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A comprehensive review of control and guidance strategies for unmanned ground vehicles in lane tracking and leader-follower applications

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Abstract:

Introduction/purpose: *Unmanned Ground Vehicles (UGVs) offer significant advantages for various operations; yet their autonomous control and guidance present substantial difficulties, especially for diverse locomotion types (e.g., tracked, wheeled) in challenging terrains due to complex dynamics, nonholonomic constraints, and environmental interactions. This paper provides a comprehensive review of control and guidance strategies for UGVs, with a specific focus on leader-follower and lane tracking with obstacle avoidance applications. It aims to synthesize the state of the art, identify key challenges generic to UGV autonomy*

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in these tasks, and discuss promising guidance and control methodologies.

Methods: *An extensive literature review was conducted, analyzing existing research on UGV, autonomy levels, system architectures, control methodologies (including classical, adaptive, robust, and intelligent approaches), guidance approaches, and specific application domains. Methodologies for guidance and control relevant to UGVs in leader-follower and lane tracking tasks were critically examined.*

Results: *The review identifies dominant trends, including the increasing use of deep learning for guidance perception and growing interest in robust control techniques capable of handling UGV operational challenges. Significant challenges persist in perception for unstructured environments, accurate dynamic modeling for diverse UGV platforms, seamless integration of perception with robust control and guidance systems, and extensive real-world validation.*

Conclusions: *Achieving robust autonomy for UGVs in complex real-world scenarios require integrated solutions addressing guidance and control. Advanced robust control methods emerge as strong candidates for UGV control, but their full potential necessitates further research into their integration with advanced guidance systems.*

Key words: *unmanned ground vehicles (UGVs), control systems, guidance systems, leader-follower, lane tracking, obstacle avoidance, autonomous navigation.*

Introduction

The field of robotics and autonomous systems has witnessed exponential growth, leading to the development and deployment of sophisticated Unmanned Ground Vehicles (UGVs) across a multitude of domains (Sethi, 2024; Fareh et al., 2021). UGVs, capable of operating autonomously or semi-autonomously without direct human piloting, offer transformative potential in areas deemed too dangerous or complex for human operators. Applications span military operations (reconnaissance, logistics, explosive ordnance disposal), agriculture (precision farming, harvesting), search and rescue, logistics (warehouse automation, last-mile delivery), and infrastructure inspection (Ni et al., 2021; Shafaei & Mousazadeh, 2023; Gadekar et al., 2023; Durst et al., 2018).

Among diverse UGV platforms, various locomotion types exist, each with unique advantages and control complexities. For instance, tracked vehicles offer superior traction in unstructured terrains but introduce challenges like skid-steering dynamics and track slippage (Sebastian & Ben-Tzvi, 2019b; Zou et al., 2018). Wheeled vehicles are efficient on structured surfaces but are limited in off-road mobility. Achieving reliable autonomous operation for any UGV type introduces significant complexities in their control and guidance, including inherent nonlinearities, platform-specific dynamics (e.g., skid-steering in tracked vehicles, Ackermann steering in some wheeled vehicles), sensitivity to terrain variations, and susceptibility to external disturbances (Al-Jarrah et al., 2019; BaniHani et al., 2021; Zou et al., 2018; Artuñedo et al., 2024).

This review paper focuses on the critical aspects of control and guidance for UGVs, specifically addressing two demanding autonomous tasks: leader-follower control and lane tracking with obstacle avoidance. Leader-follower systems, where a UGV autonomously follows a human or vehicular leader, are essential for applications like convoying, collaborative robotics, and human assistance (Ramírez-Neria et al., 2023a; Wang, 2024). Lane tracking with obstacle avoidance is fundamental for UGV navigation in semi-structured environments, such as agricultural fields, mining sites, or pathways, requiring the UGV to adhere to lane boundaries while safely avoiding obstacles (Cao et al., 2020; Zhang et al., 2023). Both tasks demand high levels of robustness, adaptability, and real-time responsiveness from UGVs operating in dynamic and often unpredictable environments.

Traditional control methods, such as Proportional-Integral-Derivative (PID) controllers, often struggle to provide the required performance and robustness for diverse dynamics encountered in UGVs, especially when dealing with strong nonlinearities, time-varying parameters, and unmodeled dynamics (Kayacan et al., 2015; Rizk et al., 2023). While advanced techniques like Model Predictive Control (MPC) or adaptive control offer potential benefits, they often rely on accurate system models or complex tuning procedures, which can be impractical for UGVs operating in diverse conditions (Zuo et al., 2021; Fareh et al., 2021).

More recent approaches, such as observer-based robust control methods, aim to address these limitations by actively estimating and compensating for disturbances and model uncertainties, often reducing the dependence on precise mathematical models and offering inherent robustness. These characteristics make them well-suited for complex and often poorly modeled dynamics found across various UGV platforms (Fareh et al., 2021; Sebastian & Ben-Tzvi, 2019a).

This paper is structured as follows: the section "Overview of unmanned ground vehicles (UGVs)" provides an overview of UGVs, covering their history, levels of autonomy, and types of locomotion. The section "System architecture for autonomous navigation in UGVs" details the system architecture for UGV autonomous navigation, focusing on the guidance system and the control system. The sections "Lane tracking task in UGVs" and "Leader-follower task in UGVs" delve into the overview for lane tracking/obstacle avoidance and leader-follower control for UGVs, respectively. The section "Synthesis of findings and dominant trends" discusses the findings and the section "Conclusion and future research directions" concludes the review and suggests future research directions applicable to UGVs.

Overview of unmanned ground vehicles (UGVs)

Unmanned Vehicles (UVs) are frequently engineered as autonomous systems, capable of environmental perception, trajectory planning, and autonomous control without human intervention (Sethi, 2024). This broad category encompasses aerial, underwater, and ground-based systems. Unmanned Ground Vehicles (UGVs), the focus here, have seen significant development driven by technological advancements and diverse application demands (Fareh et al., 2021).

To provide a comprehensive foundational framework necessary for effective control and guidance, this section will detail the various levels of autonomy in UGVs, explore their diverse types based on locomotion, and outline the inherent challenges associated with their autonomous operation.

Levels of autonomy in UGVs

UGV capabilities are often defined by levels of autonomy, indicating the degree of independent operation. The Society of Automotive Engineers (SAE) provides a standard six-level classification for driving automation (Sethi, 2024; van der Sande & Nijmeijer, 2017), illustrated in Figure 1. This ranges from **Level 0** (no automation), where humans perform all driving tasks. The next, **Level 1** (assisted driving automation), offers either steering or speed control with full human supervision, while **Level 2** (partial automation) provides both steering and speed control, requiring constant driver readiness for intervention. In **Level 3** (conditional automation) the system performs all driving tasks under specific conditions, prompting the driver for control when needed, and **Level 4** (high automation) allows the system to handle all driving tasks and fallback within a defined operational domain, even without driver's response. Finally, **Level 5** (full automation) signifies the system's ability to perform all driving tasks under all conditions, requiring no human intervention.

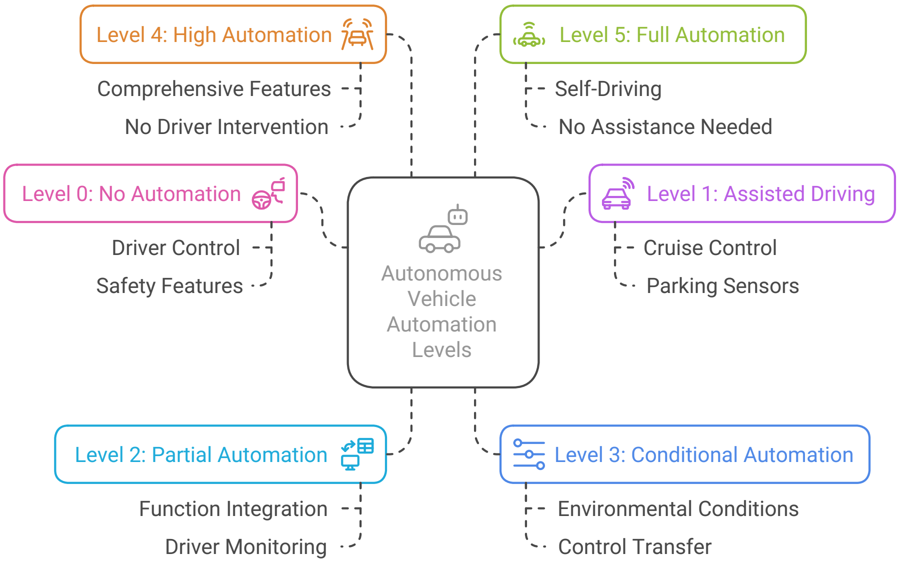

Figure 1 – Autonomy levels in UGV systems

Types of UGVs based on locomotion

UGVs have evolved into a diverse range of platforms, each with unique locomotion mechanisms and capabilities. These differences stem from the need to adapt to various operational environments and tasks. The primary locomotion strategies employed in UGVs can be categorized into four main types: wheeled, tracked, legged, and hybrid systems.

- **Wheeled UGVs**: utilize the rotational motion of wheels for movement, common for their simplicity and efficiency on structured surfaces. Various steering architectures (e.g., differential, Ackermann, omnidirectional) provide varying degrees of maneuverability and stability (Ahluwalia et al., 2022; Rubio et al., 2019; Tagliavini et al., 2022).

- **Tracked UGVs**: employ continuous tracks for a large ground contact area, enhancing traction and stability on complex, uneven terrains. Skid-steering is typically used by varying track speeds. This structural design facilitates maneuverability and robust locomotion in complex and rough environments, such as military operations and agriculture (Sebastian & Ben-Tzvi, 2019b; Zou et al., 2018; Shafaei & Mousazadeh, 2023).
- **Legged UGVs**: mimic living things (e.g., animal, human) locomotion using actuated limbs for movement in discrete steps, enabling traversal of highly unstructured terrains and obstacles (Ahluwalia et al., 2022; Zhao et al., 2023).
- **Hybrid UGVs**: combine multiple locomotion types to leverage their respective advantages and enhance adaptability across diverse conditions, leading to a more complex and flexible system (Ahluwalia et al., 2022; Teji et al., 2023).

Table 1 summarizes the advantages and disadvantages of each type.

System architecture for autonomous navigation in UGVs

Autonomous UGV operation typically relies on a hierarchical system architecture to manage the complexity from sensing to actuation. This review adopts a common conceptualization involving distinct but interconnected systems: a guidance system (encompassing perception and decision-making) and a control system (responsible for motion execution) (Ni et al., 2018; Samak et al., 2021; Yao et al., 2020; Zhang et al., 2023). Figure 2 illustrates this general architecture. The following subsections will provide the details of these two core systems, exploring their functionalities and key components in UGV autonomous navigation.

Guidance system

The guidance system acts as the ”brain” of the UGV, responsible for interpreting the environment, making intelligent decisions, and planning the vehicle's motion (Wang, 2024; Horri et al., 2024; Zheng & Gao, 2010). It forms the cornerstone of the architecture, supplying essential environmental awareness that supports higher-level decision-making and control processes (Gao et al., 2001; Durst et al., 2018; Samak et al., 2021).

UGV Type	Advantages	Disadvantages	References
Wheeled	High energy efficiency, low cost, simple control, high speed on flat terrain, suited for structured environments.	Limited off-road capability, prone to slipping/skidding on loose surfaces, poor mobility on rough terrains.	Man et al. (2018); Thrun et al. (2006); Ahluwalia et al. (2022); Rubio et al. (2019); Tagliavini et al. (2022); Teji et al. (2023)
Tracked	Superior traction/stability on challenging terrains (sand, mud, slopes, rocks), high load capacity, large ground contact.	High energy consumption, complex mechanics, less maneuverable than wheeled, complex turning dynamics, prone to slippage.	Sebastian & Ben-Tzvi (2019b); Zou et al. (2018); Shafaei & Mousazadeh (2023); Ahluwalia et al. (2022); Li et al. (2021); Alexa et al. (2023); Wang et al. (2024b); Al-Jarrah et al. (2019); BaniHani et al. (2021); Liu et al. (2024)
Legged	High maneuverability in complex/cluttered terrains, stair climbing, high adaptability/obstacle negotiation.	High system complexity, high energy/computational load, less efficient over long distances, difficult control design.	Ahluwalia et al. (2022); Tian et al. (2021); Zhao et al. (2023)
Hybrid	High versatility across terrains due to multiple locomotion mechanisms, adaptable for complex tasks, enhanced performance.	Complex control implementation, high cost/design complexity, increased hardware/computational needs.	Ahluwalia et al. (2022); Teji et al. (2023)

Table 1 – Comparison of UGV locomotion types

Types of autonomous navigation and decision making

The guidance system plans the UGV motion based on the perceived environment and mission goals. Autonomous navigation tasks for UGVs can be categorized into three fundamental types:

- **Point-to-Point navigation**: the UGV moves from a start to a goal location without a predefined path, primarily focusing on reaching the destination while avoiding obstacles, regardless of the specific path geometry or velocity profiles (Ruslan et al., 2023; Stanković et al., 2024).

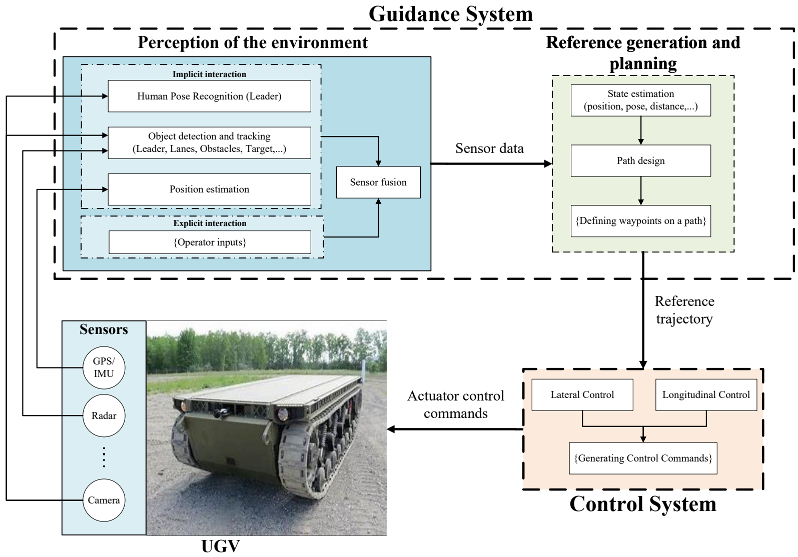

Figure 2 – Typical system architecture for autonomous UGV navigation

- **Path following**: the UGV converges to and follows a predefined geometric path (e.g., lane centerline) without strict temporal constraints. The objective is spatial convergence (minimizing cross-track error), allowing velocity flexibility along the path. The UGV's forward speed follows a predefined speed profile, while the control system primarily regulates the vehicle's orientation to ensure convergence to the desired path (Hung et al., 2023; Ruslan et al., 2023; Sarcinelli-Filho & Carelli, 2023). This typically involves regulating orientation for path convergence, often resulting in smoother control than trajectory tracking (Aguiar & Hespanha, 2007; Stanković et al., 2024).
- **Trajectory tracking**: the UGV must follow a time-parameterized trajectory specifying both position and velocity at each instant. This requires simultaneous spatial and temporal convergence, making it more complex than path following (Sarcinelli-Filho & Carelli, 2023). It is crucial for applications like leader-follower systems where precise motion (speed and orientation) replication is needed (Ruslan et al., 2023; Hung et al., 2023; Stanković et al., 2024).

In essence, Point-to-Point navigation only specifies a destination. Path following focuses on spatial adherence to a geometric path, whereas the velocity of the vehicle is defined by the designer. Trajectory tracking requires traversing the specified path while the velocity of the vehicle, in terms of both magnitude and direction, is defined by the trajectory being tracked.

Sensing and scene understanding for guidance

This sub-system acts as the system's senses, responsible for gathering and fusing information about the vehicle's internal state and its external environment to create a meaningful representation for decision making (Balasubramaniam & Pasricha, 2022). Key components include:

- **Exteroceptive sensors:** provide information about the external surroundings (Liu et al., 2021c). Common types include:
  - **Cameras (monocular, stereo, omnidirectional):** capture visual data (color, texture) for tasks like lane/object detection, leader tracking, and obstacle avoidance (Burke & Brink, 2010; Schulte et al., 2022; Liu et al., 2021c). Images are often processed by machine learning (ML) and deep learning (DL) models for real time and adaptability to various lighting conditions. Vision is critical for this review's focus on leader following and lane tracking with obstacle avoidance.
  - **LiDAR (Light Detection and Ranging):** emits laser pulses to measure distances, generating 3D point clouds for environmental mapping, obstacle avoidance, and path planning (Gadekar et al., 2023; Balestrieri et al., 2021).
  - **Radar:** uses radio waves to detect objects, measuring their distance, speed, and direction. Effective in diverse weather and at long ranges, complementing optical sensors (Balestrieri et al., 2021).
- **Proprioceptive sensors:** measure the UGV internal state (Liu et al., 2021c). Common types include:
  - **GNSS (Global Navigation Satellite System):** e.g., GPS - determines absolute vehicle position for global navigation and trajectory tracking.
  - **IMU (Inertial Measurement Unit):** provides acceleration and angular velocity data for precise state estimation and motion control, especially in GPS-denied environments.

- **Sensor fusion algorithms:** integrate data from diverse sensors to yield a more comprehensive and robust environmental understanding than possible with individual sensors (Hu et al., 2020). For instance, fusing LiDAR and camera data can enhance 3D mapping and object detection accuracy, improving overall perception reliability by combining complementary information and filtering noise.
- **Detection and recognition algorithms:** process sensor data to identify relevant entities.
  - *Object detection/tracking:* involves identifying and tracking entities like pedestrians, vehicles, obstacles, or specific leaders. Deep learning, particularly convolutional neural networks (CNNs) like YOLO and its variants (e.g., YOLOv8), are prominent for their real-time speed and accuracy (Redmon et al., 2016; Terven et al., 2023; Vijayakumar & Vairavasundaram, 2024). The name YOLO stands for "You Only Look Once", referring to the fact that it was able to accomplish the detection task with a single pass of the network (Redmon et al., 2016). YOLO models, known for efficiency with monocular cameras, have evolved to offer high performance in autonomous navigation and robotics (Terven et al., 2023; Hussain, 2024).
  - *Lane detection:* focuses on identifying lane markings or road boundaries. While traditional methods used edge detection and Hough transforms (Aly, 2008), modern approaches heavily rely on DL, often using semantic segmentation (e.g., encoder-decoder architectures) (Ni et al., 2020; Sun et al., 2019). Multi-task learning models like YOLOP advance this by simultaneously performing lane detection, drivable area segmentation, and object detection for improved efficiency and contextual awareness (Wu et al., 2022; Sridevi & Harish, 2024; Zhan et al., 2024). YOLOP architectures leverage shared backbones for panoptic perception, enhancing robustness and overall model efficiency (Li & Xu, 2024). YOLOPv2 (Sridevi & Harish, 2024) preserves the core design concepts of YOLOP and HybridNets while employing a more robust network structure and an efficient training strategy, achieving state-of-the-art (SOTA) performance in both accuracy and speed (Zhan et al., 2024).

- *Human pose estimation (HPE):* localizes human joints or landmarks in images/videos, crucial for UGV applications like gesture-based control from a leader operator. Deep learning has largely superseded classical HPE methods due to better accuracy and generalization (Kulkarni et al., 2023; Zheng et al., 2023). Frameworks like MediaPipe Pose (MPP), an open-source cross-platform framework developed by Google, provide real-time 2D/3D landmark extraction (e.g., 33 body landmarks with BlazePose), offering valuable geometric and motion data for human-robot interaction and leader following (Google, 2023).

Vision sensors are increasingly vital in UVs, complementing or replacing GPS-based navigation due to their small size, low weight, low cost, and ability to extract rich data for target/obstacle identification when paired with the appropriate image processing software (Li, 2013). As passive sensors, they operate non-invasively, reducing inter-sensor interference, and are often the most reliable option in GPS-denied or cluttered environments.

Vision-based guidance leverages camera data for critical tasks like lane tracking, leader recognition, and obstacle detection, enabling UGVs to navigate complex environments and enhancing their autonomy and human-vehicle interaction (Liu et al., 2021c; Zhang et al., 2023; Chen, 2016).

- **Leader following and pose recognition:** vision is crucial for detecting, tracking, and interpreting a human leader's intent. DL algorithms analyze real time imagery to determine leader position, orientation, and infer movement or commands via pose estimation (Burke & Brink, 2010; Schulte et al., 2022). This allows the UGV to anticipate actions and improve decision making, with CNNs often used to identify leader features and actions.
- **Lane detection and obstacle avoidance:** vision-based guidance identifies lane markings and obstacles from camera data. DL algorithms detect lane boundaries for accurate UGV trajectory generation, requiring robustness to dynamic conditions (e.g., lighting, road quality) (Artuñedo et al., 2024; Andrade et al., 2019). Similarly, DL models detect and track obstacles, enabling collision-free path planning and proactive avoidance by predicting dynamic object movements.

This layer's processing of sensory data guides the control system by providing necessary information, which ultimately enables safe, accurate, and efficient operations in complex and uncertain environments. The guidance system provides the intelligence for autonomous UGV operation, making high-level decisions and generating navigation commands. The information provided by the guidance system defines the desired behavior for the control system to execute. This crucial control system will be discussed in the following section.

Control system

The control system executes trajectories or commands from the guidance system, calculating actuator commands (e.g., track motor torques/speeds) for accurate and stable motion despite disturbances and uncertainties (Samak et al., 2021; Wang et al., 2024a; Al-Jarrah et al., 2019; Zou et al., 2018; Gao et al., 2025; Rizk et al., 2023; Xia et al., 2016; Wang et al., 2021; Azam et al., 2020). It typically involves:

- **Longitudinal control:** manages the UGV's speed and acceleration (via throttle/brakes) to maintain desired velocity, ensure safety, and optimize efficiency. It must handle varying dynamics (e.g., engine torque, road grade, resistance) and adapt to changing conditions for smooth, stable motion.
- **Lateral control:** manages UGV steering to follow the intended trajectory and maintain orientation (e.g., relative to a lane or a leader) by minimizing cross-track and heading errors. It must reject side disturbances and account for platform-specific steering dynamics (e.g., track slip in tracked vehicles, tire-road interaction in wheeled vehicles), terrain variations, and nonholonomic constraints to generate smooth, stable steering commands.

The design of longitudinal and lateral controllers can be approached in two ways (Sabiha et al., 2022; Wang et al., 2024a; Al-Jarrah et al., 2019; Samak et al., 2021):

- **Decoupled control:** longitudinal and lateral control are designed and implemented independently, neglecting the coupling effects between them. This simplifies control design but may compromise performance in highly dynamic maneuvers where coupling effects are significant.
- **Coupled control:** design explicitly considers longitudinal-lateral dynamic coupling for more coordinated and robust control, especially in challenging conditions allowing the controllers to compensate for the

effects of each other. This enhances stability and performance but increases design complexity.

The choice between decoupled and coupled control depends on system characteristics, performance needs, and design complexity, requiring a balance between implementation simplicity and potential performance gains.

Control strategies for UGVs

Selecting an appropriate control strategy is crucial for achieving desired UGV performance (accuracy, stability, robustness) in the face of evolving environmental and dynamic challenges. Strategies are broadly categorized as classical control, adaptive control, robust control, advanced control techniques (including MPC and observer-based control like ADRC), and intelligent control (e.g., neural networks NN, fuzzy logic control FLC, reinforcement learning RL). Each category encompasses various methods with distinct principles, advantages, and limitations. For a detailed comparison, Table 2 summarizes these primary control strategies.

The control strategies can also be classified by their reliance on a system model:

- **Model-based control:** these methods rely on the use of a mathematical representation to design the control law, optimizing for specific objectives while considering the system's dynamics and operational constraints. Classical control techniques such as PID and geometric controllers, along with advanced methods such as MPC, fall under this category (Kebbati et al., 2023; Samak et al., 2021; Santoso et al., 2020). While these methods have a solid theoretical base and well-known design principles, their main drawback is the dependence on a precise mathematical model, which might be difficult to achieve for complex, nonlinear, and uncertain systems.
- **Model-free control:** these control strategies, such as those implemented through artificial intelligence techniques (e.g., neural networks, fuzzy logic, and reinforcement learning), do not rely on a specific mathematical representation of the system (Kebbati et al., 2023; Rizk et al., 2023). Instead, they operate by directly interacting with the environment and updating their control laws based on operational feedback. The advantages of model-free approaches lie in their ability to operate in highly complex and uncertain environments and to learn from data (Samak et al., 2021). However, their limitations in-

Control strategy	Main idea	Advantages	Limitations
Classical control	Using simplified system models to generate control actions.	Simple and easy to implement in linear systems.	Limited in nonlinear systems with uncertainties and disturbances.
Adaptive control	Dynamically adjusts control parameters based on the system's changes and operating conditions.	Improves performance in time-varying environments.	Complex implementation and may be highly dependent on the system model.
Robust control	Designs controllers to maintain stability despite the presence of uncertainties.	Guarantees performance over a range of uncertainties.	Requires detailed mathematical models with uncertainty descriptions; sensitive to modeling errors.
MPC	Predicts the system behavior over a future horizon and finds the optimal control actions.	Handles constraints and is suitable for nonlinear systems.	Computationally intensive and dependent on model accuracy.
Observer-based control (e.g. ADRC)	Uses observers to estimate the system state and/or disturbances.	Provides state/disturbance estimation; robustness to unmodeled dynamics and external disturbances with reduced model dependency.	Tuning of observer and controller parameters can be challenging; performance relies on observer accuracy.
Intelligent control	Uses AI techniques to generate robust and adaptive control systems.	Flexible; can learn complex nonlinear relationships and adapt to changing environments.	Requires high computational power, large datasets for training, and complex parameter tuning.

Table 2 – Summary of the control strategies in UGVs

clude a significant computational load during real-time execution and the requirement for large datasets for training.

- **Hybrid control:** combines model-based and model-free aspects. A prominent example within this category is Active Disturbance Rejection Control (ADRC). ADRC's core philosophy involves treating all uncertainties (internal dynamics, parameter variations, external disturbances) as a single "total disturbance" and actively estimating and compensating for it in real time using an Extended State Observer

(ESO) (Han, 2009; Gao, 2006). This approach significantly reduces the dependence on an accurate mathematical model and offers inherent robustness against uncertainties and disturbances, making it well-suited for the complex and often poorly modeled dynamics of UGVs across various platforms. Its key advantages include robustness to uncertainties/disturbances, reduced model dependency, relative simplicity in implementation/tuning, effectiveness for nonlinear systems without explicit linearization, real-time disturbance rejection, adaptability to changing conditions (terrain, payload, environmental variations), and proven success in diverse applications (Fareh et al., 2021; Han, 2009; Sebastian & Ben-Tzvi, 2019a; Gao, 2006; Zheng & Gao, 2016; Guo & Zhao, 2015; Benyahia et al., 2025; Stanković et al., 2019; Madonski et al., 2019).

ADRC's capabilities are particularly relevant for the UGV applications discussed in this review, such as leader-following, where its real-time disturbance rejection is crucial for compensating for unpredictable leader motion and vehicle slip (Amokrane et al., 2024; Fareh et al., 2021), and lane tracking with obstacle avoidance, where its ability to handle unmodeled dynamics aids tracking on uneven terrains and can mitigate sensing errors (Teji et al., 2023; Zhang et al., 2023; Ramírez-Neria et al., 2023a). ADRC has been successfully applied across various vehicle control domains, including longitudinal velocity tracking (Gao et al., 2025; Jin et al., 2023), integrated motion control considering longitudinal-lateral coupling (Wang et al., 2024a), and lateral path following (Xia et al., 2016; Kang et al., 2022; Sang & Chen, 2020; Wang et al., 2022). Specific studies on tracked vehicles, for instance, have leveraged ADRC to address challenges like slip compensation (Sebastian & Ben-Tzvi, 2019a), robust trajectory tracking (Stanković et al., 2024), and handling disturbances in demanding environments such as mining (Liu et al., 2024).

While existing literature offers valuable insights into UGV control, the specific challenges of leader-follower and lane tracking control, particularly under uncertain conditions and with complex terrain interaction, demand careful selection and adaptation of control strategies. The following sections will present how different papers address these tasks, their perception sensors and algorithms, and their chosen control approaches.

Lane tracking task in UGVs

Lane tracking is a critical capability for UGVs, enabling them to navigate along predefined or perceived lanes in structured or semi-structured environments. This task primarily involves detecting lane boundaries and controlling the vehicle to follow them accurately. For certain UGV types, like tracked vehicles, effective lane tracking is particularly challenging due to their skid-steering dynamics, with lanes potentially poorly defined, exhibiting sharp curvatures, or being partially obscured.

A crucial aspect often considered essential for practical lane tracking is **obstacle avoidance**. While maintaining adherence to the lane, the UGV must also possess the ability to detect and safely maneuver around any obstacles encountered in its path. Therefore, robust guidance systems must encompass both lane interpretation and obstacle detection, and control systems must execute maneuvers that ensure both accurate path adherence and collision avoidance, maintaining stability against disturbances such as slippage or uneven terrain.

Categorized as **path following** (see the section “Types of autonomous navigation and decision making”), the primary objective is to maintain spatial alignment with the lane’s geometric centerline, managing speed for safety rather than adhering to strict temporal constraints. Real-time sensing, utilizing sensors such as cameras, LiDAR, and Radar to identify lane boundaries and obstacles, is foundational. This section reviews literature pertinent to UGVs performing lane tracking, including the associated challenge of obstacle avoidance, which is crucial for navigating semi-structured environments.

Given that general control systems for UGVs were comprehensively addressed previously in the section “System architecture for autonomous navigation in UGVs”, the subsequent discussion in this section will primarily focus on the design aspects of the guidance system specific to lane tracking, including sensing and detection modules. Following this, an overview of the existing solutions will be presented, covering approaches which integrate both guidance and control for this specific autonomous task.

Guidance system design in the lane tracking task

Effective guidance system design for lane tracking in UGVs relies on robust environmental interpretation. This typically involves two critical modules: a lane detection module to identify the lane boundaries, and an obstacle detection module to perceive obstacles in the environment and ensure safe navigation, both of which are detailed in the following subsections.

Lane detection module design

Lane detection methods have evolved from traditional geometric approaches to advanced ML and DL techniques, adapting to the complexities of real-world driving environments with varying lighting, road types, and occlusions (Xing et al., 2018).

Cameras are the most widely utilized sensors for lane detection (Chetan et al., 2020; Zakaria et al., 2023; Yang, 2024). A literature review from 2018 to 2021 reveals that over 53 articles focused on camera-based lane detection, while only about three published articles explored the use of other sensors, often in combination with cameras (Zakaria et al., 2023). This preference stems from vision-based imaging aligning with human driver perception (as lane markings are visual cues) and the cost-effectiveness and robustness of camera technology, supported by significant advancements in machine vision (Bar Hillel et al., 2014).

Despite its advantages, vision-based lane detection faces challenges including lighting variations (shadows, glare, low light), adverse weather (rain, snow, fog), occlusions from vehicles/objects, and misdetections from road artifacts (skid marks, cracks), necessitating advanced algorithms for robust performance (Yang, 2024; Sultana et al., 2023).

Lane detection techniques can be broadly categorized:

1. **Model-based methods:** these methods typically involve a multistage pipeline: image preprocessing (noise reduction, ROI isolation), feature extraction (edge detection, thresholding, color filtering), lane model fitting (Hough Transform, least-squares, polynomial/hyperbolic curves), and tracking (Kalman filters) (Zhang et al., 2021b; Munir et al., 2022; Ghanem et al., 2023; Lee & Moon, 2018; Aly, 2008). While simple and efficient, they require manual parameter adjustment and struggle to adapt to diverse conditions.
2. **Intelligent-based methods:** in contrast, intelligent-based methods leverage ML and DL to learn features and patterns directly from data, enabling them to handle variability in road scenes.
   - *Machine learning methods* integrate traditional feature extraction (e.g., adaptive thresholding, morphological operations) with

classifiers (e.g., Bayesian, SVM, ANN) trained on labeled data (Dhanakshirur et al., 2019; Feng et al., 2019; Fakhfakh et al., 2020). Their performance remains dependent on the quality of manually extracted features.

- *Deep learning methods* are state of the art due to their ability to automatically learn hierarchical features from raw images. CNNs are common, often used in encoder-decoder networks for semantic segmentation. Some methods use recurrent layers (e.g., convLSTM) for temporal dependency or attention mechanisms for challenging conditions. DL's adaptability makes it widely used (Sun et al., 2019; Philion, 2019; Dewangan et al., 2021; Dawam & Feng, 2020; Wu et al., 2021; Zhang et al., 2021a; Liu et al., 2021a; Baek et al., 2022; Oğuz et al., 2022). DL-based lane detection is broadly categorized into two groups (Ni et al., 2020): (1) *One-Stage methods* directly predict lane parameters (e.g., curvature, position) from the network, offering greater speed and efficiency while (2) *Two-Stage methods* first perform semantic segmentation before curve-fitting to obtain parametric representations, typically achieving higher accuracy at greater computational cost. The choice depends on application needs (real-time performance vs. precision), with both demonstrating success in addressing the challenges of lane detection in complex and dynamic environments (Ni et al., 2020).

Obstacle detection module design

Obstacle detection is critical for UGVs, especially in unpredictable off-road environments. Dima et al. (Dima et al., 2004) defined obstacles as "a region that cannot or should not be traversed by the vehicle", including pedestrians, vehicles, or terrain features. Effective systems integrate real time perception, decision making, and control to avoid collisions and maintain mission objectives (Zhang et al., 2019). System efficacy depends on sensor choice, algorithmic robustness, and environmental adaptability.

Generally, sensors for obstacle detection can be categorized as (Hu et al., 2020; Islam et al., 2022; Yu & Marinov, 2020):

1. **Range-based sensors:** include LiDAR (for high-resolution 3D point clouds) and Radar (robust in diverse weather for range, speed, and angle, but with lower resolution).

2. **Image-based sensors:** comprise monocular cameras (cost-effective, provide rich semantic data but lack inherent depth), stereo cameras (for depth via triangulation), and infrared cameras (effective for night vision).
3. **Hybrid sensors:** combine multiple data sources (e.g., RGB-D cameras capturing color and depth) for comprehensive environmental understanding, typically with limited range.

While LiDAR and radar offer valuable detection capabilities, visual cameras, both monocular and stereo, serve as essential components of obstacle detection systems. These systems employ both traditional image processing techniques and modern deep learning methods to interpret visual data, aiding in object classification (Hu et al., 2020; Islam et al., 2022).

Monocular cameras are particularly advantageous for UGV obstacle avoidance due to cost-effectiveness, versatility in extracting rich semantic information, favorable performance-to-resource balance (ideal for limited payload/power), adaptability to diverse lighting, and scalability (supporting multiple perception tasks). The synergy of monocular cameras with DL (e.g., CNNs for real-time semantic segmentation, depth estimation, obstacle classification) has significantly advanced their capabilities, making them an efficient sensing modality for resource-constrained UGVs.

Several important approaches exist for vision-based obstacle detection, including:

- **Traditional computer vision methods:** focus on extracting and tracking feature descriptors (e.g., SIFT, SURF, HOG) from images to infer obstacle presence or motion. These are often paired with classifiers like SVM or KNN (Parmar et al., 2019). Motion-based techniques analyze optical flow (Vera-Yanez et al., 2024), while appearance-based methods segment traversable regions based on learned patterns (Badrloo et al., 2022). These approaches are generally slow for real-time applications.
- **Modern deep learning methods:** leverage DL architectures, particularly CNNs, to automatically learn hierarchical features, significantly improving speed and robustness. Object detection CNNs can locate and classify pre-trained objects, outputting bounding boxes, pixel-level segmentations, or key points (Parmar et al., 2019; Badrloo et al., 2022). One-stage networks like YOLO and SSD are favored for their real-time performance and accuracy over older two-stage methods

like R-CNN variants (Terven et al., 2023; Hussain, 2024; Vijayakumar & Vairavasundaram, 2024).

Overview of the existing UGV lane tracking solutions

The control system is responsible for translating the planned path, generated by the guidance system, into specific commands for the vehicle's actuators, effectively executing the desired trajectory. Reviewing the existing literature on lane tracking for UGVs reveals that there are numerous different areas being actively explored by researchers in this field.

Some studies place a strong emphasis on the **control aspect**, developing sophisticated algorithms to ensure precise lane adherence and stability, often assuming well-defined perceptual input. For example, (Marino et al., 2009) proposed a nested PID steering control for vision-based lane tracking, where an inner PI loop controlled yaw rate error for disturbance rejection, and an outer PID loop managed lateral offset, validated via CarSim simulations. (Chen et al., 2014) developed an Adaptive Model Predictive Control (AMPC) system for lane tracking, using a linear time-variant (LTV) prediction model with real-time online tire stiffness estimation, demonstrating superior performance in simulations compared to conventional MPC. (Chu et al., 2018b) combined ADRC with Quantitative Feedback Theory (QFT) for lane tracking, with QFT tuning the ADRC controller for robustness against uncertainties; simulations and scale vehicle experiments confirmed effective lane tracking. Subsequently, (Chu et al., 2018a) further explored ADRC for autonomous vehicle lane tracking, showing its real-time compensation capabilities for internal uncertainties and external disturbances, with stability confirmed by Lyapunov analysis and improved performance over PID in simulations and experiments.

In contrast, other research studies focus more on the **guidance and perception challenges**, aiming to robustly detect lanes and obstacles, particularly in complex or unstructured environments, sometimes with simpler control strategies. (Singhal et al., 2019) introduced a real-time lane detection, fitting, and navigation approach for unstructured environments, integrating 2D LiDAR and camera data to detect lanes and obstacles and generate waypoints. The methodology was validated experimentally for robustness against illumination changes and occlusions. (Amaradi et al., 2016) detailed a real-time lane following and obstacle detection system for autonomous vehicles using a fish-eye camera and LiDAR, employing

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Hough Transform for lane detection and LiDAR for obstacle identification, demonstrating real-time performance experimentally.

Finally, other solutions adopt an integrated approach, that tightly couple advanced guidance with robust control. (Liu et al., 2021b) developed an autonomous lane tracking system that integrates deep learning (LaneFC-Net for real-time detection) with tracking and control. Experimental results showed robustness across various road conditions and lane structures. (Al-Zaher et al., 2012) presented an integrated UGV mechatronics system for lane tracking and obstacle avoidance using a single camera (enhanced Hough Transform for lanes, cone detection for obstacles) and PID control; its feasibility was shown through simulations and small scale vehicle field tests.

A comprehensive comparison of these studies, categorized by their primary focus, sensor utilization, and validation methods, is provided in Table 3.

Table 3 – Summary of the state of the art methods for lane detection and obstacle avoidance

Work	**Vehicle type**	**Lane tracking**	**Obstacle avoidance**	**Focus**	**Sensors used**	**Validation**
Control-focused approaches						
Marino et al. (2009)	Standard car model	Yes	No	Control (Nested PID)	Vision system, Gyroscope	Simulation
Chen et al. (2014)	Standard car model	Yes	No	Control (AMPC)	Not specified	Simulation
Chu et al. (2018b)	Scaled vehicle	Yes	No	Control (ADRC-QFT)	Camera	Simulation & Experiment
Chu et al. (2018a)	Scaled vehicle	Yes	No	Control (ADRC)	Camera	Simulation & Experiment
Vision-focused approaches						
Singhal et al. (2019)	Three-wheeled differential drive	Yes	Yes	Vision	2D LiDAR, Camera	Experiment
Amaradi et al. (2016)	Mobile vehicle	Yes	Yes	Vision	Fish-eye camera, LiDAR	Experiment
Integrated approaches (vision and control)						
Liu et al. (2021b)	Wheeled vehicle	Yes	No	Vision & Control (MPC)	Camera	Experiment
Al-Zaher et al. (2012)	Small-scale UGV	Yes	Yes	Vision & Control (PID)	Single camera	Simulation & Experiment

Leader-follower task in UGVs

Leader-follower control enables UGVs to track and maintain formation with a designated leader (human or vehicle). This capability is vital for collaborative tasks, convoying, and human-robot interaction (Durst et al., 2018; Islam et al., 2019). This section will first detail the key aspects of guidance system design pertinent to the leader-follower task. Subsequently, building upon the general control strategies discussed in the section "System architecture for autonomous navigation in UGVs", an overview of the existing leader-follower solutions will be presented, highlighting perception-focused, control-focused, and integrated system approaches specific to this task.

Categorization of the leader-follower systems

Leader-follower systems can be categorized based on:

- **Sensors used:** common choices include Vision (monocular/stereo cameras for detection, tracking, pose estimation (Chen, 2018; Burke & Brink, 2010)), LiDAR/LRF (for accurate distance/relative position (Chung et al., 2012)), Radar (robust to weather, good for range/velocity (Kumar et al., 2020)), RGB-D Sensors (color and depth, effective indoors (Chen, 2018)), GPS/GNSS (for absolute positioning), and Tags (UWB, RFID). Sensor fusion (e.g., Camera + LiDAR) is often employed to overcome individual sensor limitations (Fan et al., 2024).
- **Interaction mode:**
  - *Explicit:* leader provides direct commands (e.g., wireless, markers). Simpler perception but requires leader cooperation.
  - *Implicit:* follower autonomously detects and tracks the leader using onboard sensors, offering more flexibility but demanding sophisticated perception and guidance (Islam et al., 2019).
- **Follower autonomy level:** adapted from the SAE framework (Islam et al., 2019), follower autonomy ranges from Low (Teleoperated, SAE 0-1) to Partial (automates basic tasks, human supervises, SAE 2), Conditional (operates autonomously in defined conditions, human supervises/intervenes, SAE 3-4), and High (fully independent, SAE 5).

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Overview of the existing UGV leader-follower solutions

Research in leader-follower systems for UGVs similarly spans various areas of emphasis. Many contributions concentrate on the **perception challenges** inherent in robustly detecting, identifying, and tracking a designated leader, which can be a human or another vehicle. For instance, (Cao et al., 2021) enhanced UGV visual tracking for person following by introducing a Scene Analysis Module (SAM) to distinguish targets from distractors, validated on custom and public datasets, showing improved robustness in challenging scenarios. (Burke & Brink, 2010) improved human following by extracting upper body orientation using monocular vision and SURF feature matching to infer travel direction, which was then used by a simple controller. (Chung et al., 2012) presented a method for detecting human legs using LRFs, employing a leg geometry-based data approach for robust and accurate object identification in various environments.

Other research studies emphasize the design and robustness of control strategies for leader-follower tasks to accurately maintain a desired formation or distance relative to the leader, often under dynamic conditions. (Ramírez-Neria et al., 2023a) proposed an ADRC-based leader-follower strategy for omnidirectional mobile robots, integrating distance-based formation control with real-time disturbance estimation via a General Proportional Integral Observer (GPIO). (Chen, 2016) presented a 3DOF path trajectory tracking controller with closed-loop guidance for UGV vehicle-to-vehicle following, using Trajectory Linearization Control (TLC) and validated its effectiveness via MATLAB/SIMULINK. (Fan et al., 2024) addressed Unmanned Tracked Vehicle (UTV) leader following by proposing a decoupled speed and curvature control using Model Reference Adaptive Control (MRAC), reporting significant improvements over PID in following distance and braking.

Furthermore, extensive studies examine **integrated approaches** that combine advanced perception techniques with sophisticated control laws to create complete and robust leader-follower systems. (Sira-Ramírez et al., 2014) proposed a robust dynamic feedback control for non-holonomic car formations, using kinematic models with a generalized proportional integral (GPI) observer for disturbance and tracking error estimation, demonstrated experimentally on Pioneer 3-DX robots. (Ramírez-Neria et al., 2023b) introduced an ADRC strategy for omnidirectional mobile robots in leader-follower formations, minimizing reliance on time derivatives by using measurable robot positions and a special error-based ESO for disturbance rejection. (Chen, 2018) introduced "FOLO," a vision-based human-following robot using a 2D-appearance tracking method with adaptive background segmentation and a two-layer PID control for robust, real-time human following with an RGB-D camera. (Amokrane et al., 2024) presented an ADRC-based strategy for leader-follower control for UTV, highlighting its capability in compensating for unpredictable leader motion, vehicle slip and noise measurements, validated through a comprehensive experimental setup utilizing camera and laser sensors for error signals and human pose recognition.

Table 4 summarizes these representative works, detailing their vehicle type, perception system, control approach, and validation.

Reference	**Vehicle type**	**Perception system**	**Control approach**	**Experiments**
Cao et al. (2021)	Not applied	Monocular vision with Scene Analysis Module	Not applied	Simulation
Burke & Brink (2010)	Not defined	Monocular vision with SURF	Basic controller	Experiment
Ramírez-Neria et al. (2023a)	Omnidirectional mobile robots	Multi-camera, marker-based motion capture system	ADRC + GPIO	Simulation + Experiment
Chen (2016)	UGV	Target seeker (camera + laser range finder)	TLC + PPG	Simulation
Fan et al. (2024)	UTV	Cameras, Lidar, and inertial navigation	MRAC	Simulation + Experiment
Sira-Ramírez et al. (2014)	Non-holonomic mobile robot	Range-finding sonar	ADRC+ GPI	Experiment
Ramírez-Neria et al. (2023b)	Omnidirectional mobile robots	Infrared cameras	ADRC + special ESO	Experiment
Chung et al. (2012)	Omnidirectional mobile robots	Single laser range finder	Not mentioned	Simulation + Experiment
Chen (2018)	Mobile robots	RGB-D camera	Two-layer PID	Experiment
Amokrane et al. (2024)	UTV	Monocular camera, Lidar	ADRC (lateral and longitudinal)	Simulation + Experiment

Table 4 – Summary of the current approaches in the leader-follower task

Synthesis of findings and dominant trends

The reviewed literature demonstrates significant progress in UGV control and guidance, while simultaneously highlighting critical gaps and challenges for autonomous UGV operation in complex tasks like leader following and lane tracking with obstacle avoidance. Several key trends emerge:

- **Increasing autonomy sophistication:** a clear progression from simple teleoperation towards systems capable of handling complex scenarios with minimal human intervention.
- **Deep learning dominance in perception:** DL methods (e.g., CNNs, YOLO, YOLOP, MPP) have largely superseded traditional techniques for tasks like object/lane detection and pose estimation, offering superior robustness to environmental variations by learning features directly from data (Ni et al., 2020; Terven et al., 2023).
- **Growing interest in robust control:** recognizing classical PID limitations, advanced control strategies are increasingly explored. While MPC is popular for constraints and optimization (Zuo et al., 2021), its computational cost and model dependency are drawbacks. Robust control techniques, particularly observer-based methods like ADRC that offer disturbance estimation and rejection with reduced model dependency, are gaining traction for UGV applications (Fareh et al., 2021; Sebastian & Ben-Tzvi, 2019a; Stanković et al., 2024; Han, 2009).
- **Shift towards integrated systems:** there is a growing understanding that robust autonomy necessitates integration between guidance and control (Liu et al., 2021b). However, achieving seamless, real-time integration under uncertainty remains a challenge.
- **Importance of platform-specific considerations:** the unique characteristics of UGV platforms (wheeled, tracked, legged) significantly impact design, with platform-specific challenges (e.g., skid-steering and track-slip in tracked vehicles, tire-road interaction in wheeled vehicles) being increasingly investigated, highlighting the need for tailored solutions.

Conclusion and future research directions

This review has synthesized the state of the art in control and guidance for UGVs, focusing on leader-follower and lane tracking with obstacle avoidance applications. Despite significant advancements, particularly in DL-based sensing, robust autonomous operation of UGVs in complex, unstructured environments remains challenging. Advanced robust control methodologies, including observer-based techniques like ADRC, emerge as promising strategies for UGVs. These are well-suited to handle inherent nonlinearities, uncertainties, and disturbances, often with reduced model dependency and real-time compensation capabilities (Han, 2009; Gao, 2006). Further research and validation of such robust methods in integrated UGV systems are key for future progress in critical civilian and military operations.

The following directions are recommended for future research:

1. **UGV environment specific perception:** develop DL perception models trained on diverse UGV operational data, emphasizing robustness to clutter and adverse off-road conditions.
2. **Advanced robust and adaptive control for UGVs:** investigate and enhance robust control strategies (e.g., adaptive versions of ADRC, sliding mode control, MPC with uncertainty handling) for UGVs, including online parameter tuning for varying terrain, slip, and mission requirements, with experimental validation on real systems.
3. **Optimized sensor fusion:** investigate optimal sensor fusion strategies (e.g., vision, LiDAR, Radar, IMU) to provide robust state, terrain, and disturbance information, crucial for effective performance of advanced control systems.
4. **Real-World UGV validation:** conduct thorough experimental validation of the proposed UGV systems on full-scale platforms in challenging real-world environments, establishing metrics for objective performance comparison.

Addressing these directions is crucial for advancing UGV autonomy and enabling their reliable deployment in demanding applications.

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Una revisión exhaustiva de las estrategias de control y guía para vehículos terrestres no tripulados en aplicaciones de seguimiento de carril y líder-seguidor.

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CAMPO: robótica, sistemas autónomos, control y regulación, ingeniería mecánica, ciencias de la computación;

TIPO DE ARTÍCULO: artículo de revisión

Introducción/objetivo: *Los Vehículos Terrestres No Tripulados (UGVs) ofrecen ventajas significativas para diversas operaciones pero su control y guiado autónomos presentan importantes dificultades, especialmente para diferentes tipos de locomoción (por ejemplo, de orugas o ruedas) en terrenos desafiantes, debido a la dinámicas complejas, restricciones no holonómicas e interacciones con el ambiente. Este artículo proporciona una revisión exhaustiva de las estrategias de control y guiado para UGVs, con un enfoque específico en aplicaciones de seguimiento de carril y líder-seguidor con evasión de obstáculos. El objetivo es sintetizar el estado actual, identificar los principales desafíos genéricos para la autonomía de los UGVs en estas tareas, y discutir metodologías prometedoras de orientación y control.*

Métodos: *Se realizó una revisión extensa de la literatura, analizando investigaciones existentes sobre UGVs, niveles de autonomía, arquitecturas de sistemas, metodologías de control (incluyendo enfoques clásicos, adaptativos, robustos e inteligentes), enfoques de guiado y dominios de aplicación específicos. Se examinaron críticamente las metodologías de guiado y control relevantes para UGV en tareas de líder-seguidor y seguimiento de carril.*

Resultados: *La revisión identifica tendencias dominantes, incluyendo el uso creciente del aprendizaje profundo para la per-*

cepción de guiado y un interés creciente en técnicas de control robusto capaces de enfrentar los desafíos operativos de los UGVs. Persisten desafíos importantes en la percepción en entornos no estructurados, el modelado dinámico preciso para diversas plataformas UGV, la integración perfecta de la percepción con sistemas robustos de guía y control, y la validación extensa en condiciones reales.

Conclusión: *Lograr una autonomía robusta para los UGVs en escenarios reales complejos requiere soluciones integradas que aborden tanto el guiado como el control. Los métodos avanzados de control robusto surgen como candidatos fuertes para el control de UGVs, pero su máximo potencial requiere más investigación en su integración con sistemas de guiado avanzado.*

Palabras clave: *Vehículos Terrestres No Tripulados (UGVs), Sistemas de control, Sistemas de guiado, Seguimiento de líder, Seguimiento de carril, Evasión de obstáculos, Navegación autónoma.*

Всесторонний обзор стратегий управления и навигации наземных беспилотных транспортных средств при выполнении задач автономного движения по полосе и следования за лидером

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РУБРИКА ГРНТИ: робототехника, автономные системы, управление и регулирование, машиностроение, вычислительные науки;

ВИД СТАТЬИ: обзорная статья

Введение/цель: *Несмотря на то что наземные беспилотные транспортные средства (НБТС) пользуются значительными преимуществами в различных операциях, их* *автономное управление и навигация сопряжены с серьёзными трудностями, собенно когда речь идет о различных типах передвижения (например, гусеничных или колёсных) по труднопроходимой местности из-за сложной динамики, неголономных ограничений и взаимодействия с окружающей средой. Данная статья представляет собой всесторонний обзор стратегий управления и навигации НБТС, делая особый акцент на взаимодействие лидера и последователя и отслеживание полосы движения с помощью приложений для объезда препятствий. Цель статьи — представить современное состояние данной области, выявить ключевые проблемы, общие для автономии НБТС, и рассмотреть перспективные методологии управления и навигации.*

Методы: *В ходе исследования проведен обширный обзор литературы, на основании которого были проанализированы существующие исследования по НБТС, уровням автономии, системным архитектурам, методологиям управления (включая классический, адаптивный, надежный и интеллектуальный подходы), подходам к навигации и конкретным областям применения. Были тщательно изучены методы, применимые к задачам «лидер-последователь» и «отслеживание полосы движения».*

Результаты: *Обзор выявил доминирующие тенденции, включая растущее использование методов глубокого обучения для восприятия и возросший интерес к робастным методам управления, способным справляться с операционными вызовами НБТС. Были выявлены серьёзные проблемы в области восприятия в неструктурированных средах, точного динамического моделирования для различных платформ НБТС, интеграции восприятия с робастными системами управления и навигации, а также необходимость общей валидации в реальных условиях.*

Заключение: *Для достижения робастной автономии НБТС в сложных реальных сценариях требуются интегрированные решения, охватывающие как навигацию, так и управление. Продвинутые робастные методы управления представляются многообещающими в управлении НБТС, однако для полного раскрытия их потенциала необходимо продолжать исследование их интеграции с современными системами навигации.*

Ключевые слова: *наземные беспилотные транспортные средства (НБТС), системы управления, системы навигации, следование за лидером, движение по полосе, объезд препятствий, автономная навигация.*

свеобухватни преглед стратегија управљања и вођења беспосадних возила у задацима аутономног праћења возне траке и праћења вође

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ОБЛАСТ: роботика, аутономни системи, регулација и управљање, машинство, рачунарске науке
КАТЕГОРИЈА (ТИП) ЧЛАНКА: прегледни рад

Увод/циљ: *Беспилотна земаљска возила (БЗВ) пружају значајне предности за различите операције, али при њиховом аутономном управљању и вођењу долази до знатних потешкоћа, које се посебно односе на различите типове локомоције (нпр. гусеничне, точкашке) на изазовним теренима, услед сложене динамике, нехолономних ограничења и интеракција са окружењем. У раду је представљен свеобухватан преглед стратегија управљања и вођења за БЗВ, са посебним фокусом на примене праћења вође и праћења траке са избегавањем препрека. Циљ је да се синтетише тренутно стање технике, идентификују кључни изазови генерички за аутономију БЗВ у овим задацима, и размотре обећавајуће методологије управљања.*

Методе: *При опсежном прегледу литературе, анализирана су постојећа истраживања о историји БЗВ, нивоима аутономије, системским архитектурама, методологијама управљања (укључујући класичне, адаптивне, робустне и интелигентне приступе), као и специфичним доменима* *примене. Критички су испитане методологије за вођење и управљање релевантне за БГВ у задацима праћења вође и праћења траке.*

Резултати: *Идентификовани су доминантни трендови, укључујући све чешћу употребу дубоког учења за перцепцију и растуће интересовање за робусне технике управљања способне да одговоре на оперативне изазове БЗВ-а. Значајни изазови и даље постоје у перцепцији за неструктурирана окружења, тачном динамичком моделирању за различите платформе БЗВ-а, беспрекорној интеграцији перцепције са робустним управљањем и опсежној валидацији у реалним условима. Стратегије управљања засноване на осматрачима, као што је активно потискивање поремећаја (ADRC), показују значајан потенцијал у управљању нелинеарностима, несигурностима и поремећајима БЗВ-а са смањеном зависношћу од модела.*

Закључак: *Постизање робустне аутономије за БЗВ у сложеним реалним сценаријима захтева интегрисана решења која обухватају вођење и управљање. Напредне робустне методе управљања, укључујући ADRC, појављују се као снажни кандидати за управљање БЗВ-има, али њихов пуни потенцијал захтева даља истраживања њихове интеграције са напредним сензорским системима и темељну експерименталну валидацију у циљаним оперативним доменима БЗВ-а.*

Кључне речи: *беспилотна земаљска возила (БЗВ), системи управљања, системи вођења, праћење вође, праћење траке, избегавање препрека, аутономна навигација.*

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