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Autonomous Navigation for Unmanned Ground Vehicles in Unstructured Terrain

DOI: 10.34739/si.2024.31.09

Abstract. The problem of autonomous navigation for Unmanned Ground Vehicles (UGVs) in unstructured environments is both challenging and crucial for their deployment in real-world applications. Perception is important, as it provides the necessary information for terrain traversability and environmental awareness. In this article, the developed manned-unmanned vehicle designed to carry out autonomous missions in unstructured terrain is presented, along with the system requirements essential for such operations. Challenges related to environmental perception and navigation in unstructured environments are discussed. Achievements in developing AI models capable of interpreting sensor data are highlighted, demonstrating significant progress in the field of autonomous navigation. However, several gaps remain, particularly in the areas of sensor fusion, real-time decision-making, and adaptability to highly dynamic conditions. Development in the field of autonomous systems allows for a wider expansion of the potential applications of UGVs in various fields, including disaster response, environmental monitoring, and exploration of hazardous environments.

Keywords: Autonomous systems, Unmanned Ground Vehicles navigation, unstructured terrain.

1 Introduction

Unmanned Ground Vehicles are equipped with advanced technologies that integrate environmental perception, navigation, path planning, decision-making, and control [1]. These technologies are related to fields like computer science, data fusion, machine vision, and deep learning. UGVs offer the primary advantage of operating autonomously, replacing humans in tasks such as agricultural, logistics, and military operations including reconnaissance, transportation, explosive detection, fire support, and battlefield rescue. Significant advancements in autonomous navigation have been achieved in urban environment. However, the development of unmanned vehicles has underscored the challenges posed by unstructured terrain. Achieving fully autonomous and reliable navigation in such conditions remains a technological challenge due to the diverse terrains, vegetation, and the presence of irregular obstacles [2]. Off-road environment requires from unmanned platform demanding robust object recognition and optimized sensor performance. Situational awareness is crucially provided through sensor systems and advanced algorithms that extract information from raw data. Sensors are categorized into passive types (such as cameras and infrared sensors) and active types (like LiDAR and radar), each fulfilling specific roles in environmental sensing [3]. Advancements in machine learning, influenced by improved computing power and sensor technologies, drive progress in autonomous navigation. Artificial intelligence and deep learning techniques improve the interpretation of sensor data and the formulation of control strategies, promising advancements in UGV autonomy in complex environments. This study discuss challenges of autonomous navigation for UGVs in unstructured terrain, focusing on the developed TAERO manned-unmanned vehicle system.

2 Description of the Developed Unmanned Platform

The unmanned ground vehicle TAERO (Fig. 1), developed by a collaboration including Military Institute of Armour and Automotive Technology (WITPiS), Stekop, Auto Podlasie, and AP Solutions, is based on modular design that allows it to adapt for different missions.

Figure 1. View of TAERO vehicle (a) and an operational environment(b). Source: own elaboration.

Taero is equipped with a central processing unit, precise GPS with an inertial navigation system (IMU), situational awareness sensors, and mechatronic drives for managing its operation. The modular approach allows integration of various modules like observation heads, weapons, and threat detection systems, making platform versatile. In unmanned mode, TAERO can perform a range of tasks including remote-controlled driving, following predefined routes, autonomous navigation between waypoints, follow guide, operate as shuttle, leading convoys, acting as a mobile control station or conducting reconnaissance using silent mode powered by electric drive.

3 Terrain Traversability Requirements

Unmanned vehicles in unstructured environments cover a wide range of challenging conditions, such as rough terrain, forests, deserts, and mountains. These vehicles are essential for tasks like search and rescue, logistics, and surveillance. Mobile platforms must be able to navigate narrow paths, cross rivers, and handle steep slopes and thick vegetation often blocked by rocks and trees. Changing weather and lighting conditions also affect their performance. To operate effectively, these vehicles use advanced sensors such as LiDAR, cameras, and radar to assess the terrain. Real-time path planning and decision-making algorithms help them avoid obstacles and choose the best routes. A ground vehicle's ability to navigate through different terrain regions depends on several factors, including the terrain model, the vehicle's design and its kinematic constraints [4]. Traversability analysis methods can generally be categorized into two approaches: regression of traversal costs and terrain classification.

Regression methods provide a continuous measure of traversal difficulty, indicating how challenging it is for UGV to traverse a given route. In contrast, terrain classification focuses on identifying different topography types based on their navigational properties. There are also hybrid approaches that combine regression and classification techniques, crating synergy of both. [5] A common approach for navigating unstructured environments involves classifying terrain types, and recent advances in deep learning have greatly improved this method. For instance, the Soil Property and Object Classification (SPOC) tool utilizes a convolutional network to segment terrain types from images, implementing the identification of suitable landing sites and predicting wheel slip [6]. Further improvements in terrain segmentation have been achieved by integrating multispectral imagery, which combines RGB, depth, and near-infrared (NIR) images to handle varying light conditions. Convolutional neural networks (CNNs) have also been used to classify terrain using height maps generated from vehicle simulations, categorizing terrain patches as either traversable or not [7]. Another advancement is the use of semantic 3D mapping, which integrates LIDAR and image data to create detailed maps with both geometric and semantic information. Additionally, path prediction has been acheived through stereoscopic visual odometry, which automatically labels training data by marking drivable areas in images to train segmentation models [8]. Similarly, stereo camera data has been used to build and classify 3D terrain maps using CNNs. These advancements collectively enhance terrain classification and navigation in challenging environments, improving the overall effectiveness of autonomous systems. In autonomous navigation systems, a critical step is translating the results of traversability analysis into actionable movement commands, ensuring that the vehicle can navigate effectively and safely through diverse and challenging environments.

4 Perception Sensors Limitations

Perception systems in unmanned vehicles face significant challenges from adverse weather, impairing object recognition and causing discrepancies between real-time data and maps, which affects localization accuracy. Rain, fog, and snow notably impact these systems. LiDAR, a crucial sensor in unmanned driving, is especially affected by weather. Its performance attributes—range, accuracy, point density, and scan speed—are all impacted. Modern LiDARs offer flexible signal return modalities, providing consistent point clouds in clear conditions. However, in dense fog, the last signal return performs better than the strongest return. Rain and fog reduce LiDAR's range, accuracy, and point density. Rain's impact varies with drop size, causing up to 0,5 attenuation. Condensed water drops on the emitter can cause over 0,5 power loss, making signals unreliable. Rain also affects the point cloud's accuracy and integrity, complicating modeling and simulation. Snow poses different challenges, as snowflakes can form larger objects, causing false detections or obstructing the line of sight. Other phenomena like sandstorms and smog can reduce LiDAR's range by up to 0,75 due to dust particles.

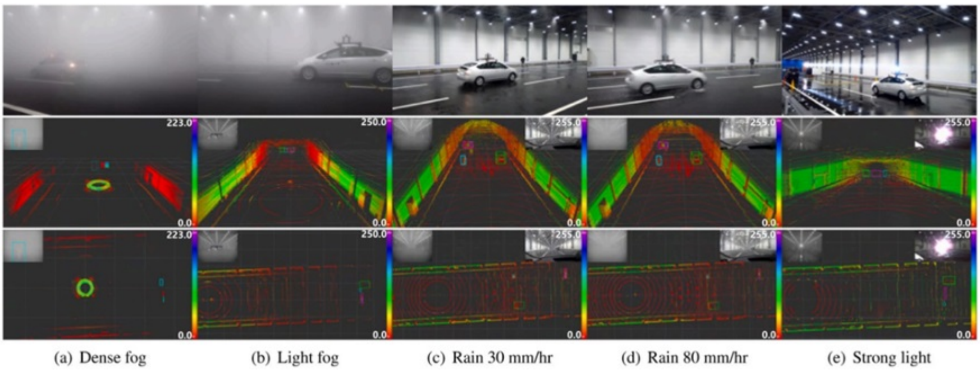

Figure 2. Adverse weather results, top row depicts sample conditions resulting for the 3D LiDAR point cloud thermal camera image. Source: [9]

Cameras in unmanned ground vehicles are sensitive to adverse weather. Rain can render high-resolution cameras ineffective with a single water drop on the lens. Fog obscures visual information, while snow can melt and refreeze on the lens, causing blockages. Strong light sources, like the sun or headlights, also disrupt camera effectiveness and can even impact LiDAR sensors. Automotive radar, operating at millimeter-wave frequencies between 24 GHz and 77 GHz, is robust and less affected by atmospheric fluctuations. However, it faces challenges with higher snow rates due to increased signal attenuation. Additionally, radar has limitations in spatial resolution, which affects its ability to accurately detect and classify object shapes and sizes. One research gap is the difficulty of designing sensor systems that maintain high accuracy and reliability across a wide range of environmental conditions. Most studies focus on improving individual sensor modalities, like enhancing LiDAR or camera algorithms, but few address the combination of different sensor types for improved navigation in unstructured terrains. Furthermore, the use of ultra-wideband (UWB) radar, with its superior penetration capabilities, has not been fully explored for UGVs, especially in terrain filled with vegetation and natural obstacles. The proposed by author solution can penetrate obstacles like grass and bushes, effectively distinguishing them from solid objects, thus reducing the false positives that complicate navigation. The integration of UWB radar with other sensors, such as cameras and LiDAR, could lead to advanced sensor fusion systems improving real-time decision-making even in adverse weather conditions.

5 Conclusions

The difficulties in recognizing and classifying obstacles in dense vegetation and under adverse weather conditions have been examined. Traditional perception systems, including those based on machine learning and image processing, often fail to provide accurate results in unstructured environments. The limitations of existing systems in special-purpose vehicles, such as TAERO, requires more sophisticated and effective solutions. To address these challenges, the integration of advanced sensor fusion techniques, neural networks and improved computer vision models is essential. Future developments should focus on combining dedicated radar sensors with data from LiDAR and cameras to improve obstacle detection.

Acknowledgements This work is supported by project 59.24688.PR at the Military Institute of Armoured and Automotive Technology in Poland.

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