Review Paper

Recent developments in terrain identification, classification, parameter estimation for the navigation of autonomous robots

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Received: 3 October 2020 / Accepted: 26 February 2021 / Published online: 20 March 2021
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Abstract
The work presents a review on ongoing researches in terrain-related challenges influencing the navigation of Autonomous Robots, specifically Unmanned Ground ones. The paper aims to highlight the recent developments in robot design and advanced computing techniques in terrain identification, classification, parameter estimation, and developing modern control strategies. The objective of our research is to familiarize the gaps and opportunities of the aforementioned areas to the researchers who are passionate to take up research in the field of autonomous robots. The paper brings recent works related to terrain strategies under a single platform focusing on the advancements in planetary rovers, rescue robots, military robots, agricultural robots, etc. Finally, this paper provides a comprehensive analysis of the related works which can bridge the AI techniques and advanced control strategies to improve navigation. The study focuses on various Deep Learning techniques and Fuzzy Logic Systems in detail. The work can be extended to develop new control schemes to improve multiple terrain navigation performance.

Keywords Autonomous robots · Terrain parameters · Planetary rover · Terrain classification · Fuzzy logic control

1 Introduction

The advancements in robotics have addressed the challenges in unknown environments where human actions are limited. Autonomous robots are now widely used in various applications such as disaster management activities [1], military operations [2], Mars missions [3], self-driving cars [4] etc. In most cases, prior information regarding the trajectory and nature of terrains are not available with the system. Hence robot needs to learn the trajectory, presence of obstacles, nature of the terrain, etc. using built-in sensors. For example, a robot deployed for rescue missions during a landslide has to navigate through different kinds of terrains like rocks, mud, concrete, etc. The ability of robots to understand the existing terrain can improve their performance.

The field of autonomous robots is now attracting researchers to areas such as navigation, localization etc. Fig. 1 shows major research areas of autonomous robots. In this work, we investigate terrain-related issues influencing the performance of robot. Conventional motion control and path planning strategies assume smooth navigational surfaces and terrain variations are less considered. The study of terrain profiles involves classification and parameter estimation through suitable models. The developments of learning techniques as well as control algorithms have improved the researches in terrain identification problems [5]. These works are fueled by the researches in new robot system designs [2].

To the best of our knowledge, most of the recent review works on autonomous mobile robots is focusing on trajectory planning, localization, and obstacle avoidance [6–8] with less focus on terrain strategies. The trends in terrain

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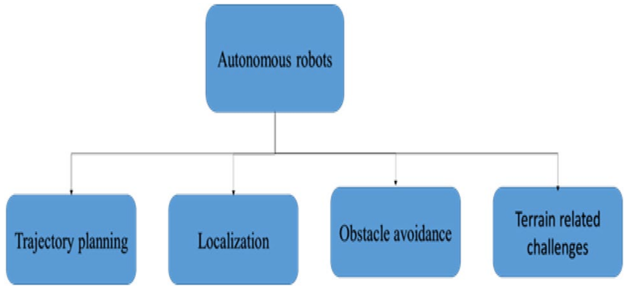


Fig. 1 An overview of research areas in autonomous robots

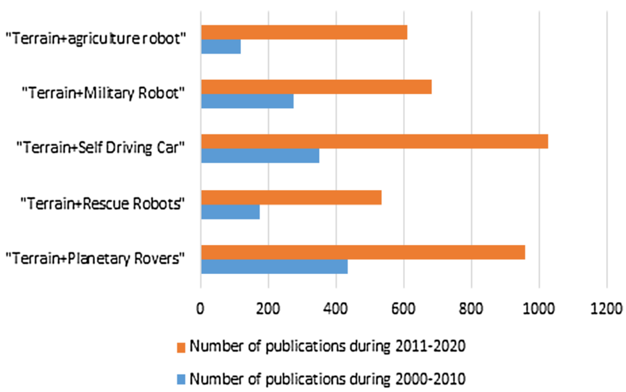


Fig. 2 An overview of research areas of autonomous robots

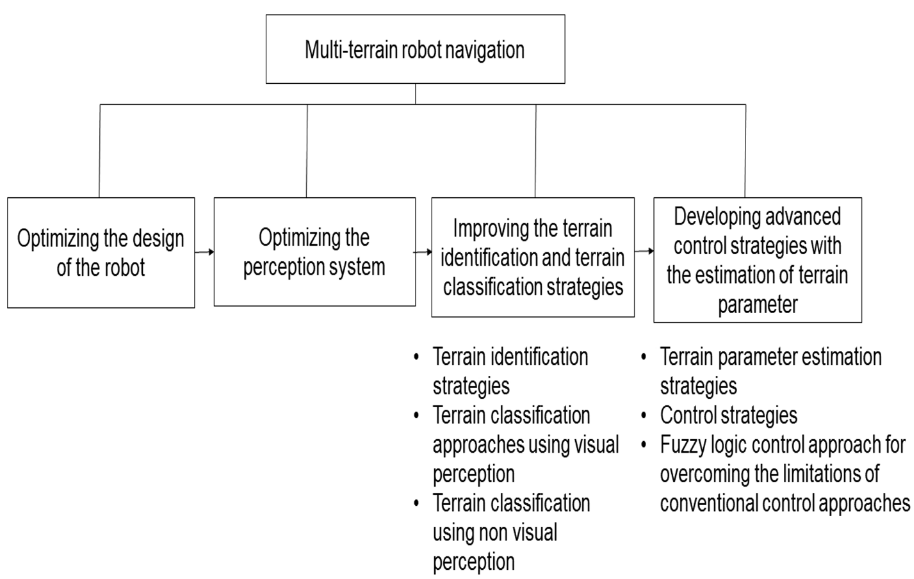
based researches in the field of mobile robots for applications like agriculture, military robots, self-driving cars, rescue robots, and planetary rovers are plotted in Fig. 2 with reference to the corresponding keywords in Science direct website.

The number of researches in the last decade is a sign of the increasing impact of this topic. It motivated us to explore the recent trends in terrain-related challenges in autonomous robots. This challenge is addressed as a unique problem since it affects all other aspects of autonomous robots. This paper is arranged in the following pattern; the researches in robot design are analyzed in the first section, followed by the different sensors used for terrain identification in robots. The terrain-traversability analysis for path planning, recent trends in terrain classifications, terrain parameter estimation methods, the relationship between robot model and the terrain are analyzed in the following sections. In the last two sections, the advancement in control strategies are investigated with focus on fuzzy logic controllers. In short, the recent developments in multi-terrain navigation of robots is investigated and the summary is represented in Fig.3.

2 Recent trends in the robot design

The design of robot has an important role in the process of motion planning through dynamic terrains. Wheeled robots are among the popular designs in autonomous robot systems. Also, any development in the design of wheeled robots produced a great interest in the research of self-driving cars. The wheeled robot has an advantage over other popular designs, due to its efficiency and ease of control. The wheeled robot is classified into the following types; mecanum-wheeled robots [9, 10], differential drive robots, two-wheel balancing robots [11], car-like robots, multi-wheeled robots, etc. To improve the performance in discontinuous structures, researchers investigated the performance on legged robots [12, 13]. Legged

Fig. 3 areas of research in robot multi-terrain navigation



robots are classified according to the number of legs such as biped (e.g.: humanoids), four-legged or quadrupedal robots, hexapod, etc. The design of legged ones is popular due to their less dependency on terrains. The research also includes robust shapes and biologically mimic robots like snake robots (Takemori et al. [14], caterpillar robots [15] and some other robust designs too. Deformable type robots are employed for desired locomotion [16] developed a deformable polygonal type robot with its dynamics. Innovative shapes using elastic structures are developed in [17, 18]. These promising approaches require further investigations for better control strategies and incorporation of different learning strategies

3 Robot perception methods and latest developments

The section analyses the state of the art of sensors used in mobile robots for terrain identification and classifications. Di Feng et al. [19] reviewed the sensors used in mobile robots. Vision-based systems provide a good response. But conventional cameras have shown inferior performance to thermal counterparts for the analysis at night or low light conditions. Various other sensors also used in mobile robots for better performance including LiDARS, RADARS, LiDARS (Light Detection and Ranging) are showing better performance than vision systems in a challenging environment. LiDARS used in 3-D object detection without contacts. The classification will be difficult for LiDARs since it cannot catch the fine texture of the objects. RADARS (Radio Detection and Ranging) uses Doppler Effect for detecting the obstacles as the radio waves emitted by sensors reflected from obstacles. Ultrasonic sensors radiate high-frequency waves to find obstacles but in a challenging environment though it has limitations during high-speed robotic operation. IMU (Inertial Measurement Unit) gives the internal state of the robot. The use of external tools such as the Global Positioning System (GPS) is common in the application of mobile robots. In this context. Along with the navigation, techniques of localization are also investigated. Almeida et al. [20] uses an unidirectional sonar for localization. The authors compared machine learning methods with the Bayesian method and found that the Optimum Forest method (OPF) has better performance than the conventional approach. Hence recent developments in learning techniques have an impact on sensors used in basic mobile robot operations. In his review, Kuutii et al. [21]. explains the recent trends in localization methods. In summary, the authors point out the localization with a single sensor cannot produce an accurate result. Integrated sensory action is required for efficient results. The properties like surface texture, object stiffness, are measured with tactile sensors and frequency domain analysis. These are used for the navigation and localization of mobile robots. The design of 3-D sensors including NIPON Signal F6, IFM O3D200, Fotonic E70P, Microsoft Kinect, and ASUS Xtion Pro Live, have improved the autonomous performance of mobile robots [22]. The possibilities of using low-cost sensors for 3-D detection are also investigated using RADAR and learning techniques [23].

4 Terrain identification and terrain classification strategies

In this session, we are discussing the advanced approaches for terrain identification and classification strategies. These analyze the traversability of surfaces where robot is navigating. Both global and local analysis are executed according to the situation. The robot can decide whether to avoid or navigate through the terrain based on intelligent algorithms. The recent developments provide advanced algorithms to generate paths for robots to avoid difficult terrains. In terrain classification methods, the classes used in different works are analyzed. Then discusses the conventional and modern approaches for accurate classification, which are discussed under session 4.2 and 4.3.

4.1 Terrain identification using geometry based approaches

The Traversability of autonomous robots is influenced by navigating terrains. Researchers have globally approached the issue of traversability, in which the global map is prepared considering the terrain irregularities, and in some other cases, locally i.e., preparing a real-time map for navigation. R. Omar Chavez-Garcia [24] uses a global map from top of the terrain, termed as a height map. The experiments were done using a V-REP simulator. They have investigated two different methods for analyzing the data. The first is a feature-based approach where the histogram of gradient of height map is computed and Random Forest Classifier. The second method is using Convolutional Neural Networks (CNN). In CNN, the system automatically learns the properties with ReLU activation function. Since the mapping is prepared globally, the effect of dynamics of the robot will play a key role and hence the application is limited. Belter et al. [25] used an intelligent algorithm using RGB-D camera and popular classification algorithms like Support Vector Machine, to identify the terrain and developed a motion planning strategy using A* algorithm. The works on global traversability taken on a global scale have limitations for local terrain irregularities. Most methods like Triangular meshes, DEMs (Digital Elevation Maps), or 3D grid maps, may require huge computation in real-time to concatenate the points and to obtain the terrain. Along with the identification of terrains, there are gaps in traversability through the terrains. In general, offline training based methods are tedious and time computing. Philipp Krüsi [12] presented an onboard online terrain analyzing mechanism using 3D mapping. They presented a learning mechanism for both understanding the terrains and the traversability. The concept of point cloud map used for localization is used for terrain assessments. Wermelinger et al. [13] uses a traversability map for navigation of legged robots. Cheng et al. [26] used vision-based techniques to classify the upcoming path and determines traversability by classifying based on a dead-end, left-right turns, junctions using image processing and deep learning techniques and Bayesian classifier. In general, the local approaches for determining the maps are attracting modern researchers. These works are suited for planetary rovers as well as unknown conditions. In the next session, we will see how the advanced learning methods influenced classifying the navigating terrains

4.2 Terrain classification using visual perception

The above works have limitations with geometrical parameters for terrain analysis. An onboard sensor-based analysis can give better results than geometric based mapping that cannot ensure the real factors affecting the traversability in unknown terrains. The conventional vision-based systems provide better real-time performance with the help of other haptic sensors. Manduchi et al. [27] addressed the terrain classification problem by two approaches; using RGB camera and LiDAR. The limitations of vision-based systems affecting the performance of surface reflectivity concerning normal and near-infrared spectra. The classification based on reflectivity faces drawbacks due to the non-linearity in response due to moisture variations, contents etc. The approach of brightness normalization converts the vector $f(r,g,b)$ to $f(r,g)$. The white point calibration of the images and the efficiency of various color based sensors analyzed in vision-based techniques. The LiDAR-based system has been used for terrain classification to overcome the limitations of vision-based systems. Tai et al. [28] developed a multilayer deep learning neural network capable of obtaining data from a simple RGB-D camera. The terrain classification using simple vision techniques requires large data sets and not able to navigate in unfamiliar surroundings. The physical conditions have a big role to play. Kyohei Otsu et al. [29] approached this problem concerning Mars missions. Semi-supervised algorithms are used in place of supervised ones for visual classification systems. The data from different sensors are classified using the Support Vector Machine (SVM). The experiments included An ATV-Jr. Rover is equipped with a stereo camera unit consisting of Point Grey Flea2 cameras and Kowa 3.5 mm wide-angle lenses with a baseline of 0.1 m. Dan Barnes [30] focuses on limitations of semantic segmentation of terrains such as the requirement of a larger data set. To reduce the data set, researchers use virtual data set and using direct learning methods. Lorenz Wellhausen et.al [31] used a multisensory approach in terrain identification with legged robots. Their foothold positions are recorded in camera and labeled for each terrain with the help of onboard sensors. A ground reaction score is marked for the purpose. Convolutional Neural Network (CNN) method is used for training. The possibilities of different camera techniques are investigated. Gray scale, RGB, NIR, thermal cameras are used for basic terrain identification. The recent development of deep learning techniques and improved demand for independent vision-based systems together address the navigation challenges of mobile robots. Rothrock et al. [32] presented a novel software to predict the slip ratio and traversability for mars missions, using the deep learning CNN. The authors connect the techniques of terrain classification to the control strategies of navigation. Vision-based classifications are also investigated in [22, 33–35]. The challenges of visual perceptions are already addressed and several researchers preferred a vision-independent analysis for the terrain classification process. The following session describes some important works which evaluate various sensors and their positioning to address the issue.

4.3 Terrain classification without visual perception

The alternatives to vision-based systems are becoming popular for autonomous robot researchers, as vision-based systems have many limitations. A. Brooks et al. [36] use onboard accelerometer and the vibration measured is trained using Waveform representation. Principal Component Analysis (PCA) is applied in the identification of terrain during online processes. The classes are identified through Probabilistic Distance Measure, analyzed by Class Distribution Analysis carried out offline. As per the findings, the accuracy represented in terms of confidence levels gives 96% to 100% for the four classes of terrain that is gravel, dirt, sand, and unclassified. Dupoint et al. [37] presented a frequency response method for classifying terrains from the vibration-based transfer function. The authors have classified the surface into packed gravel, loose gravel, tall grass, sparse glass, and f sand. Sensor data is processed using FFT (Fast Fourier Transform). A probabilistic neural network is used to obtain the terrain information based on feature extraction by FFT. Giguire et al. [38] focused on solving the limitations of tactile sensors and vision sensors used for terrain identification, normally mounted on the robot, and issues like inertial effect will be affecting it. A probe mounted in the wheel can be flexible to use in any robot irrespective of the design. They used a tactile probe that is in contact with the environment and its output is trained using classification methods which resulted in an accuracy of 94.6%. The tactile probe is designed considering the features to represent each terrain. The sensors should sensitive to power spectral density and Visco-elasticity properties. Solid Aluminium is used for making the probe. The authors preferred to use accelerometers considering various other sensors.

Walas et al. [39] suggested a Laser Range Finder (LiDAR) detect the terrain profile. Intensity of the reflected beam is calibrated in terms of the terrains. Though some previous works use LiDAR, the number of identified terrains was only four. The authors propose 12 terrain profiles which are listed as follows; black rubber tiles, wooden boards, rocks, PVC tiles, ceramic tiles, carpet tiles, artificial grass, grit, pebbles, sand, green rubber tiles, concrete ground. Four different approaches were used to classify the terrains from the intensity output of LIDAR. They are the Statistical Approach, Texton, Fast Fourier Transform, and elevation map. The best result is generated by the 2D FFT approach with 98.47%. But the experiments are conducted on a laboratory scale, and in real-time operation, there exists the possibility of errors.

Chengchao Bai [40] also addressed the issue of terrain identification based on multi-sensor fusion. The authors classified terrain into five types; brick, sand, flat, cement, and soil. The process incorporated offline trained data for feature extraction in vision-based online terrain processes. Dutta et al. [41] use multiple sensors such as GPS, IMU, Laser, and metal detector. The authors motivated for a low coast approach for terrain identification systems. They investigated the replacement of one of the conventional classifiers, SVM (Support Vector Machine), as the on-board computational cost for SVM is high. The authors propose ensembles KNN methods with multiple K values for classification. The terrains are brick, grass, rock, sand, and concrete.

Seyedmeysam Khaleghian et al. [42] classified terrain identification strategies into two types, with contact sensors and non-contact ones. The acceleration signal is collected from the mounted sensor in the tire, slip ratio, and wheel speed collected from the encoder feedback.The experiment repeated at different speeds. Bednarerk et al. [43] refers to tactile based sensing focuses on simulation type environment. Force and torque sensor readings are trained using a neural network for terrain identification. The authors also considered the analysis of speed variations in terrain. Recurrent and convolutional neural networks analysis are conducted for two different models; fixed length step model, variable-length model. An error function is developed for analyzing loss performance. The labeling is done using an encoder-decoder approach. The terrains are classified into six different types, sand, rubber, concrete, floor, artificial grass, chipping, and gravel. The experiments are conducted at three different speeds and six directions. An FFT based processing is done for variable-length signal sampling. Nampoothiri et al. [44] developed a machine learning-based approach for unknown terrain navigation using Inertial Measuring Unit (IMU). The authors investigated a generalized approach for terrain identification with a view of implementing control strategies by real-time terrain identification. The work examines performances of 23 different machine learning algorithms for the real-time classification of terrains where the robot is navigating and observes Ensembles Subspace KNN showing the best accuracy in classifying the slope profile of the terrains. Summary of these methods is given in Table.1.

5 Recent developments in terrain parameter estimation of wheeled robots

The development in study of terrain classification discussed in the previous section can extend to the research of mobile robot motion planning and control with the help of a suitable robot model [45, 46] and tire terrain interaction model [47–51]. The section investigates the role of terrain parameters in controlling torques to the wheels. The robot model is used to implement classical and advanced control strategies such as Model Predictive Control (MPC), Fuzzy Logic Control etc., and with the help of a dynamic model, advancements in soft-computing techniques used for improving the performance of navigation control systems. The approach can be used in any type of mobile robot, for example, by using a dynamic model of autonomous car, its performance can be improved with help of the concepts explained in the survey. The classification techniques in the previous sections as well as the control strategies under our investigation can be applied for the research of the autonomous vehicles, with the help of perception systems and advanced controllers.Similarly, the trends in researches related to terrain parameter estimations show the impact of the same in improving the performance of planetary rovers. In last decade, the works on terrain parameter estimation of planetary rovers have outpaced autonomous robots in terms of nomenclature [52]. It is notable if the works on planetary rovers can be extended to the support of complex actions like agriculture and disaster management.

Iagnemma [53] presented a novel terrain model of wheeled robot generating functions of different terrain parameters in multiple predefined terrains. The predicted values are used to determine the shear strength

Table 1 Recent studies in Terrain classification strategies

Work	Perception	Methodology	Output	Limitations
Tai et al. [40]	RGB Camera, LiDAR	Terrains labeled into soil/rock, dry vegetation, green vegetation and outlier. An algorithm with preprocessed data with nonlinear filter and special coherence approach is proposed.	The algorithm used for obstacle avoidance along with terrain identification.	RGB Camera's use is limited in night and difficult environmental conditions.
Kyohei Otsu et al. [29]	Visual camera, vibration sensors	Terrains are labeled into bedrock, soil and sand (for mars mission). The training is done via co- training and self-training approaches of visual and vibration sensors	Accuracy of 82 % is obtained with Support Vector Machines (SVM) on visual sensors with colour and wavelet based features.	Limitations of visual systems may affect the performance
Dan Barnes [30]	Monocular camera	Terrains classified under asphalt and gravel, grass. A weakly supervised algorithm is for segmentation.	The method is efficient in various external environmental conditions like rain, lightning conditions	The performance is affected by the quality of camera
Chengchao Bai [40]	Vibration sensors	Terrains classified into brick, flat, cement, sand and soil. The terrain is identified online using of an offline terrain data using Deep Multilayer Perception Neural Training (DMLPNN)	The algorithm provide better accuracy, at different speeds and different platforms.	Two levels of training, online and offline is required.
Wellhausen et al. [31]	RGB camera and torque sensor	Terrains are labelled as asphalt, gravel path, grass, dirt and sand. The foothold positions of a legged robot are recorded in camera and labelled for each terrain using of on-board sensor	"Ground reaction score" was generated and this value is used for analyzing terrain properties.	The work is designed for legged robot, and can be implemented in other robots.
A. Brooks et al. [36]	Vibration sensors	Terrain types: Grass, sand and clay. The time domain data is classified to frequency domain data and used for training. Online classification is done by Principle Component Analysis (PCA)	The performance is evaluated and confidence level of 90-100% for various terrains identified	
Dupoint et al. [37]	Vibration sensors	Terrain classes: Packed Gravel, Loose Gravel, Sparse Glass, Tall Grass, Asphalt, Beach Sand. The sensor data is processed by FFT and trained using Probabilistic Neural Network (PNN)	Real time terrain classification under different velocities were tested. Identification of some of the terrain classes were reported 100% at low speeds. (Packed gravel and sand). The accuracies decreased under higher speeds by a little.	Accuracy of the classification can be improved.
Giguire et al. [38]	Tactile probe with metallic sensor and accelerometer attached to wheels	Terrain classes: 6 indoor classes and 4 outdoor classes. Terrains were classified using Artificial Neural Network (ANN)	Eight features from accelerometer output is selected as features. Accuracies of 70-100% under different terrains were produced.	The sensor attached to the tire will reduce the performance
Krzysztof Walas and Michal Nowicki [39]	Laser Range Finder (LIDAR)	Terrain classes: 12 classes including different materials like rubber, wood, rock etc. Support Vector Machines (SVM) were used for classification.	Accuracy of 98% for all classes.	Real time implementation needed assessment

from Coulomb's equation. Iagnemma et al. [54] Introduced a simulation tool for analyzing terramechanical properties of planetary rovers. Timon Homberger et al. [55] proposed a vision-based system, for developing terrain identification parameters of legged robots. The parameters such as roughness and step height are characterized using Inertial Measurement Units (IMU). Yuankai Li [56] proposed an online terrain parameter estimation model for wheeled robots with multimodal methods for different terrains. The sinkage coefficient and internal friction angle, derived from the slip ratio and normal stress equation, are used here. These parameters are preferred over the slip ratio as the latter is ineffective in rough terrains. This work provides an improved algorithm of the work by Yuankai Li [57]. The real-time terrain estimation by two-layer process improves the performance of Extended Kalman filter [58, 59] and Recursive Gaussian Newton algorithm [60]. The algorithm provides a switching property to select between filters. Gao et al. [61], evaluated the performance of vision-based sensors and tactile sensors. The estimated parameter is the sinkage coefficient. In complex missions like mars rowers, the latter part is not able to calculate with ease. A visual camera is used to identify wheel-soil interaction image through a camera and slippage is calculated with a nonlinear adjustment for image processing.

Bijo Sebastian et al. [62] proposed a terramechanics estimation with the help of state sensors. Vision-based terrain identification systems have limitations in terms of variations in surface properties. The sensors like LiDAR, sonar, etc., also prone to errors, and hence the number of sensors needs a reduction. Features of interest that represent the terrains are defined. Principle Component Analysis reduces the data and the Support Vector Machine classifier identifies the terrain class. The terrains are classified into asphalt, grass gravel, artificial turf, and vinyl flooring. The authors used the POZYX tool for the recording of path followed by the robot during training. A linear regression model is formed. James Dallas et al. [51] investigated the formulation of terrain parameters based on soil cohesion and internal friction angle. The model is analyzed using the least square method, Neuton Raphton method, and Simpson's rule, with inputs from the measured internal forces [63]. The work highlights the limitations of existing models where robot parameters and terrain class are linearized, may cause errors, and the outputs from force or torque sensors, may not be feasible in some conditions. A nonlinear model of the road is combined with the bicycle model. An unscented Kalman Filter is used to identify the terrain using a parameter, sinkage exponent. The tire is fixed with a mesh and the terrain parameters are estimated using two models. The bicycle model parameters are determined from the terradynamics model with the help of Unscented Kalman Filters(UKF)). The Bayesian techniques have also performed well in the estimation of terrain parameters. Interestingly, these techniques have a good real-time performance too [64]. Many other recent works [65–68] also focus on the possibilities of new approaches for terrain parameter estimations and simulating the condition [69].

The advancements in machine learning methods have helped to understand the terrain parameter methods of WMR [70, 71]. Using these techniques, the hardness and steepness can be identified. Both supervised and unsupervised algorithms are investigated for this purpose. In unsupervised algorithms, it is important to choose suitable parameters for feature extraction. The comparison studies of both supervisory and unsupervisory learning methods have investigated to predict the slip ratio. A combination of supervisory and unsupervisory learning algorithms have been found successful in predicting the slip ratio [72]. The success of these methods depends on the kind of sensors used for the purpose. The challenges of slips are investigated concerning Mars Rowers and hence the researchers prefer methods like IMU over visual odometry. Proper placing of IMU sensors is also important in determining the success of the machine learning algorithm [73]. One of the major challenges of using machine learning models is to balance between the prediction time and accuracy of the process. Also, the selection of the learning algorithms is important. The recent advancement in machine learning tries to obtain the slippage as a regression value rather than classifying it as categories like a low slip, medium slip, and high slip [74]. The challenges involve factors such as mechanical structure and gravitational field effects, especially for planetary rovers. The challenge related to the parameters of mobile robots such as torque control and velocity control will also play an important role in machine learning-based slip estimation [47].

6 Control strategies for overcoming the effects of terrain variations

The effect of terrain variations is influencing the navigation of mobile robots, as reviewed from the above works. Now we are focusing on the possible control strategies used for compensating the errors caused by terrain variations. Among the various types of mobile robots, we will focus more on WMR (Wheeled Mobile Robot) since it is superior in many aspects such as design, robust mobile control strategies, etc. The navigation of WMR under uneven terrains requires a wheel-terrain interaction model and a dynamic model of the robot. The review focus on how the different control strategies used in addressing terrain-related challenges in autonomous robots.

The relationship between the wheel and its navigating terrain is important in the optimization of traction performance. Terrain estimation models are used to modify the dynamics of mobile robots, and used for control purposes. To regulate the errors caused by terrain irregularities, either the torque control to the wheels or any terrain-related wheel parameter control is used. The variation of slip ratio according to the change in terrain profiles is considered while designing robust control strategies. An optimized slip ratio helps to determine the traction control strategy [75] and thereby improve battery performance. The dynamic model of the robot is required for the torque control in varying terrains. Thus along with slip control, the torque control enables the robot to choose the optimum velocity, hence improved performance [76]. Researches focus on generating a control structure for reducing the terrain effects on wheels, using optimized slip ratio values [77]. The steps of developing an adaptive controller include a slip optimizer, slip controller, and compensator. Terrain modeling can be both empirical and analytical. Bijo Sebastian et al. [78] use Kalman filter and an augmented control to compensate for the terrain irregularities, measured in terms of slip rate. Adaptive controllers with the advancement in Neural Networks have performed well in terrain irregularities. Ngoc-Bach Hoang and Hee-Jun Kang [79] presented an adaptive controller for compensating the dynamic disturbances and wheel slip with a Neural Network based structures, (NN). Mingyue Cui et al. [80] addressed the issue of external disturbance affecting the trajectory control taking the effects to design a state observer function for compensating the error dynamics. Spyros G. Tzafestas [81] reviewed the control architectures affecting autonomous robots. The approaches involved in adaptive control strategies of linear and angular velocities of WMR. Nampoothiri et al. [44], along with an intelligent terrain identification algorithm, proposed a control strategy to overcome terrain irregularities. The approach indicates switching control in terrain-related controls. A general structure of an Adaptive Network-based Fuzzy Inference System (ANFIS) for addressing terrain-related issues is shown in Fig. 4. The error (e) in the position of WMR is transformed by T matrix to the kinematic controller. Hybrid controllers as shown in the figure are developed using various approaches as the combination addresses the limitations due to the non-linearity of dynamic terrains. The desired position and velocity can be obtained with proper control parameter selection, realized by the fuzzification of wheel terrain models and optimized using Neural Network based adaptive mechanism. The Model Reference Adaptive control techniques are also useful in unstructured environments [82]. The adaptive control schemes have limitations in providing exact modeling and switching control schemes for multiple terrains are beneficial in advanced control design. Mauricio Begnini [83] introduced Variable Structure Control (VSC) for mobile robots. VSC is a high-speed switching strategy to control nonlinear trajectories. Previous works on Variable Structure Control are discontinuous and cause errors while switching. The introduction of fuzzy logic provides real-time implementation with logical reasoning. Ming Yue [84] contributed to the control strategy by introducing Sliding Mode Control, a type of Variable Structure Control, along with Fuzzy controllers by defining a sliding surface with a slippage effect. Three types of frictions are considered in the design. They are Coulomb, Viscous, and Stribek Effect frictions. Among various strategies, Neural Network is good in intelligently selecting the proper control. Also, terminal sliding mode control (TSMC) is used. A sliding surface is designed and a Lypanauv function is generated. The use of sliding mode control and fuzzy logic control in path planning strategies to carry different payloads in planetary missions [85], can be extended to address the issue of terrain challenges. The next section focuses on fuzzy logic controllers used in mobile robot control since a high percentage of recent works use fuzzy systems. The understanding of recent developments in fuzzy systems will be helpful for the researchers who are looking to develop control strategies to address terrain issues.

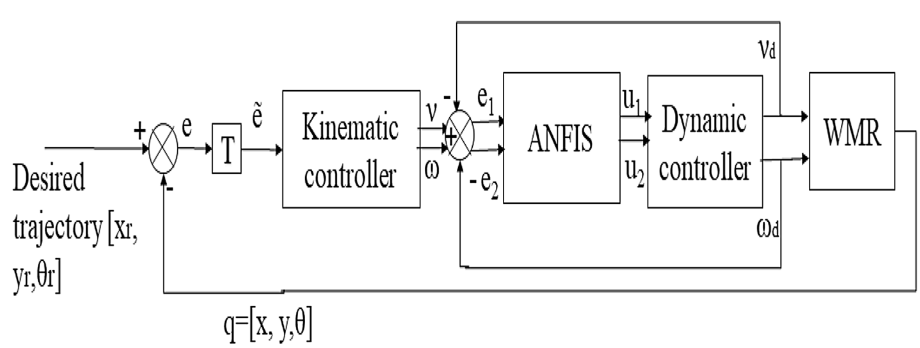


Fig. 4 Structure of Adaptive Network based Fuzzy Inference System (ANFIS) for addressing terrain related issues of a Wheeled Mobile Robot (WMR)

7 Recent developments in using fuzzy logic controllers for autonomous robots

Fuzzy based systems are widely researched in nonlinear mobile robot control with minimal complexity. The ability of fuzzy systems to produce magical results with an intelligent selection of input, output membership functions and fuzzy rules made it very useful for robotic researchers. Yusuke Tanaka et al. [86] use a fuzzy-based approach for reducing terrain disturbance. The authors approached the problem in five steps, first an elevation map of the terrain is generated using a LIDAR and in second step a rectangular grid from the data is generated. Third, the roughness and slope are calculated. Fourth, Fuzzy rules are with these as input membership functions and traversability as output membership functions. Fifth, A Vector Field Histogram (VFH) is created using the result and the optimum path is selected for navigation. Since mobile robots are dealing with multiple challenges, implementing fuzzy controllers show improved performances. Omrane et al. [87] suggested two fuzzy controllers, one is for navigation, and the other is for obstacle avoidance by traversability analysis. The navigation control is realized by distance and angle as input membership functions and left wheel and right wheel velocities as output membership functions. The obstacle avoidance fuzzy controllers use sensor output as an input membership function. It has 62 rules in it. It also has wheel velocities as an output membership function. Both the controllers together provide intelligence for robot navigation. Adaptive control laws are used to address the issues of task planning, environmental modeling, multi-sensory fusion, path planning, and localization of robot in an indoor environment (Azzeddine Bakdi et al. [88]. This approach can optimize the navigation length, travel time ensures the robot's safety using visual perception. The fuzzy logic controllers for mobile robots are analyzed by Budiano et al. [89], Mac et al. [90]. The conventional Fuzzy systems called Type-1 are having some limitations [91]

1. Inputs to the fuzzy controller are from sensors, which may be noisy due to the variations in the environment, cause errors in the Output Membership Function(OMF).
2. The variations in control actions such as force or torque in the actuators will cause errors in the OMF.
3. Fuzzy logic controllers are dependent on linguistic commands that lead to errors.
4. For a complex control problem, the fuzzy rule set will be large. The number of rules will increase exponentially with the of inputs.

A Hierarchical Type-2 Fuzzy controller will be useful to address this issue for mobile robots. A Type-2 fuzzy controller is associated with fuzzy membership function, in place of crisp membership functions in Type-1 controllers. The uncertainty in the membership function termed as the Footprint of Uncertainty (FOU).

The problems of path and trajectory tracking, etc. belong to the deliberative approach whereas navigation, wall following, obstacle avoidance as a Hierarchical Type-2 Fuzzy controller will be useful to address this issue for mobile robots. Cheol-Joong Kim [92] investigated both Type-1 and Type-2 fuzzy logic controllers. Type-1 Fuzzy controllers gave limited results but Type -2 provides better results. An example of Type-2 fuzzy obstacle avoidance for the soccer system developed. A Type-1 fuzzy controller designed with four input membership functions. These are the distance from goal and the nearest obstacle, inclination angle to the goal, and the nearest obstacle. The Type-2 fuzzy membership function is realized by adding mean and standard deviation. This concept extended to overcome the difficulties of terrain irregularities. Abiyev et al. [93] used a Type-2 fuzzy system for optimum performance of mobile robot navigation by avoiding obstacles. The type-2 method has shown superior performance over various other obstacle avoidance algorithms like Vector Field Algorithm Plus (VFH+), Local Navigation, etc. The angles of right and left wheels, as well as the distance to the goal point, are taken as input membership functions, and the turn angle is the output membership function with upper and lower limits. Khalid-Al-Mutib et al. [94] also introduced a Type-2 fuzzy controller for mobile robot navigation. Santiago et al. [95] investigated Type-2 Fuzzy control for mobile robot navigation. The studies of Type-2 fuzzy controllers are expanded to navigation under unstructured environment [96]. The membership function consists of target location and angle as input membership functions and linear and angular velocities as output functions.

Many recent studies suggested the better performance of Type-2 controllers over Type-1 counterpart. Castillo et al. [97] reviewed Type-1 and Type-2 fuzzy intelligent systems. The authors focus on the control where Type-2 fuzzy systems for the left and right wheel torques. Sanchez et al. [98] had a focused analysis on torque control of mobile robots and found the Generalized Type 2 fuzzy controller (GT2FC) performed better than Type-1 fuzzy controller (T1FC) and Interval Type 2 Fuzzy Controller (IT2FC). Martínez et al. [99] also performed GT2FC algorithms on dynamic control of mobile robots and obtained better performance compared with T1FC. A study was conducted by Chia-Feng Juang and Chia-Hung Hsu [100] suggests a Type-2 controller with ant colony optimization for wall following of Autonomous robots. In their further studies, Chia-Hung Hsu and Chia-Feng Juang [101] evaluates species-differential-evolution-activated continuous ant colony optimization (SDE-CACO) along with Type 2 fuzzy control. Castino et al. [102] investigated the bio-inspired optimization techniques for type 1 and type 2 fuzzy controllers for torque control of mobile robots. The recent development in optimization algorithms has influenced fuzzy-based mobile robotics control. Melin et al. [103] introduced chemically inspired optimized algorithms for Type 1 and Type 2 controllers. Hence the possibilities of terrain-based parameters can contribute to the optimization of robot performance by suitable control selection Figueroa et al. [104] presented a Type-2 fuzzy controlled mobile robot for playing soccer games. A vision system is mounted on top of an experimental soccer ground and the camera inputs a membership function for Type 2 FLC. The important take away is the efficiency of Type-2 systems in mobile robots for dealing with uncertainty. Amador-Angulo et al. [105] proposed a hybrid controller with T1FC, IT2FC, and GT2FC along with Bee colony optimization algorithm in trajectory control of mobile robots. Jyun-Yu Jhang [106] suggest a Type-2 fuzzy system with particle swarm optimization for behavior-based mobile robot control approach. Fuzzy logic controllers give better results for reactive approaches.

8 Conclusion

The performance of autonomous robots can be improved by learning the variations in navigating terrains. The recent technological advancements in the navigation of autonomous robots in different terrain structures are analyzed in detail. The terrain-related analysis is necessary for mobile Robots in various strenuous applications. The works in planetary rovers also require indistinct terrain analysis. The review covered various facets of this issue, as follows

1. The researches on the design of the robot, addresses the multi-terrain navigation challenges and improved designs are formed. But focusing on design variations can increase the complexity, in manufacturing and control.
2. The sensors enjoy a key role in the terrain challenges, as they identify and classify different terrains. Visual and non-visual techniques such as haptic sensors are used to address the issue. Specific sensors compatible in size and able to communicate in real-time with the processors are ideal for the purpose.
3. The developments of intelligent techniques like Deep Learning methods influenced real-time terrain identification and classification strategies. The hybrid structures integrating the vision and tactile mechanisms are showing improved performance.
4. The relationship between terrain parameters and robot parameters are important in developing optimal control strategies. The accuracy of the terrain estimation process depends upon robot-terrain modeling. These estimations are influenced by the development in computing techniques. The performance of robots is optimized by the implementation of intelligent control strategies, like Variable Structure Control, Fuzzy Logic Control, etc. The Fuzzy Logic Controllers show optimal performances in nonlinear applications. The recent developments in the field of Fuzzy Logic Controllers for mobile robots are also covered in our survey, as Type-2 systems are used in recent control strategies.

The future scope of the terrain related mobile robot navigation will be to incorporate the development in soft computing techniques to the intelligent control strategies considering the terrain classification and estimation procedures.

Funding The financial support of APJ Abdul Kalam Technological University, Kerala (CERD Research Seed Money) Grant No: KTU/RESEARCH 2/3894/2018 is gratefully acknowledged.

Availability of data and material Not Applicable.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Code availability Not Applicable.

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