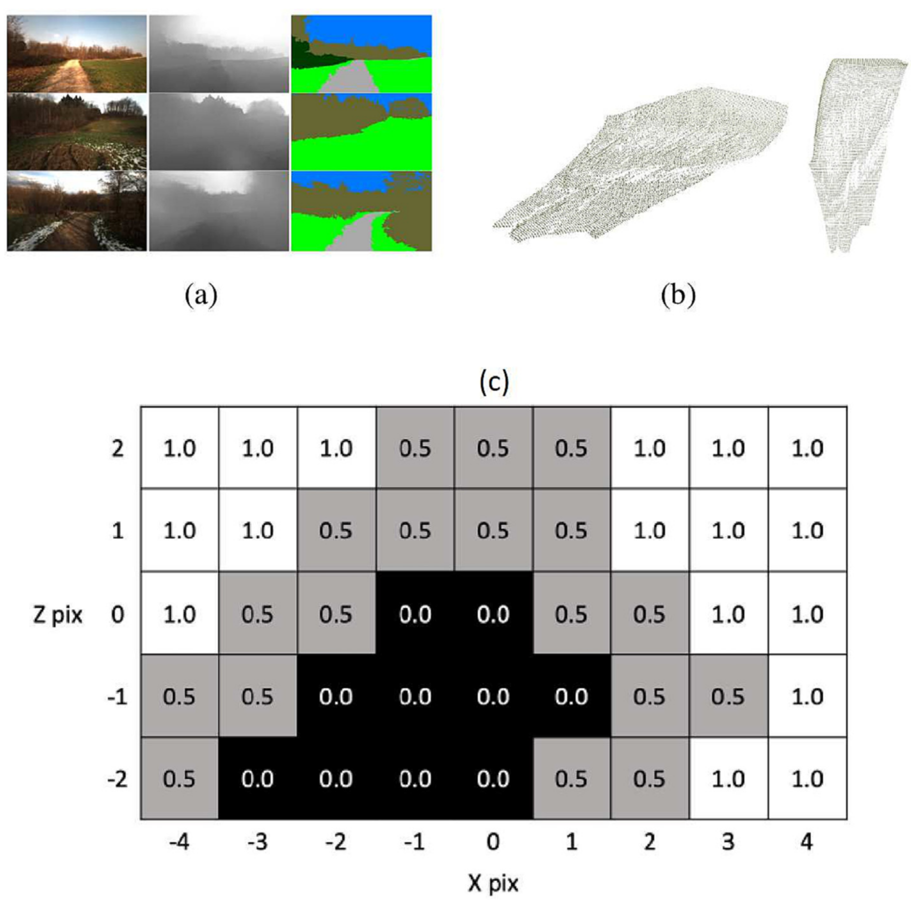

Fig. 12. Broatch-et-al: (a) Freiburg Forest Dataset snapshot, (b) Terrain point cloud, (c) Pixel Position and Depth Values [15].

A method based on images converted to height maps that represent the terrain of 10 m × 10 m by synthesizing data was presented in [99]. Then, features such as terrain steepness and height of the steps were calculated and CNN-based approaches were used to predict the traversability of the terrain. The proposed method was verified using various datasets and tested with a real

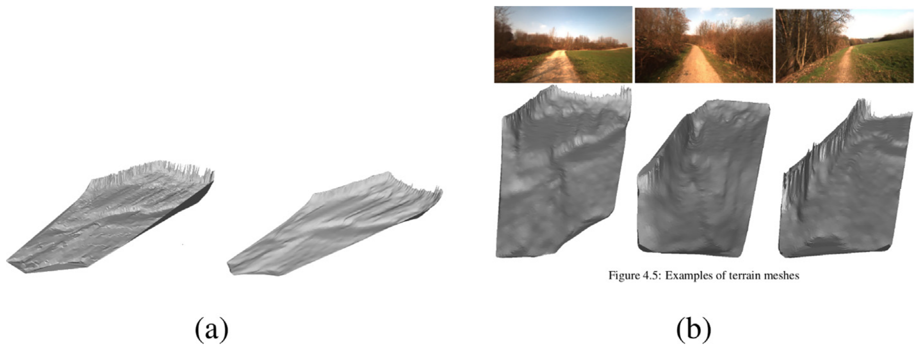

Fig. 13. (a) Raw (left) and Smooth (right) Terrain Mesh, (b) Terrain image and mesh examples, from [15].

platform i.e. Pioneer 3-AT. The test has shown that the CNN-based method is better than the feature-based and baseline classifier methods. The main shortcoming of the study is that the method has been trained with simulation data only.

A semantic map-generating method based on the SLAM algorithm has been proposed by [29]. The semantic segmentation algorithm has been set using Inception-v3 learning architecture and RGB dataset generated in the RoboCup Rescue-Robot-League environment. Then, a SLAM algorithm has been implemented to create a geometric map using depth and RGB images. Also, labelled images have been converted to refined semantic images with a flood-filling algorithm using semantic images and depth information from a stereo camera. With these semantic images and geometric maps, semantic and filtered semantic maps have been generated to reflect the environment. This method has been provided by using dense information from the environment and more reliable mapping.

Authors in [51] proposed a path-planning method for Mars surface missions. In the study, the terrain traversability model has been obtained from the digital elevation model (DEM), cumulative fractional area (CFA) map and terrain classes. CFA map has been labelled into low, medium and high classes and the slope computed from DEM has been divided into five classes. The traversability map has been created based on these terrain and vehicle features and the velocity map has been labelled with five different velocity ranges and an untraversable label. The terrain has been segmented into benign, rough, sandy and untraversable areas. Then, the traversability map was updated with new measurement information. After creating the expected velocity category map, Yen's k-shortest paths algorithm [164] has been implemented to find the most reliable path planning options. By this proposed method, the terrain can be learned by the platforms simultaneously.

In another recent study, [79], RGB images, point cloud from Lidar and robot motion data have been used to generate the traversability cost map. The method has three main stages i.e. converting RGB images to the semantic mask with a supervised semantic segmentation algorithm, generating a 2.5-D robot-centric elevation map and obtaining the traversability cost map. The Gated-SCNN [140], ERFNet [119] architectures and RELLIS-3D [63], ImageNet [28] datasets, which have 18 different terrain types, was used to train semantic segmentation algorithms. The 2.5-D elevation map that includes the height information on the terrain in each grid cell was generated using 3D point cloud and robot motion data. After that, the robot-centric cost map has been created with several transformations such as converting coordinates from map to camera and from camera to pixel (Fig. 11 (c)). Also, the slope, roughness and step height of the terrain has been calculated from height information on the elevation map. Combining maps based on terrain types and geometric information, the traversability cost map was thus generated. The main framework and visualization of the traversability map can be seen in Figs. 11 (a) and 11 (b), respectively. In this way, a reliable traversability map is obtained based on both appearance and geometric information for the terrain. A path-planning algorithm can be followed for navigation tasks with this method. The proposed method is not yet tested on a real terrain setup for traversability mapping and path planning.

Continuing with traversability application, Broatch in his work [15] proposed a method using the DeepScene Freiburg dataset [146] (Fig. 12 (a)) to create an environment model in Gazebo simulation. The terrain point cloud has been generated from depth

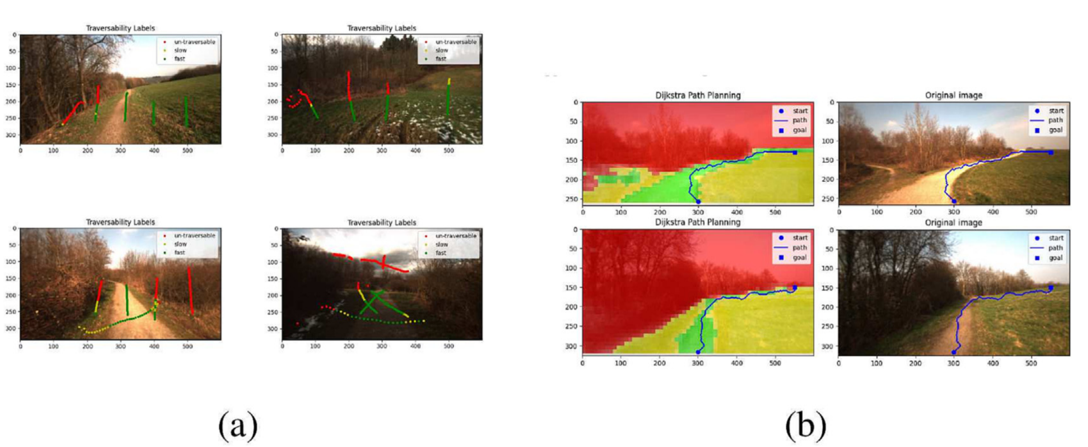

Fig. 14. Kester-et-al: (a) Labelled Images snapshot, (b) Path Planning Algorithm results [15].

images according to their pixel position and depth values (Figs. 12 (c) and 12 (b)), and it has been meshed and smoothed with MeshLab 3D software to use in the simulation environment (Figs. 13 (a) and 13 (b)). In this way, the simulation environment based on the provided real terrain data has been generated. The vehicle's longitudinal and lateral slip and the terrain slope have been calculated, and the friction coefficients have been appointed according to terrain types such as 0 for the sky, 0.1 for the grass and 0.72 for the road. Noting that zero means "untraversable" one refers to fully traversable. Then, a terrain traversability algorithm has been implemented based on this information/properties. It is noted that if the terrain type is marked as "sky" or "tree", it is labelled as untraversable, if the vehicle slip is more than 10, the slope is more than 20 also the terrain type is not untraversable, then it is labelled "slow". In the case of the slip and slope being less than 10 and 20, respectively, and the terrain is traversable (low friction), it was labelled a "fast" area. After this labelling progress (Fig. 14 (a), 2D terrain images were formed. Also, artificial labels have been added for sky and trees to decrease the probability of wrong classifications. A CNN-based learning algorithm was implemented, and a path planning algorithm has been performed to investigate the reliability of the method, as seen in Fig. 14 (b). The method proved successful but was tested only in a simulation environment. In addition, using more extensive terrain types can improve the approach further (i.e. considering terrain types such as short, medium and large height grass area, stone, wood and sand area).

A 2014 study by Rasmussen et al. [110] worked on a wheeled robotic system which navigates along outdoor "trails" intended for hikers and bikers. The researchers used a traversability solution combining the appearance and structural cues derived from stereo omnidirectional colour cameras and a tiltable laser range-finder. Tests were run in a real environment and some interesting insights were listed esp. on considering nocturnal traversability opportunities.

2.4. End-to-end methods

End-to-end methods are learning-based approaches that combine all system steps from perception to control. This is different from the other methods mentioned above. For example, while other methods try to recognize, map or understand the environment and need another step for navigation and control, end-to-end methods include both these and the navigation & control steps. That is, end-to-end methods can be seen as a combination of perception and control blocks.

In this section, we discuss these methods as a part of terrain traversability enablers, since the methods are incorporated in several traversability assessments. The sub-sections for the end-to-end methods are deep learning and reinforcement learning-based approaches.

2.4.1. Deep learning based end-to-end methods

Deep learning approaches receive increasing interest from the research community widely. In this context, a recent study by [16] proposed a road detection method using a camera and Lidar. Point clouds from Lidar were converted to different feature maps and, the neural network was used as input for the feature maps and camera images. Also, different fusion algorithms, early, late, and cross-fusion have been presented to compare information fusion effects. According to the results, the best accurate model with 96.03% was found in the case of cross fusion using the KITTI dataset[36]. The model shows good performance, but this algorithm is suitable just for on-road environments.

The training architectures of the Segnet [7], Fully Convolutional Network (FCN) [80] and U-Net [121] have been used to segment the dataset, and the self-supervised learning approach to label the dataset using visual odometry. Also, the NVIDIA learning model [13] has been implemented to predict steering angle. It is noted that the input shape was scaled to 256x136 size from 200x66 to gain more information from the image. For validation of the study outcomes, a dataset consisting of 1000 RGB images and vehicle parameters was gathered with two different cameras from a real environment. Approximately 95% accuracy rate has been obtained for segmentation and path planning tasks in the three deep learning algorithms and 3.5° error for steering angle. The main contribution of this study is that the method can estimate the vehicle path as well as the vehicle control parameter.

Within the same methodology framework, author [134] proposed a modified ResNet-18 [49] model named TrailNet used to predict six navigation parameters, i.e. facing left, facing centre, facing right, shifted left, centred and shifted right. Also, YOLO [112] object detection network and direct sparse odometry-based monocular SLAM algorithm was implemented to study safety [33]. The study has been tested with a micro aerial vehicle and the dataset has been collected using three cameras in the Pacific Northwest region.

A weakly-supervised learning-based drivable path prediction method has been developed by [10]. The huge amount of data has been segmented with a self-supervised labelling method, and this data enabled the use of a deep learning-based semantic segmentation algorithm to find a reliable path. The approach has been performed using KITTI[36] and Oxford RobotCar datasets under different weather, traffic and lighting conditions. Other researchers, in [166], published the Baidu Driving Dataset(BDD) that has been gathered with sensors of three monocular cameras, Lidar, IMU and GPS. With this dataset, the navigation parameters for lateral and longitudinal control have been predicted by a deep learning model that includes LSTM. In the learning algorithm, just the camera image has been used as an input to predict vehicle curvature and speed.

Moreover, drive torques and steering angles have been estimated from a supervised learning method where a point cloud has been used as input. Also, a safety system has been implemented to increase the reliability of the method such as the detection of a collision. Adding such a safety system to the system has made the method more reliable. This work was presented by the authors in [42].

In the study of [69], the RGB image from the camera and a point cloud from Lidar have been used as inputs to the learning algorithms to predict the throttle and angle data. The image and distance information has been processed with different learning networks, MobileNetV2 [126] has been used as an encoder and the Dense Atrous Spatial Pyramid Pooling-based (DASPP) [162] as a decoder. Then, these have been combined via a concatenate layer. The method has been verified with a dataset that has been collected with a 1/16 scale platform and it has been tested in a real environment after the training step. A method for the navigation of agricultural robots was presented [8]. In their study, the steering angle has been predicted from the orientation of the robot using an

Table 1
Deep Neural Network Architectures training results from [12].

Learning Architectures	Parameter Type	Model 1	Model 2
Inception-v4	Steering Angle	44%	61%
	Speed	68%	73%
Resnet-152	Steering Angle	50%	65%
	Speed	66%	78%
$\boxed{\text{NVIDIA}}$	Steering Angle	$\boxed{68\%}$	$\boxed{81\%}$
	Speed	$\boxed{77\%}$	$\boxed{88\%}$
Densenet-169	Steering Angle	36%	55%
	Speed	54%	65%

RGB image. The method has been trained with the IDSIA Swiss Alps trail dataset [39] and their own dataset.

Also, researchers have proposed a regression algorithm to predict exact navigation parameters. These two methods have been used together in various studies for improved prediction. The authors in [92] looked at twelve driver actions such as left turn, straight and right turn predicted from a Driver Behavior Classification (DBC) algorithm, and steering angle from a Steering Angle Regression (SAR) algorithm. The image, Lidar and odometry data have been used in the SAR algorithm as inputs, just the image was used in DBC. Also, the Gated Recurrent Fusion Unit (GRFU) learning algorithm similar to LSTM has been implemented for improving prediction accuracy. The study has been verified with the Open Racing Car Simulator (TORCS)[160] and Honda Driving datasets[109] that have been gathered in the simulation and also using the real environment, respectively. The proposed method was shown to have improved the Mean Squared Error (MSE) and mean Average Precision (mAP) score.

In addition to data from cameras on board the vehicle, GPS data has been used to predict control parameters as part of the end-to-end learning method. This is the case in the work presented in [2]. After extracting terrain features from the left, right, and front camera sensors and unrouted maps, these were fused to predict probabilistic control navigation parameters. Also, the fused data has been combined with a routed map obtained via GPS sensor to estimate the deterministic control parameters such as left turn and right turn. The method was evaluated using a real environment.

The authors in [50] proposed an end-to-end architecture to predict both steering angle and speed. GPS data, driving map by route planner, and images from left, front-view, rear-view and right cameras have been collected for the learning network. With such data available, the prediction model has been created using CNN and LSTM learning architectures. Also, a large dataset named the Drive360 dataset has been gathered to implement the proposed methodology. Moreover, authors in [130] demonstrated an end-to-end method for vehicle navigation (using deep learning as well), and installed a simulator named TORCS [160] and all necessary packages. After gathering the dataset in the simulator, they applied the steering angle prediction architecture and tested the method with the autonomous mode capability.

Lidar and camera sensors were used in the research work in [21]. In their study, the authors first removed from the images any unnecessary parts or objects and the images were resized to use as inputs in the learning network. Also, the 3D point cloud has been converted to a feature map using a Python-based algorithm. The point cloud was also down-sampled to 16384 points to decrease training time with a toolbox named CloudCompare [38]. Three deep learning networks, NVIDIA, Resnet-152 and Inception-v4 have been used to train with these data. Also, the training results for different input combinations such as image, image-point cloud, and image-feature map have been presented and compared. The biases values of steering angle and speed prediction have been chosen as 6° and 5 km/h, respectively. These are not reliable and safe tolerance values for real driving. Also, a large and comprehensive dataset named DBNet which represented a complicated environment that included pedestrians, houses, and vehicles has been published.

The authors in [12] propose an algorithm that provides an estimate of steering angle and speed using a deep learning-based end-to-end approach with the same dataset. In this work, camera and Lidar sensor data were pre-processed for eliminating noise from Lidar data and transforming pixel-based images into segmented images using the semantic segmentation technique. The navigation parameters were predicted from image information, and from the fusion of the image and 3-D point cloud. The following NN models were used for training: *Inception-v4*, *Resnet-152*, *NVIDIA* and *Densenet-169*. The best prediction results were obtained with the NVIDIA NN model that provided 81% accuracy for steering angle and 88% accuracy for vehicle speed. The relevant results can be seen in Table 1.

The literature includes a large part of end-to-end methods. The interested reader is referred to further resources in the literature that study this topic. Various image quality levels have been employed in the study of [131]. Steering angle has been predicted a deep-learning-based method by [72,32,132,60,22,89,71].

The authors of [54] proposed a stereo vision odometry-based technique for the automatic production of training data. They utilised FCN, VGG16, and UNet network architectures to predict a driveable path from a single image containing visible tracks or roadways. The output of a trained CNN is segmented images including the detected path trajectory. Islam et al. [59] developed a vision-based autonomous driving system that relied on a deep neural network to navigate the AVS safely in a region with unexpected road hazards. Yang et al. [163] suggested a multi-modal multi-task vehicle control network that predicts both steering angle and vehicle speed using images from the camera and prior vehicle speed as inputs. Similar to this study, Jugade et al. [65] proposed a supervised machine learning to predict steering wheel angle and vehicle speed by discerning human intentions from previous driving decisions and representing projected human driving decisions. The authors of [129] proposed a method for predicting environment traversability using annotated images generated without human intervention. A state-space search algorithm has been suggested by [70] to handle common local movements like sharp turns, overtaking, parking, avoiding obstacles, and navigating in narrow passages. A self-tuning system based on probabilistic methods and machine learning techniques was presented by [108] to improve the path-tracking capability of autonomous vehicles moving through changing terrain.

2.4.2. Reinforcement-based end-to-end methods

Manderson et al., [82], have proposed a visual and learning-based method to predict difficult terrain types and their overall setup can be seen in Fig. 15 that the aerial images and images from the on-vehicle camera have been fused for improved performance. Labelling the training dataset was performed on aerial images, vehicle camera images, the terrain class, and steering data to estimate the terrain type via self-supervised learning. The authors

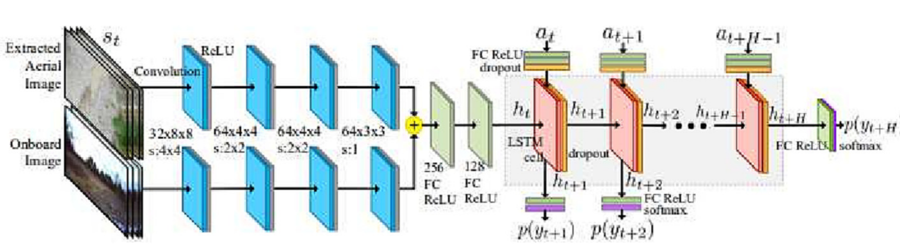

Fig. 15. The proposed learning-based setup of Manderson et al. model to categorize terrain types [83].

implemented a Long Short-Term Memory (LSTM) learning approach to predict terrain types (discussion on LSTM can be seen in [53]). It was shown that the accuracy increased by about 10% and operating in the demanding terrain improved considerably when aerial images were used.

In the study performed by the authors in [168], the depth images, the orientation of the robot and the elevation map which represent the obstacle around the robot have been used as inputs in deep reinforcement learning. In the work image resizing was implemented. Depth images $(84 \times 84 \times 1)$ and elevation map $(200 \times 200 \times 1)$ fused with 3D robot orientation have been reshaped to the size of $576x1$. After this, both have been fused to predict the navigation action (actor) that is front, back, right, and left commands and value function (critic). The proposed method was deemed successful in simulation, albeit not verified in a real case scenario. It is also noted that the terrain area utilised in the simulation had limited features.

Deep Reinforcement Learning (DRL) has been used to predict the navigation parameters in the work by the authors in [64]. In this study, four models were used, i.e. DRL zero-range, immediate range, and two local ranges sensing (different locations). The proposed model has been verified using the ROS/Gazebo simulation environment and a 200×200 m^2 off-road terrain was generated to validate the methods in the simulator. Although the methods showed good performance, the study has not been verified in a real environment or an extensive simulation environment that included an extensive set of terrain types.

Furthermore, research [167] proposed a path-planning algorithm based on deep-reinforcement learning, using a reward function relating to terrain slope. The angle and distance of height, the angular and linear velocities, images from visual sensors, and a 3-D point cloud from Lidar were used as inputs and linear and angular velocities as outputs for the neural network. For testing the method, the lunar terrain model and vehicle model have been established in a Gazebo simulator and the method was verified in this simulation-based environment.

Authors in [66] looked into an approach using three event labels, i.e. collision detected by Lidar (like a drop), bumpiness case determined by IMU sensing, and the position measured by fusion of IMU and odometry. These labels have been added to the data for generating a large-labelled dataset with self-supervised learning. A training model based on deep reinforcement learning was presented with inputs being labelled camera images and intended behaviour, and outputs being navigation actions. This study, which considers not only the geometry properties but also the appearance properties, is successful to learn navigation operations. Also, researchers tested their method in real environments, and with the automatic labelling process, these were the main contributions. The shortcomings of the approach though are: the number of labels is not sufficient, and the performance in various unstructured environment scenarios has drawbacks.

Wulfmeier et al. in their paper [159] proposed a path planning algorithm based on end-to-end methods. In their study, the point clouds have been generated with 3D Lidar and the grid-based elevation map has been provided using the features of height information and cell visibility obtained from the point cloud. From this feature map, the terrain has been divided into classes such as traversable area, obstacle (untraversable) and unknown area (the latter being cases when Lidar has not managed to capture information). A cost-based path planning algorithm was implemented according to the obtained traversability map using a maximum-entropy-based, non-linear inverse reinforcement learning (IRL) method. Also, different neural network methods that are standard, pooling and multi-scale fully convolutional neural networks(FNC) have been used in the proposed algorithms. For validating the study, two Velodyne HDL-32E Lidar and Bumblebee

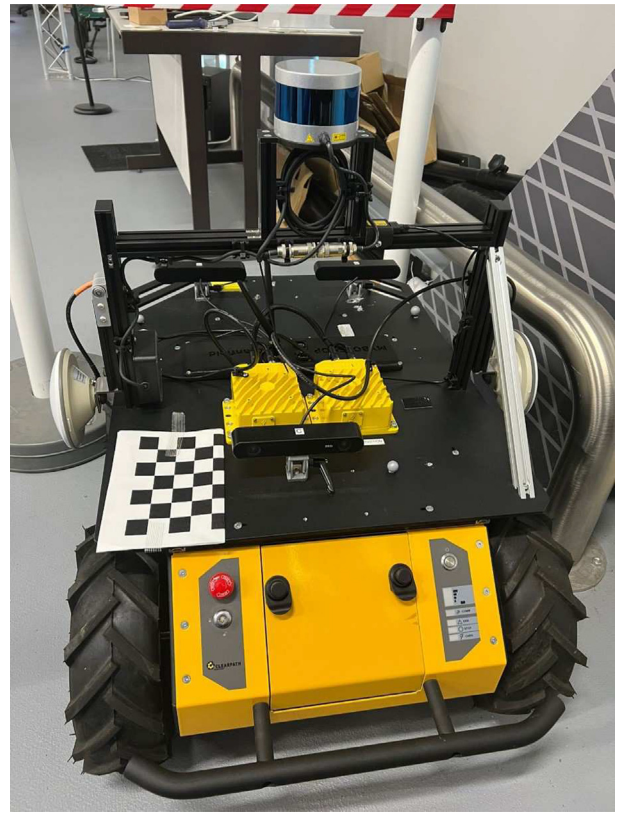

Fig. 16. Husky A200 Vehicle Platform snapshot with VLP 16 Lidar, Stereo Camera, Duro RTK GPS sensors payload (Centre for Autonomous & Cyber-Physical Systems, Ground autonomy Lab, Cranfield University).

XB3 stereo-camera have been placed on a modified electric golf car. The dataset has been collected with this platform driven 120 km by different operators in the Milton Keynes, UK, area. It is demonstrated that the method is suitable and provided good results in urban scenarios.

Another recent study, i.e. in [55], proposed a deep reinforcement learning-based navigation method that predicted the navigation actions: forward, tiny left, tiny right, hard left and hard right using images as inputs. Firstly a 2D semantic distance map was obtained from the Lidar, next the map was converted to the size of the $80x80$ grey-scale image to train the learning algorithm. The study was performed both using real terrain and a Gazebo simulation environment.

Prediction of vehicle navigation using deep reinforcement learning was also proposed by [168]. Their algorithm used the depth image, elevation map and 3D orientation of the platform as inputs. After the elevation map and 3D orientation were combined, the map and depth image were fused via a concatenate layer after some pre-processing algorithm to extract the useful features. The study has been performed in the Gazebo simulator. In this limited simulation-based scenario, the method provided useful results.

The literature contains additional papers on navigation, path planning, road segmentation and recognition, and obstacle avoidance (these are popular topics for both in-ground and aerial vehicles). The research by authors of [148] investigated the subject of mobile robot navigation by combining reinforcement learning and neural networks. The hybrid technique has been evaluated in the Gazebo simulator, and the results demonstrate its stability and viability. A deep-reinforcement-based end-to-end approach using depth and RGB pictures to forecast navigation parameters has been suggested by [96].

Table 2
Listing of popular robotic (vehicle) platforms for traversability studies.

Model	Dimension (mm)	Weight (kg)	Max Payload (kg)	Max Speed (m/s)	Battery Runtime (Hours)	Battery Charging (Hours)	Ground Clearance (mm)	Wehicle Type	Operating Temperature
Husky A200	990 × 670 × 390	50	75	1	3	4	13	Wheeled	−10 to 40 °C
Rr100	864 × 658 × 800	90	50	2.5	4.5	4	120	Wheeled	0°C to 45°C
Jackal	508 × 430 × 250	17	20	2	2	4	65	Wheeled	−20 to 45 °C
Moose	2960 × 1500 × 1140	1077	513	8	6	24	240	Wheeled	−10 to 50 °C
Warthog	1520 × 1380 × 830	280	272	5	2.5	4	254	Wheeled	2–20 to 40 °C
Scout Mini 1.0	612 × 580 × 245	23 **	–	2.7	2	2	115	Wheeled	”-10 to 45 °C
Scout UGV 2.0	930 × 699 × 348	62	50	1.5	3	2.5–3	135	Wheeled	0°C to 40°C
Hunter UGV 2.0	980 × 745 × 380	65	150	1.5	4	3.5	105	Wheeled	”-10 to 65 °C
Bunker UGV 2.0	1020 × 760 × 360	130	80	1.5	2	2	100	Tracked	”-20 to 60 °C
Leo Rover	447 × 433 × 249	5	6.5	0.4	4	2	–	Wheeled	–
The Super Mega Bot	838 × 838 × 406	99.7	113.3	6	4	–	139	Wheeled	–
Mana	800 × 1150 × 1000	130	90	8.3	8	–	100	Wheeled	–
Telemax Eva Pro	775 × 400 × 750	77	35	2.6	10	–	–	Tracked	–
Macrousa Scorpion S	386 × 522 × 170	22	20	2.6	2	–	45	Wheeled	–

3. Sensors and platforms used in the studies of terrain traversability analysis

Practical considerations in traversability analysis and related studies are normally not looked at in detail. This is a particular feature of this review paper as part of the traversability analysis research review. We present information and insights on the vehicle platforms and sensors' consideration in this topic.

A variety of vehicle platforms are utilised in traversability analysis. A typical research and development platform, namely, a Husky platform from Cranfield University, is shown in Fig. 16. It is strongly believed that these need to be featured in a rigorous review paper, and in this contact Table 2 lists the most used vehicle platforms in the wider research and industrial sector. This review paper is not meant to promote any particular vehicle platform, hence details on each individual platform are not included. We leave it to the interested reader to refer to the relevant vehicle platform brand's website.

Integrated with the vehicle platforms, are several sensors to visualize, perceive and map the environment and/ or calculate vehicle-related and environmental/surrounding information. These form vital subsystems for traversability and can be categorized in two main categories, i.e. *exteroceptive* sensors that measure the environment's features directly from contact-less sensors like Lidar and Camera, and *proprioceptive* sensors that measure robotic interaction and require some form of contact with the environment such as measuring the position of the wheel mechanically contacting the terrain, joint angle or friction using wheels as tactile sensors.

Regarding the sensor technology (nature), cameras, Lidar, ultrasonic sensors (for proximity) and Radars tend to be the most commonly used exteroceptive sensors for traversability assessment/analysis.

Lidar is well known for using laser beams to provide angle, range, and size information. Lidar is seen as offering several advantages such as a wide field of view (FoV), high accuracy and resolution, providing 3D information and being capable to monitor long distances. However, Lidar tends to be expensive sensors, can be power-hungry, affected by weather conditions (i.e. poor performance under rainy conditions, fog, and snow), and require mechanical-part maintenance.

Radars are alternative sensors that use electromagnetic waves to identify the angle, range, size, and velocity information. The advantages of using radars are as follows. They are less expensive and more robust, less sensitive to weather conditions, small and light, can work long distances, offer good distance detection and speed information, etc. However, Radars do not provide dense information and high accuracy, and resolution, as well as no 360-degree coverage.

Ultrasonic sensors (proximity sensors), devices using sound waves to provide range information are cheap, small, light, very good in detecting near objects and non-metal objects, have good short-range resolution and are less affected by weather conditions and surface factors. They do come with limitations such as near-

Table 3
General Information and Features of Sensor Types that Used in the TTA.

Sensor Type	Sensor Tecgnology	Information Type	Sensor Type	Size	Resolution	Maintenance	Sensor Life	Overall Cost
Ultrasonic sensor	Sound Wave	Distance	Active	Very Compact	Sparse	Easy	Long	Low
Radar	Radio Wave	Angle, distance, size, and velocity	Active	Compact	Higly Sparse	Difficult	Long	Medium
Lidar	Laser Beam	Angle, distance and size	Active	Bulky	Sparse	Difficult	Medium	High
Monocular Camera	Light	Visual	Passsive	Very Compact	Dense	Easy	Long	Low
RGB-D Camera	Light	Depth, visual	Active	Compact	Dense	Easy	Long	Low & Medium
Stereo Camera	Light	Depth, visual	Passsive	Compact	Dense	Easy	Long	Low & Medium
Event Camera	Light	Visual	Passsive	Compact	Dense	Easy	Long	Medium
Omnidirectional Camera	Light	Visual	Passsive	Very Compact	Dense	Easy	Long	Low & Medium
Infared camera	Infrared Energy	Temperature	Passsive	Compact	Dense	Easy	Medium	Medium & High

Table 4
Listing Mostly Used Camera Types.

Camera Type	Model	Weight (g)	RGB and Depth FoV HxV	Power Consumption (W)	Max Frame Rate (fbs)	Depth Resolution	Colour Resolotuin	Max Depth Measuring (m)
RGB-D	Kinect v1	1140	R:62° × 48.6° D:57° × 43°	12.96	30	320x240	640x480	0.4–3.5
RGB-D	Kinect V2	1400	R:84.1° × 53.8° D:70° × 60°	115	30	512x424	1920x1080	0.5–4.5
RGB-D	Azure Kinect	440	R:90° × 74.3° D:120° ×120°	6	30	1024 × 1024	4096 × 3072	0.25–5.46
RGB-D	Xtion Pro Live	540	R:83° D:58° × 45°	2.5	30	640 × 480	1280 × 1024	0.8–3.5
RGB-D	RealSense 515	95	R:69.4° × 42.5° D:70° × 55°	3	30	1024x768	1920x1080	0.25–9
RGB-D	RealSense D435	72	R:69.4° × 42.5° D:87° × 58°	2.5 W	90	1280x720	1920x1080	0.3–3
RGB-D	RealSense D455	–	R:90° × 65° D:87° × 58°	2.5 W	90	1280X720	1280X800	0.6–6
Stereo	ZED	135	D:90° × 60°	5 W	100 fbs	2208 × 621	4416x1242	0.3–25
Stereo	ZED 2	124	D:110° × 70°	5 W	100 fbs	2208 × 1242	2208x1242	0.3–20
Stereo	Bumblebee XB3	505	R:50° and 70°	4 W	16 fbs	–	1280x960	–
Monacular	Hero-4 (4 K)	569.8	Wide	0.03–5 W	–	–	3840x2160	–
Event	DVS128	–	–	150mW- 1 W	–	–	128 × 128	–
Omni-directional	Gear 360	130	D:270° × 60°	–	–	–	5472 × 2736	–

range working distance, being affected by heat, wind and noise, mutual interference problems, low resolution, and can be unsuitable for high-speed operation.

Cameras utilise colour information, there are many camera versions with high resolution, capable to provide dense and 3D information, typically easy to deploy and having wide FoV. Camera technologies have progressed significantly and now offer small sizes and weights, and long-range capabilities that can provide depth information (i.e. stereo or RGB-D cameras). However, they tend to require feature extractions progress, they can be affected by weather and light conditions, and don't provide direct velocity and distance information. In general, the immense popularity of computer vision applications resulted in the extensive use of camera sensors in-vehicle applications.

Features of different types of sensors are listed in Table 3, and camera examples used in the TTA studies are shown in Table 4 as a comprehensive summary of practical considerations in traversability. To set up these tables, a number of manufacturer data sheets and technical articles [170,90,111,93,138,94,170] including review articles [1,9,152,150,165] are referred to.

4. Discussion on traversability methods presented

This section evaluates and discusses the methods and approaches presented in this review paper to highlight the pros and cons of the relevant studies.

4.1. Terrain traversability related insights

Terrain classification, in particular in demanding off-road terrains, plays a major role in determining which area (or pathway) portion is safe (reliable) or faster for the vehicle to traverse in a more optimised way.

Appearance-based terrain classification methods have many contributions to literature and off-road navigation studies or projects. With the appearance information of the environment, the terrain can be classified into various types such as asphalt, lawn, stony, rocky area, smooth, rough, semi-smooth, or very rough and the path planning can be performed according to these terrain types. Nowadays, the biggest advantage of vision-based terrain classification is that it can be applied with high accuracy using machine learning algorithms, especially with advances in computer processing and data storage. It is worth noting that classification or driving based solely on colour information tends to be not realistic. For example, in cases of high-grass terrain environment (although this can vary depending on the characteristics of the vehicle platform) is not traversable in many cases, although grassy terrain types, based on colour detection, tend to be considered traversable by many researchers. Conversely, low grass areas were classified as untraversable areas in several studies. Further, it is difficult that the complicated part of terrains such as holes, water areas, and transition parts between terrain types to be detected efficiently by just appearance-based methods. Hence, this method alone may not be sufficient for reliable terrain analysis.

Geometric-based terrain classification has been studied by several researchers [85,124,116,117,98]. Geometric-based terrain classification methods refer to using geometric features such as height, terrain anatomy, slope, slip characteristics etc. Detection of the difficult part of terrains like holes or measuring objects' heights can be achieved with this method. But the terrain classification methods based on just geometric features may yield unreliable results due to incorrect measurement and sensor noise/ distortion. In addition, the fact that the sensors used in these methods such as Lidar, Radar or rarely GPS are expensive and require some data processing. These shortcomings tend to make this kind of method costly, complex and not more reliable than appearance-based methods.

Various studies considered the fusion of geometric and appearance-based information, examples can be seen in [74,161,11,135,141,75,101,10,57]. In these fusion-based approaches, the terrain is classified in general by appearance-based techniques, while demanding parts of terrains e.g. transmission parts, holes and grass height are detected by the geometric-based methods. The aim is to enable more reliable and safe driving by combining both feature types for the classification problem, albeit with increased complexity. In this context, cost and the required data processing capabilities are rather significant shortcomings of such methods.

Conventional planning for driving is normally performed under an ideal scenario, i.e. deterministic terrain, terrain with smooth features, and no hindering objects for traversability. In practice, one faces a more complex and challenging environment scenario (off-road-wise). In such environments, mapping the environment and creating terrain traversability cost function utilizing geometric or appearance-based information on terrain and vehicle is of paramount importance. It is also multiple objective problems as seen in a variety of studies on mapping the terrain and processing various characteristics such as vibration, vehicle speed and acceleration, slip, slope and anatomy of terrain, size and the shape of (if any) objects, that are important to perceive the environment and enable safe traversability mission. An alternative, yet not as consistent Also, it is possible to make a terrain traversability analysis only from the cost function (without a map) that includes various information such as vibration, size, slip, and slope. Although, it is not a better approach.

For exact traversability analysis, the terrain should be observed and areas that are safe for going and including the speed by which to traverse it is identified. Further, it should be determined not only whether the terrain is passable or impassable, but also which part of the terrain is full-, semi-, or non-passable, or which part is the fast-speed, medium-speed, and low-speed passable (in some cases, also which terrain part can be utilised as or urgency passable region). For such a comprehensive analysis, both terrain classification and terrain mapping and cost function-based methods (hybrid methods) should be explored. The current literature offers a wealth of papers on the hybrid methods that provide terrain classification and traversability mapping using both appearance- and geometry-based information. What is noted from the studies is that hybrid methods tend to provide more efficient terrain analysis with dense information for terrain classification and mapping, and some further examples can be seen in these papers [158,86,5,123,120,99,29,51] for the interested reader.

The end-to-end methods have several advantages especially direct control and lesser requirements. In particular, deep learning-based methods provide good results in specific scenarios, but when the method is tested in a different environment (scenario), reliability reduces substantially. Comprehensive datasets are paramount for use in this set of methods, including various features such as various weather conditions and lighting conditions. This is not a cost-effective solution due to the challenge of collecting a large number of datasets and requiring demanding computing power. In addition, end-to-end methods results depend on vehicle characteristics (such as speed) and terrain characteristics (features that cannot be simply generalised and fixed) and such uncertainty impact their performance. Reinforcement learning-based methods attempt to provide more comprehensive solutions and consider various terrain and vehicle parameters such as slip, slope, velocity, and distance between line sections. However, they require extensive training.

The cons of the traversability analysis methods are summarized below.

- APPEARANCE-BASED METHODS:
  -Classification of transition parts, i.e. between vegetation and low vegetation areas (high grass, long grass) or smooth terrain/semi-smooth terrain
  -Predicting hole, mud and water areas
  -Real-time response time of the prediction algorithm
- GEOMETRIC-BASED METHODS:
  -Requiring various pre-processing algorithms, i.e. converting Lidar points to point cloud or to feature maps.
  -Increase cost due to sensors price that provides geometric features of terrains (it is more expensive than sensors used in appearance-based methods)
  -Predicting water areas, thin objects such as twigs, thin sticks and sparse areas
  -Timing (simultaneous working) and calibration of sensors
- TERRAIN CLASSIFICATION:
  -Unreliable terrain analysis with just classification algorithms (geometric information of terrains such as the height of objects, terrain slip or slope are also very important parameters for traversing unstructured environments)
- TERRAIN MAPPING AND COST-BASED ANALYSIS:
  -Determining the weighting of algorithm parameters (the effect of parameters such as slope, terrain slip or object height) on the traversability cost function
  -Challenging task of creating a real-time map with several information characteristics
  -Increased cost of traversability solution due to sensor pricing these tend to be expensive in situations where intensive information from the terrain environment is required)
- END-TO-END METHODS:
  -These methods require comprehensive datasets (ideally gathered under different weather and light conditions trials)
  -Requiring long training time and high-spec computers for real-time implementation
  -Highly depends on prediction tolerance

Another significant parameter when it comes to terrain traversability studies is the dataset availability (which in many cases is taken for granted or different datasets, more on-road tend to be used). Most of the off-road or demanding terrain existing datasets are not comprehensive and contain only a few thousand data. Many datasets may not have sufficient vehicle and terrain parameters or information provided (which can hinder the validation of new research solutions). For end-to-end studies, while there are various (as mentioned) datasets for on-road environments, there are a few small datasets for off-road environments. Also, from a vehicle control viewpoint, only the steering angle is shared as part of many of these datasets. However, speed is also an important parameter for navigation.

Hence, using a hybrid approach based on geometry and appearance information can enable providing more optimised driving solutions in an off-road environment with a comprehensive and multi-scenario dataset. The authors propose the following important recommendations for future research according to the analysis of existing literature.

- Enabling a comprehensive dataset availability that includes various terrain features such as grass, tall grass, gravel, stone, rock, wood, and stone terrain and includes geometric information from vehicle and terrain such as pose, slip, slope and object height after some pre-processing or raw data from sensors such as Lidar, IMU, Odometry, GPS. Sensor configuration (and information fusion) on the vehicle platform is of paramount importance.
- Enabling a variety of datasets (including labelling semantic, instance or pixel-based) collected under various weather (including adverse weather conditions) and light conditions.
- Developing terrain classification approaches with various classes (not just smooth and rough labels) and learning algorithms with an increased level of prediction accuracy.
- Using appearance and geometric-based methods including mechanical properties of terrains such as friction or deformability via proprioceptive (contacted) sensors with hybrid methods for reliable and sustainable traversability analysis.
- End-to-end methods may be used for an emergency case to predict navigation parameters such as steering angle and vehicle speed.
- Using aerial images may increase the prediction accuracy of terrain classification and detect the difficult part of terrains such as holes, waters and transmission parts, dramatically.
- Validating terrain traversability under extensive simulation study and tested in a realistic environment condition where possible.

4.2. Sensor related insights

As discussed earlier, several sensor technologies have been used for traversability assessment. From the study is concluded that mixing exteroceptive and proprioceptive sensors can enable reliable sensing and better perception of the environment.

Lidar, radar, camera, GPS (where available), wheel odometry and IMU have been used to detect geometric features of the environment. Lidar is seen as the more useful sensor for calculating slip, slope, road shape or obtaining 3D environment maps compared to other sensors. This is due to its features of working in a long and wide range, using full 360 degrees environment maps and typically dense information. Other sensors such as IMU or wheel odometers are necessary for a more reliable perception of slip value which is quite important to identify safe driving. It is worth noting that Lidar is an expensive and weather-sensitive sensor (i.e. poor performance in rainy weather). Multi-radar systems can be a good option for obtaining data in challenging weather conditions, although, they provide sparser and not full 360-degree information of the surroundings. The use of Lidar and radar sensing can be beneficial in traversability analysis.

For appearance features of the environment, cameras are the natural option to use. There is a variety of types, some low cost, some higher costs with extra features of object detection. Moreover, RGB-D cameras provide both appearance and geometric features of environments. Of course, Lidar and Radar can be used for appearance information by converting images of feature maps.

Data processing-wise such as converting point cloud to the feature map (Lidar), resizing images, noise removal or filtering in data, and sensor fusion (either from the same type of sensors, i.e. left/right camera, or heterogeneous sensors i.e. incl. Lidar and radars) is another important area to highlight for terrain traversability analysis. Appropriate processing provides more efficient and usable data obtained from sensors, especially where sensor fusion is followed.

5. Conclusion

We have presented a comprehensive survey of ground vehicle terrain traversability emphasizing demanding environments and including sensor technology insights (the latter being a unique feature of this paper). Terrain traversability analysis has been extensively studied referring to a large number of recent research paper materials (especially covering the period 2014–2022). The relevant research studies were classified into three main sections, i.e. terrain classification, terrain mapping, and the combined cost-based traversability and hybrid approaches. Each section has been sub-categorised by three different methodology viewpoints, i.e. appearance-based, geometry-based and mixed-based. This offers an informative and rigorous review for the research community and the interested reader in terrain traversability analysis. Moreover, we studied end-to-end methods extensively looking at deep learning and reinforcement learning approaches.

This rigorous survey review paper includes the important point of practical consideration in traversability studies, i.e. lists vehicle platforms used for traversability analysis and examines sensor technology enabling this. We present multiple perspectives in traversability research, aiming to avoid being biased towards a particular approach or a particular platform setup for a fairer representation.

Traversability studies have received increased attention in recent years, however, there are still various research gaps to be addressed in the terrain traversability analysis esp. in an unstructured environment. The following points are highlighted by the authors:

- The development of a novel terrain traversability analysis/mapping method based on both appearance and geometric approaches applicable in various environments for safe motion is required.
- The need for developing robust and safe algorithmic solutions for the classification of various terrain characteristics such as asphalt, soil, sand, gravel, rocky surface, and grass.
- The effort of aiming to improve the accuracy of the vehicle learning of the classified terrain types.
- Developing methods to determine multiple options for vehicle navigation such as fast (traversable) route, slow (traversable) route, medium (traversable) route, untraversable route, and emergency route (semi-traversable).
- The topic forms a clear example of an integrated system solution, with the requirement of developing an integrated solution for the above.

The authors' view is towards a more effective method by fusing appearance and geometry-based information for improved terrain environment analysis. Using both exteroceptive and proprioceptive sensors combined, although increasing the system architecture complexity, enables richer datasets. Pre-processing/processing sensor information such as feature extraction, converting point cloud to feature map, data augmentation, converting images to grey-scale, down-sampling Lidar-obtained number of points, removing noise information from data, improving the quality of data will further provide a pathway for more useful data or dataset for these methods. An important element yet time-consuming, especially during training of the ML/AI techniques for traversability, is that of data labelling. While many studies refer to the training of algorithms with different datasets, data labelling lacks detailed investigation for the relative impact on the methods training for traversability.

CRediT authorship contribution statement

Semih Beycimen: Conceptualization, Methodology, Writing - original draft. **Dmitry Ignatyev:** Conceptualization, Supervision. **Argyrios Zolotas:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Complementary tables list

The appendix, in the next pages, lists a set of complementary tables that are referred to accordingly in the main body of the paper.

We categorized the studies according to the use of general methods. Some researchers used completely or more analytic-based methods such as cost or optimization-based classification, which means they didn't use any learning-based method. And some of them used learning-based methods such as semantic segmentation-based classification. This classification has been added so readers to can choose articles directly from the listings.

Tables 5, 6, 7, 8.

Table 5
Important Literature Relating to TERRAIN CLASSIFICATION.

Article Ref.	Category	Road Type	General Method	Sensors	Environment	Speed	Vehicle Type	Simulator	Vehicle Model
[88]	Geometric	Unstructured	Analytic	Lidar	Real	–	–	–	–
[158]	Mixed	Unstructured	Learning	Camera	Real and Simulation	–	Wheeled	Unreal Engine	The U5023
[142]	Geometric	Unstructured	Analytic	Camera. Radar Lidar, GPS	Real	Low	Wheeled, Legged		
Tracked	–	Husky, Telemax, X-Maxx, Spot							
[2]	Mixed	Unstructured	Learning Analytic	Camera, IMU	Real	Low	Wheeled	–	Rocky8 LAGR
[99]	Mixed	Unstructured	Learning Analytic	Camera	Real and Simulation	Low	Wheeled	Gazebo	Pioneer P3
[6]	Mixed	Unstructured	Learning Analytic	Camera, IMU	Real	Low	Wheeled	–	Rocky8 LAGR
[100]	Mixed	Unstructured	Learning	Camera	Real	Low	Wheeled	–	Athena Rover
[86]	Mixed	Unstructured	Learning	Camera, Lidar	Real	–	Wheeled	–	–
[30]	Mixed	Semi-Structured	Learning	Camera	Real	–	Wheeled	–	RoboCup
[5]	Mixed	Unstructured	Learning	–	Real	Low	Wheeled	–	LAGR
[52]	Mixed	Unstructured	Analytic	Camera, IMU	Real	Low	Wheeled	–	Pluto Research Rover
[51]	Mixed	Unstructured	Analytic	–	Real	Low	–	–	–
[120]	Mixed	Structured Unstructured	Learning	Camera	Real	–	Wheeled	–	–

Table 6
Important Literature Relating to TERRAIN MAPPING

Article Ref.	Sub Categorization	Road Type	General Method	Sensors	Environment	Speed	Vehicle Type	Simulator	Vehicle Model
[124]	Geometric Based	Unstructured	Analytic	Camera, Lidar	Simulation	–	Wheeled	Gazebo Matlab	–
[147]	Apperance Based	Unstructured	Learning	Camera	Real	Low	Wheeled	–	Viona
[141]	Geometric Based	Structured Unstructured	Learning	Camera, Lidar	Real	–	Wheeled	–	–
[11]	Mixed	Unstructured	Learning	Camera	Real	High	Wheeled	–	QUAD-AV
[117]	Geometric Based	Unstructured	Learning	Camera, Lidar	Real	High	Wheeled	–	–
[84]	Geometric Based	Unstructured	Learning	Lidar	Real and Simulation	Low	Wheeled	Gazebo	Andabata
[128]	Apperance Based	Structured Unstructured	Learning	Camera	Real	–	Wheeled	–	–
[87]	Apperance Based	Unstructured	Learning Analytic	Camera	Real	–	Wheeled	–	POSS-V
[145]	Apperance Based	Structured Unstructured	Learning	Camera	Real	–	Wheeled	–	–
[18]	Mixed	Unstructured	Learning	Camera	Real and Simulation	–	Wheeled	ANVEL	–
[98]	Geometric Based	Semi-Structured	Analytic	IMU	Real	Low	Wheeled	–	Pioneer P3
[123]	Mixed	Unstructured	Learning	Camera	Real	Low	Wheeled	–	–
[85]	Geometric Based	Unstructured	Learning	Lidar	Real and Simulation	Low	Wheeled	Gazebo	Andabata
[74]	Mixed	Unstructured	Learning	Camera, Lidar, and IMU	Real	Low	Wheeled	–	Husky
[73]	Mixed	Unstructured	Learning	Camera, IMU	Real	Low	Wheeled	–	Husky
[135]	Mixed	Unstructured	Learning	Lidar	Real	High	Aerial	–	–
[161]	Mixed	Unstructured	Learning	Camera	Real	Low	Wheeled	–	Pioneer P3
[116]	Geometric Based	Unstructured	Learning	Camera, Lidar	Real	High	Wheeled	–	–
[57]	Mixed	Unstructured	Learning Analytic	Camera	Real	–	Wheeled	–	–
[101]	Mixed	Structured	Learning	Camera, Lidar and Odometry	Real	High	Wheeled	–	–
[153]	Apperance Based	Unstructured	Learning	Camera, Force-Torque Sensor	Real	Low	Legged	–	ANYmal Quadruped
[78]	Geometric Based	Unstructured	Analytic	Lidar	Real	–	Wheeled	–	An UGV

Table 7
Important Literature Relating to HYBRID Approaches.

Article Ref.	Sub Categorization	Road Type	General Method	Sensors	Environment	Speed	Vehicle Type	Simulator	Vehicle Model	Dataset
[44]	Mixed	Struct.	Learning	Camera, Lidar	Real	High	Wheeled	–	–	KITTI Benchmark
[105]	Geometric Based	Unstr.	Analytic	Lidar	Real	Low Medium	Wheeled	–	–	–
[19]	Geometric Based	Unstr.	Analytic	Lidar, IMU and GPS	Real	High	Wheeled	–	SUV	–
[31]	Apperance Based	Unstr.	Learning	Camera	Real	High	Wheeled	–	AutoRally	–
[61]	Geometric Based	Unstr.	Analytic	Lidar	Simulation	Low	Legged	Gazebo	ANYmal	–
[103]	Mixed	Unstr.	Analytic	Lidar, IMU, GPS	Real and Simulation	–	Wheeled	V-REP	–	KITTI
[157]	Mixed	Unstr.	Analytic	–	Real and Simulation	High	Wheeled	–	GatorX855D, Unimog U5023	–
[106]	Mixed	Unstr.	Analytic	Camera	Real and Simulation	Low	Tethered	–	JPL's Axel	–
[155]	Geometric Based	Unstr.	Analytic	Lidar	Real and Simulation	Low	Legged	Gazebo	Quadruped StarlETH	–
[127]	Geometric Based	Struct. Unstr.	Learning	–	Simulation	Low	Tracked	V-REP	–	–
[171]	Mixed	Unstr.	Learning	Camera, Lidar, IMU, GPS	–	–	Wheeled	–	–	–
[41]	Geometric Based	Struct. Unstr.	Analytic	Camera	Real	–	Wheeled	–	–	–
[97]	Geometric Based	Unstr.	Learning	–	Real	–	Wheeled	–	Pioneer P3	–
[37]	Apperance Based	Unstr.	Analytic	Camera	Simulation	–	Wheeled	–	–	–
[139]	Mixed	Struct. Unstr.	Learning	Camera, Lidar	Real	–	Wheeled	–	–	–
[169]	Geometric Based	Unstr.	Analytic	Lidar, IMU, and GPS	Real and Simulation	–	Wheeled	Gazebo	–	–
[156]	Geometric Based	Unstr.	Analytic	Lidar, IMU and GPS	Real	High	Wheeled	Simulink	Loc8	–
[71]	Apperance Based	Struct.	Learning	Camera	Real	–	Wheeled	–	–	Commaai, Udacity, HCE

Table 8
Important Literature Relating to END-TO-END Approaches.

Article Ref.	Sub Categorization	Road Type	General Method	Sensors	Environment	Speed	Vehicle Type	Simulator	Vehicle Model	Dataset
[39]	Deep Learning	Unstr.	Learning	Camera	Real	Low	Human Quadrotor	–	–	–
[43]	Deep Learning	Unstr.	Learning	Lidar	Real	–	Wheeled	–	–	–
[66]	Deep Learning	Struct. Unstr.	Learning	Camera, Lidar, and IMU	–	Low	Wheeled	–	Jackal	BADGR
[166]	Deep Learning	Struct.	Learning	Camera	Real	High	Wheeled	–	–	Baidu
[130]	Deep Learning	Struct.	Learning	Camera	Simulation	High	Wheeled	TORCS	–	–
[64]	Reinforcement	Unstr.	Learning	Camera	Simulation	–	Wheeled	Gazebo	–	–
[56]	Reinforcement	Unstr.	Learning	Lidar	Real and Simulation	Low	Wheeled	Gazebo	–	–
[8]	Deep Learning	Unstr.	Learning	Camera	Real	Low	Wheeled	–	–	IDSIA Swiss Alps Trail
[50]	Deep Learning	Struct.	Learning	Camera, GPS	Real	High	Wheeled	–	–	Drive360
[163]	Deep Learning	Struct.	Learning	Camera	Real	High	Wheeled	–	–	Udacity SAIC
[60]	Deep Learning	Struct.	Learning	Camera	Simulation	–	Wheeled	PreScan	–	–
[10]	Deep Learning	Struct.	Learning	Camera	Real	High	Wheeled	–	–	KITTI, RobotCar
[69]	Deep Learning	Indoor	Learning	Camera, Lidar	Real	Low	Wheeled	–	–	–
[92]	Deep Learning	Struct.	Learning	Camera, Lidar and Odometry	Real and Simulation	–	Wheeled	–	–	Honda, TORCS
[159]	Reinforcement	Unstr.	Learning	Camera, Lidar	Real	Medium	Wheeled	–	GEM Car	–
[82]	Reinforcement	Unstr.	Learning	Camera, Lidar, IMU, GPS	Real and Simulation	Low Medium	Wheeled	Unreal Engine	–	–
[54]	Deep Learning	Unstr.	Learning	Camera, Odometry	Real	–	Wheeled	–	–	–
[167]	Reinforcement	Unstr.	Learning	Camera, Lidar and IMU	Simulation	Low	Wheeled	Gazebo	Jackal	–
[16]	Deep Learning	Struct.	Learning	Camera, Lidar	Real	–	Wheeled	–	–	KITTI
[21]	Deep Learning	Struct.	Learning	Camera, Lidar	Real	High	Wheeled	–	–	DBNet
[168]	Reinforcement	Unstr.	Learning	Camera, Lidar	Simulation	–	Wheeled	Gazebo	–	–
[32]	Deep Learning	Struct.	Learning	Camera	Real	–	Wheeled	–	–	UDACITY

(continued on next page)

Table 8 (*continued*)

Article Ref.	Sub Categorization	Road Type	General Method	Sensors	Environment	Speed	Vehicle Type	Simulator	Vehicle Model	Dataset
[65]	Deep Learning	Struct.	Learning	Lidar	Real	High	Wheeled	SCANeR	–	–
[132]	Deep Learning	Struct.	Learning	Camera	Simulation	–	Wheeled	Udacity	–	–
[134]	Deep Learning	Unstr.	Learning	Camera	Real	Low	Aerial	–	MAV	–
[2]	Deep Learning	Struct.	Learning	Camera, GPS	Real	High	Wheeled	–	–	–
[60]	Deep Learning	Struct.	Learning	Camera	Simulation	–	Wheeled	Webots	–	–
[22]	Deep Learning	Struct.	Learning	Camera	Real	–	Wheeled	–	–	UDACITY
[133]	Reinforcement	Struct. Unstr.	Learning	Camera	Simulation	–	Aerial	NYU2	–	–
[96]	Reinforcement	Indoor	Learning	Camera	Real and Simulation	–	Robot	Gazebo	Turlebot2	–
[168]	Reinforcement	Unstr.	Learning	Camera, Lidar	Simulation	–	Wheeled	Gazebo	4x4 Jaguar Mobile	–
[67]	Reinforcement	Indoor	Learning	Camera	Real and Simulation	–	Wheeled	Bullet	An RC Car	–
[20]	Reinforcement	Unstr.	Learning	Camera, Lidar	Simulation	–	Wheeled	Gazebo	Ranger XP900	–

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