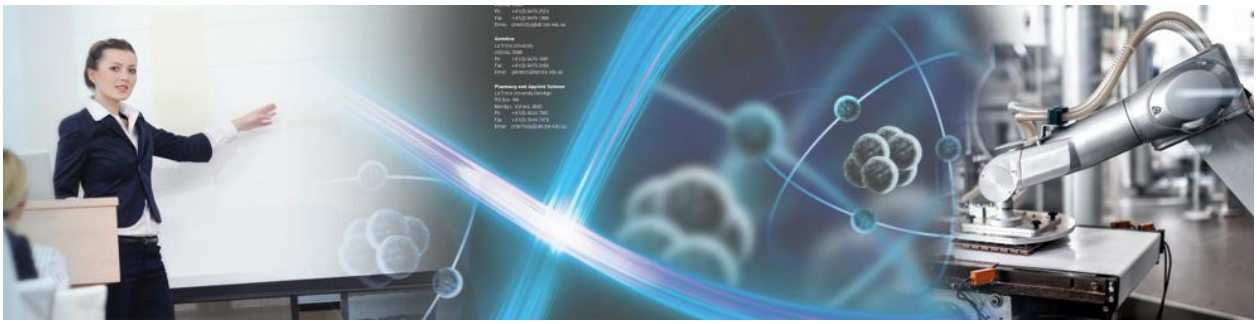
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Інна Хондак

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Methods of Terrain Traversability Assessment Based on Image Analysis for Mobile Robots

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Annotation: The research highlights critical aspects of autonomous mobile robot navigation in unstructured environments. The main focus is on analyzing modern terrain traversability assessment methods based on visual data, including classical computer vision algorithms and advanced deep learning methods. The work discusses the importance of using RGB-D sensors and robust semantic segmentation systems as fundamental components of the architecture of intelligent decision support systems. Particular attention is paid to a comprehensive approach that combines the geometric analysis of the surface with the semantic understanding of the scene. The tables summarize the role of the methods and compare early and late fusion strategies. In addition to the analysis, the paper gives practical recommendations for deploying deep learning models on embedded robotic platforms (INT8 quantization, data augmentation, self-supervised learning, encoder-decoder architectures). Overall, the research emphasizes the important role of a multimodal approach in ensuring the reliable operation of mobile robots in off-road conditions.

***Key words*:** mobile robots, terrain traversability, semantic segmentation, computer vision, deep learning, decision support systems, RGB-D.

I. INTRODUCTION

In today's digital and industrial landscape, autonomous mobile robots have become an integral part of logistics, search and rescue missions, and the exploration of challenging environments [1-10]. Their growing popularity and functionality are accompanied by increased demands on navigation systems. Mobile robots process vast amounts of visual information to build safe routes, making the task of accurately assessing the environment critically important.

The processes of global automation have significantly changed the landscape of control algorithms. Modern navigation tasks are becoming increasingly complex, requiring movement not only on flat surfaces but also in conditions of complex natural or destroyed urban terrain [11-18]. Traditional obstacle avoidance methods often prove insufficient to meet new challenges, such as the false recognition of tall grass or shallow puddles as insurmountable barriers. In this context, the development and implementation of intelligent traversability assessment systems becomes a critical task.

Ensuring effective navigation is closely linked to the development of deep learning methods and neural network-based control systems. The use of deep learning algorithms, robust semantic segmentation mechanisms, and the implementation of self-supervised learning principles can significantly increase the reliability of robot movement. The integration of these technologies contributes to the formation of new, more resilient decision support systems that can adapt to future challenges in autonomous navigation.

Thus, in the context of constantly complicating working environments, the relevance of this research becomes obvious. A comprehensive approach to traversability assessment, combining geometric and semantic data, opens up new opportunities for improving the reliability and efficiency of mobile robots.

This work aims to analyze vision-based terrain traversability assessment methods (semantic segmentation, geometric analysis, and their multimodal fusion), to compare early and late fusion strategies, to substantiate the use of a multimodal RGB-D approach for improving the reliability of autonomous mobile robot navigation in unstructured environments, and to formulate recommendations for deploying deep learning models on embedded robotic platforms.

To achieve this aim, the following tasks are addressed:

- to examine the role of semantic segmentation, geometric analysis, and RGB-D fusion in ensuring safe navigation;
- to describe the processing pipelines of the semantic and geometric approaches, from raw sensor data to a traversability costmap;
- to compare early and late sensor fusion strategies and to substantiate the choice of a multimodal approach;
- to evaluate the advantages of deep learning methods and the challenges of deploying them on embedded platforms (Edge AI load, domain gap, annotation cost);
- to formulate practical recommendations for implementation (INT8 quantization, data augmentation, self-supervised learning, U-Net-type architectures).

II. ROLE OF SEMANTIC, GEOMETRIC, AND FUSION METHODS IN TRAVERSABILITY ASSESSMENT

In the modern environment, where the number of autonomous systems is growing rapidly and their operating conditions are becoming increasingly complex, the role of visual sensors is becoming critical. Modern intelligent tools allow not only for a faster and more accurate assessment of terrain traversability but also for adaptation to new types of surfaces, thereby increasing the overall level of autonomy.

Traversability assessment relies on three groups of methods: semantic segmentation of RGB images, geometric analysis of depth and LiDAR data, and their fusion. Table 1 summarizes the role of each in ensuring navigation safety.

Analysis of the presented methods demonstrates a multi-layered approach to ensuring navigation. Semantic segmentation forms the basic level of understanding, providing spatial categorization. Geometric analysis creates a second layer of defense, monitoring the physical possibility of passage.

Table 1. Role of semantic, geometric and fusion methods in traversability assessment

Analysis method	Role in ensuring mobile robot navigation
Semantic segmentation (RGB) [19]	Classification of surface types (asphalt, grass, mud, water) at the pixel level.
	Ensuring the understanding of the scene context to ignore "soft" obstacles.
	Formation of a basic visual Costmap.
Geometric analysis (Depth / LiDAR) [20]	Assessment of the physical shape of the surface (slope, presence of deep pits, step height).
	Calculation of terrain roughness based on point cloud variance.
	Protection against collisions with hard obstacles invisible on a flat 2D image.
Data fusion (RGB-D Fusion) [21]	Verification of semantic data using three-dimensional geometry.
	Compensation for the shortcomings of optical cameras in poor lighting conditions.
	Creation of a comprehensive intelligent decision support system.

The comprehensive application of these mechanisms is critically important for creating a reliable system. Each layer compensates for the potential weaknesses of others, forming an effective multi-layered decision-making architecture.

III. MAIN METHODS OF IMAGE ANALYSIS AND ALGORITHMS

The collection and analysis of visual data is a top priority in ensuring navigation, as errors can lead to serious consequences ‑ from the robot getting stuck to physical damage. Modern systems face a wide range of visual disturbances, requiring a comprehensive approach. The most common methods include texture analysis, semantic segmentation using CNNs, and geometric analysis. Texture analysis is a classical computer vision approach that characterizes surfaces by statistical texture descriptors (for example, gray-level co-occurrence matrices, local binary patterns, or Gabor filters); it is computationally inexpensive, but it is sensitive to lighting changes and is less accurate than deep learning methods in complex natural scenes; therefore, it is considered here as a classical baseline, and the further analysis focuses on segmentation, geometry, and their fusion. Semantic segmentation is one of the most effective tools for traversability assessment: it allows a neural network to divide the image into surface and object classes. The semantic segmentation process represents a continuous visual data processing pipeline. At the initial stage, the system receives a standard color RGB image from the mobile robot's optical camera, which serves as the primary source of environmental information. This input data is then fed into a deep learning architecture, where convolutional neural networks (CNNs) or vision transformers scan the image to extract hidden patterns, low-level details such as boundaries and colors, and high-level semantic features like surface textures and obstacle shapes. Based on these extracted features, the neural network generates a segmentation mask by assigning a specific category – such as asphalt, grass, or water – to each pixel or group of pixels, while simultaneously smoothing boundaries and removing visual noise to improve overall accuracy. Subsequently, the recognized semantic classes are evaluated according to the physical capabilities of the specific robot, allowing the system to classify the environment into safe navigational zones and dangerous obstacles. In the final stage, this classified data is transformed into a topographical traversability costmap, which is directly integrated into the robot's navigation stack and utilized for planning an optimal and safe route [22].

At the feature extraction stage, the network analyzes texture and color patterns; convolutional filters (in CNNs) and attention mechanisms (in transformers) extract features at different levels of abstraction. At the mask generation stage, the features are transformed into a class map, where each pixel is assigned a probability of belonging to a specific surface class.

Geometric analysis uses depth data to estimate slope and roughness. Depth information is obtained by measuring the distance to surface points (by stereo disparity, time-of-flight, or laser ranging) and is represented either as a depth image or as a point cloud. In this work, both forms are considered as visual data: a point cloud can be projected onto an image plane (a range image) or onto a grid (a height map), which allows it to be processed with image analysis methods and fused with the RGB image.

The geometric surface analysis process begins with the acquisition of spatial data from stereo cameras or LiDAR sensors, which generate a raw point cloud of the surrounding environment. This initial data undergoes a filtering stage to remove noise and outliers, which improves the accuracy of the three-dimensional representation. The filtered point cloud is then projected onto a range image or a height map, which allows the geometric data to be processed with image analysis methods, consistent with the semantic pipeline. Following this, the system calculates surface normals for the projected data to determine the spatial orientation and slope of the terrain. Subsequently, height variance is estimated to evaluate surface roughness, identifying irregular features such as steep bumps or deep depressions. Based on these combined geometric metrics, the system makes a final decision regarding geometric traversability, determining whether the physical characteristics of the terrain allow for safe passage. The resulting geometric traversability estimates are projected onto a grid map and form a geometric costmap, which is combined with the semantic costmap for route planning.

To maximize navigation reliability, multimodal sensor fusion combines the strengths of both approaches: the semantic context obtained from RGB imagery is complemented by the surface geometry obtained from depth sensors or LiDAR. This enables an intelligent decision support system to analyze both the visual context and the physical structure of the environment, which ultimately

leads to safe movement execution. Depending on the stage at which the modalities are merged, early, intermediate, and late fusion are distinguished. In early fusion, data is combined at the input to form a four-channel RGB-D image, allowing the network to learn color and spatial correlations from the ground up. Intermediate fusion merges features from separate encoders inside the network. In late fusion, each modality is processed by a separate branch, and the results are merged only at the decision stage to form a navigational command.

The main differences between early and late fusion, as the two extreme options, are summarized in Table 2.

Table 2. Comparison of early and late fusion strategies

Criterion	Early fusion (four-channel RGB-D input)	Late fusion (separate branches, merged at decision level)
Accuracy	Potentially higher, since the network learns joint color-geometry correlations from the lowest level; requires accurate spatial alignment and calibration of the sensors.	May miss low-level cross-modal correlations, but each branch can use the model best suited to its modality.
Computational load	Lower: one network, one forward pass.	Higher: two branches (or networks), more memory and energy; branches can run in parallel or at different rates.
Robustness to sensor failure	Low: a corrupted or missing depth channel degrades the whole network's output.	High: if one modality fails, the other branch still produces a result (graceful degradation).
Data requirements	Needs synchronized, pixel-aligned RGB-D training data with joint annotation.	Branches can be trained separately, including on large RGB-only datasets; joint data is needed only for the fusion stage.

Thus, early fusion is preferable for compact platforms with limited computing resources and reliable, calibrated sensors, whereas late fusion is better suited to cases where redundancy and graceful degradation are critical, for example, off-road conditions where poor lighting or dust degrades one of the modalities; intermediate fusion offers a compromise between the two. Accordingly, the comprehensive approach considered in this work is a multi-layered scheme that combines a semantic layer, a geometric layer, and a fusion layer, where the fusion strategy is selected according to the computing resources of the platform and the reliability of its sensors.

The overall scheme is shown in Fig. 1.

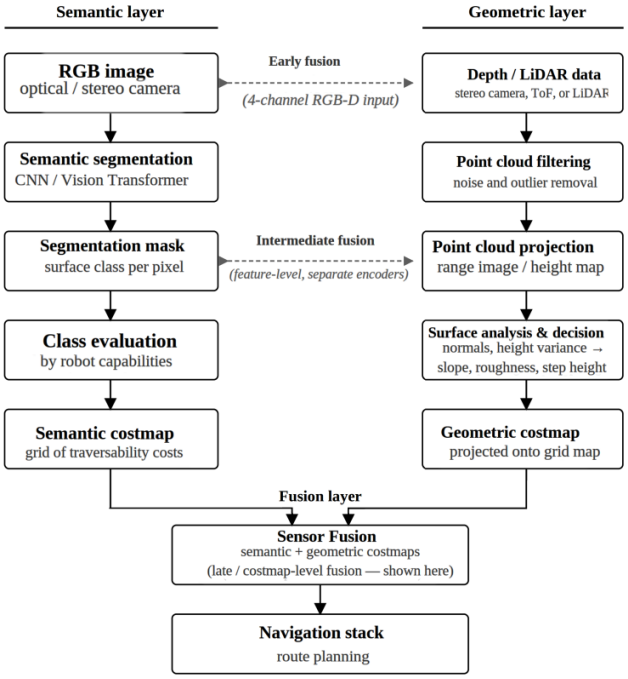


Fig. 1. Multi-layered scheme of terrain traversability assessment

Solid arrows show the pipeline implemented in this scheme (late, costmap-level fusion); dashed arrows mark alternative points where early (input-level) or intermediate (feature-level) fusion could instead be applied.

IV. DEEP LEARNING METHODS AND IMPLEMENTATION PROBLEMS

Deep learning algorithms represent a fundamental component of intelligent decision support systems in modern robotics. The primary benefit of employing these methods lies in their high accuracy when operating in unstructured environments. Such systems demonstrate a good understanding of the global context, allowing them to capture the scale and physical properties of objects, such as distinguishing soft grass from a hard stone of a similar color. Furthermore, advanced models exhibit good robustness to visual noise and offer self-supervised learning capabilities. This allows the robot to use proprioceptive data, such as chassis vibration or motor torque, for the automatic supplementary labeling of visual information, significantly reducing the reliance on manual data processing.

Despite these substantial benefits, the deployment of deep neural networks on mobile platforms is accompanied by a number of technical and operational difficulties. One of the most critical issues is the heavy computational load associated with Edge AI. The inference of complex models, particularly Vision Transformers, requires significant processing power, which directly strains the limited energy

resources and battery life of mobile robots. Additionally, developers frequently encounter the domain gap problem, where a navigation system successfully trained in a simulated environment sharply loses its accuracy when transferred to a real-world forest or urban setting. Other significant hurdles include the algorithms' heavy dependence on dynamically changing lighting conditions and the high financial and time costs of manual data labeling in off-road scenarios.

To mitigate these implementation challenges, several practical strategies should be considered during the development phase. Utilizing model quantization, specifically by reducing neural network weight bitness to INT8, significantly decreases the computational burden and allows these complex models to run efficiently on low-power, energy-efficient chips. Furthermore, implementing robust data augmentation methods that simulate various weather, lighting, and seasonal conditions can effectively help bridge the domain gap between simulation and reality. To reduce the cost of manual labeling, self-supervised learning from proprioceptive data (chassis vibration, motor torque) can be used to generate supplementary labels automatically. Finally, applying widely used encoder-decoder architectures, such as U-Net, can provide a good balance between processing speed and segmentation accuracy, which helps to achieve real-time performance on constrained mobile robotic platforms.

V. CONCLUSIONS

This work presents an analysis of key aspects of mobile robot navigation in the context of terrain traversability assessment in unstructured environments. The main results of this work are as follows:

1. Systematic analysis of key methods. The study has examined visual approaches: classical texture analysis (as a baseline), semantic segmentation of RGB images, geometric analysis of depth and LiDAR data, and their integration. The operating principles of the semantic and geometric methods are described, from raw sensor data to a traversability costmap. Semantic segmentation classifies surface types (asphalt, grass, mud, water) and forms the base costmap, which helps to avoid treating "soft" obstacles such as tall grass as impassable. Geometric analysis evaluates slope, roughness, and step height and protects against collisions with hard obstacles that are hard to see in a 2D image. Classical texture analysis, based on statistical descriptors, is computationally inexpensive but sensitive to lighting changes and less accurate than deep learning methods in complex natural scenes.

2. Analysis of multi-layered fusion strategies. Multi-layered strategies (Sensor Fusion) are described, in which semantic and geometric layers verify and complement each other. Early and late fusion strategies are compared: early fusion (four-channel RGB-D input) is less computationally demanding and can learn joint color-geometry correlations, but it is sensitive to sensor failure and requires accurate sensor calibration. Late fusion (separate branches merged at the decision stage) is more robust, allows the branches to be trained on separate datasets, and is better suited to cases where redundancy is critical, while intermediate fusion offers a compromise. The choice of strategy depends on the platform's computing resources and sensor reliability. This analysis makes it possible to select a fusion strategy for a specific robotic platform.

3. Evaluation of deep learning methods. The research has analyzed the role of neural networks in scene understanding, examining both their advantages (high accuracy in unstructured environments, robustness to visual noise, self-supervised learning from proprioceptive data) and implementation challenges (Edge AI computational load, power consumption, domain gap, dependence on lighting conditions, high cost of manual data labeling). Practical measures to mitigate these challenges are recommended: INT8 quantization, data augmentation simulating weather, lighting, and seasonal conditions, self-supervised learning from proprioceptive data, and encoder-decoder architectures such as U-Net, which can balance speed and segmentation accuracy.

4. Substantiation of the multimodal approach. The analysis indicates that a multimodal approach combining semantic and geometric data (RGB-D) is the most promising way to ensure reliable navigation in off-road conditions, since each modality compensates for the weaknesses of the other, including poor lighting for optical cameras. The specific fusion strategy should be selected according to the platform's computing resources and sensor reliability.

The described concepts and recommendations can be used in the design of intelligent control algorithms for mobile robots. Further development of this work should focus on domain adaptation between simulated and real environments, robustness to changing lighting conditions, optimization of models for low-power embedded hardware, improvement of self-supervised learning without human intervention, and experimental comparison of CNN-based (e.g., U-Net) and transformer-based segmentation models on a real robotic platform.

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