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Automatic UAV trajectory control systems with obstacle avoidance

The article considers modern approaches to building systems for automatic trajectory control of uncrewed aerial vehicles with obstacle avoidance. The relevance of the topic is underscored by the expansion of UAV applications and the growing need for safe autonomous navigation in environments with incomplete a priori information, dynamic obstacles, and time constraints for decision-making. The architectural, algorithmic, and sensory features of modern control systems that combine environmental perception, localization, mapping, global and local planning, safe trajectory generation, and motion control are summarized. Reactive, geometric, graph, selective, optimization, and predictive approaches are analyzed, along with systems based on SLAM/VIO and computer vision. It is shown that reactive and geometric methods are characterized by high speed but have limited global optimality. Graph and selective algorithms are effective in a known environment, but less suitable for rapidly changing scenes. Optimization and predictive methods provide a high level of adaptability, but require significant computational resources. Special attention is paid to computer vision systems, in particular YOLO-like detectors, which are considered effective semantic perception modules within hybrid architectures but not self-sufficient means of trajectory control. It was found that the most promising for practical implementation are multi-level hybrid systems that combine multisensory perception, SLAM/VIO, global and local planning, and predictive safe control methods.

Keywords: *UAV; automatic control; trajectory planning; obstacle avoidance; computer vision; multi-sensor integration; autonomous navigation; intelligent systems.*

Relevance of the topic. The significant development of unmanned systems, especially unmanned aerial vehicles (UAVs), has substantially expanded their range of applications in agriculture, energy facility inspection, logistics, search-and-rescue operations, environmental monitoring, control of critical infrastructure, and other domains. However, the practical use of fully autonomous UAVs is complicated by the need to ensure collision-free motion in environments with incomplete a priori information, changing obstacle configurations, and certain time constraints on decision-making. Therefore, problems related to the automatic trajectory control of UAVs with real-time obstacle avoidance have become widespread in contemporary research on autonomous navigation [1–4].

Unlike «classical» navigation tasks, where a route can be constructed in advance in a static environment, the defining feature of autonomous UAV flights under real-world conditions is the need for a continuous closed-loop control process that includes environmental perception, prediction, planning, control, and correction. The drone's motion must remain dynamic, energy-efficient, and safe even in the presence of moving obstacles, external disturbances, limited visual information, and partial loss of navigation data. In this context, «real time» refers not only to rapid trajectory computation but also to the ability to close the entire decision-making loop with stable, predictable latency [2, 3, 6].

Analysis of recent research and publications referenced by the authors. In the field of UAV control, there has been a gradual transition from individual trajectory planners to full-fledged motion-planning architectures, as confirmed by the analysis of the scientific publications discussed below.

Article [1] reviews 670 publications and shows that the most effective systems combine global and local planning, obstacle-detection modules, and mechanisms for adapting to dynamic environments. Similar conclusions are presented by the authors of publication [2], who formalize three interrelated components of the autonomous navigation problem, namely: representation of the surrounding environment map, path planning, and trajectory optimization.

The review in [3] focuses directly on «Obstacle Detection and Avoidance». It demonstrates that a significant portion of existing solutions is oriented either solely toward static obstacles or solely toward dynamic ones. In contrast, real-world autonomous flight tasks require both to be considered simultaneously, along with energy consumption indicators.

Works [6] and [7] confirm that in recent years the emphasis has shifted toward optimized and hybrid control, in which MPC (Model Predictive Control), CBF (Control Barrier Functions), or Adaptive Nonlinear MPC are combined with neural network learning algorithms to improve adaptability and the quality of trajectory generation.

A separate direction is represented by studies devoted to specialized perception tools. In particular, publications [4, 5, 8, 12] investigate the use of LiDAR, radar, and event cameras for high-speed navigation under challenging conditions such as low illumination, smoke, dust, or intensive environmental changes. For tasks involving the flight of multiple UAVs or groups of drones, the results of works [9–11], which analyze Formation Control and Velocity Obstacle approaches, are also relevant.

There are also significant developments in the field of computer vision. Convolutional neural networks (CNNs), which are used to process video streams and camera images, including those from optical modules mounted on UAVs, have become particularly widespread. The use of such technologies enables object recognition, target tracking, visual navigation, and related functions [13, 14].

Work [15] notes that persistent unresolved problems remain associated with computer vision, such as small objects, high scene density, scale changes, variations in camera viewpoint, and similar challenges.

The performance of an obstacle avoidance system cannot be evaluated solely by the percentage of potential collision objects correctly detected. It is also necessary to consider trajectory length, computation time, energy consumption, smoothness, safe clearance from obstacles, and robustness to environmental uncertainties. The growing importance of the multi-sensor approach is also emphasized, as a camera provides detailed information about the surrounding environment but performs poorly in fog or low-light conditions, whereas active sensors are better suited to capturing environmental geometry [16].

The above indicates that, at present, various methods and systems exist for UAV control with obstacle avoidance. It should also be noted that the effectiveness of different approaches and methods depends on several factors, including environmental conditions, the onboard hardware platform, and the tasks assigned to the system as a whole.

The objective of the article is to systematize modern approaches to the development of UAV trajectory control systems with obstacle avoidance, to generalize their architectural, algorithmic, and sensory features, and to provide a comparative analysis of reactive, geometric, graph-based, optimization-based, SLAM/VIO, hybrid, and computer-vision-based approaches in order to identify the most promising solutions for autonomous navigation tasks in dynamic environments.

Presentation of the main material. Modern automatic UAV trajectory control systems with obstacle avoidance represent a comprehensive technical approach: a multi-level architecture that combines environmental perception, localization, mapping, global and local planning, safe flight trajectory generation, and trajectory control via regulators. Reviews published in 2024–2025 [1, 3] consider «Obstacle Detection and Avoidance» as a process that integrates obstacle detection, environment mapping, and path planning, rather than merely as separate software tools, namely, trajectory planners.

In a generalized form, the problem of UAV trajectory planning in an environment with obstacles can appropriately be described by a discrete nonlinear state and observation model:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) + w_k, \\ z_k &= h(x_k) + v_k, \end{aligned} \tag{1}$$

where x_k is the UAV state vector at the k-th discretization step, typically including coordinates, velocities, orientation, and, if necessary, angular velocities; u_k is the control input vector; z_k is the sensor measurement vector; $f(\,)$ is the nonlinear dynamics equation; $h(\,)$ is the measurement model; w_k and v_k are the process and measurement noises, respectively, representing model uncertainty, external disturbances, and sensor subsystem errors [20, 21]. Under such a formulation, the trajectory planner or controller predicts the system's future evolution and generates an optimal sequence of reference states or control actions within a finite-horizon MPC (Model Predictive Control) optimization problem. Mathematically, this can be represented as the minimization of the following cost functional:

$$\min_{\{u_k\}_{k=0}^{N-1}} \left[\sum_{k=0}^{N-1} \left(\left\| x_k - x_k^{ref} \right\|_Q^2 + \llbracket u_k \rrbracket_R^2 + \lambda \phi_{obs}(p_k, O_k) \right) + \left\| x_k - x_k^{ref} \right\|_{Q_f}^2 \right], \tag{2}$$

where x_k^{ref} is the reference state or a point of the desired trajectory; Q, R and Q_f are weighting matrices that define the trade-off between tracking accuracy, the energy or dynamic effort (cost) of control, and the terminal quality of the prediction; $\phi_{obs}(p_k, O_k)$ is the penalty function for the proximity of the positional component of the state p_k to the set of obstacles O_k [20, 21]. In this case, it is appropriate to combine a soft penalty for proximity to obstacles with hard safety constraints, for example:

$$d(p_k, O_k) \geq d_{\min}, \tag{3}$$

where $d(p_k, O_k)$ is the distance between the UAV geometry and the obstacle, and $d_{\min}$ is the minimum allowable safety clearance [20, 21]. Such a formulation is valid for nominal trajectory planning; however, the term «guaranteed safety clearance» is fully justified only when uncertainties are explicitly taken into account within robust, probabilistic, or barrier-based approaches, in particular Chance-Constrained MPC or Control Barrier Functions, since it is precisely these methods that make it possible to relate avoidance conditions to statistical or invariant safety guarantees in the presence of localization errors, sensor noise, and motion disturbances.

In modern automatic trajectory control systems for unmanned aerial vehicles, trajectory planners are divided into global and local ones (Fig. 1). Such a division is appropriate for building a multi-level autonomous navigation architecture, since each of these classes, or groups, solves its own range of tasks and operates at different decision-making levels. Global trajectory planners construct a route from the start point to the target based on a map or a known environmental model. In contrast, local planners adjust motion in real time using sensor data and are primarily needed to avoid sudden obstacles. Global planners are oriented toward generating a route from the initial point to the destination while taking into account the available environmental map, the space's traversability model, no-fly zones, and other a priori known conditions. They determine the overall structure of UAV motion, form a sequence of reference points or a spatial trajectory, and provide the general approach to navigation. This group includes graph-search algorithms (Dijkstra, A*, D*, Jump Point Search, etc.), sampling-based approaches (PRM, RRT, RRT*, Informed RRT*, and BIT), and metaheuristic and optimization methods (PSO and ACO). These methods are used when the flight environment is fully or partially known, and the main objective is to construct a rational, feasible, and safe route while accounting for spatial constraints.

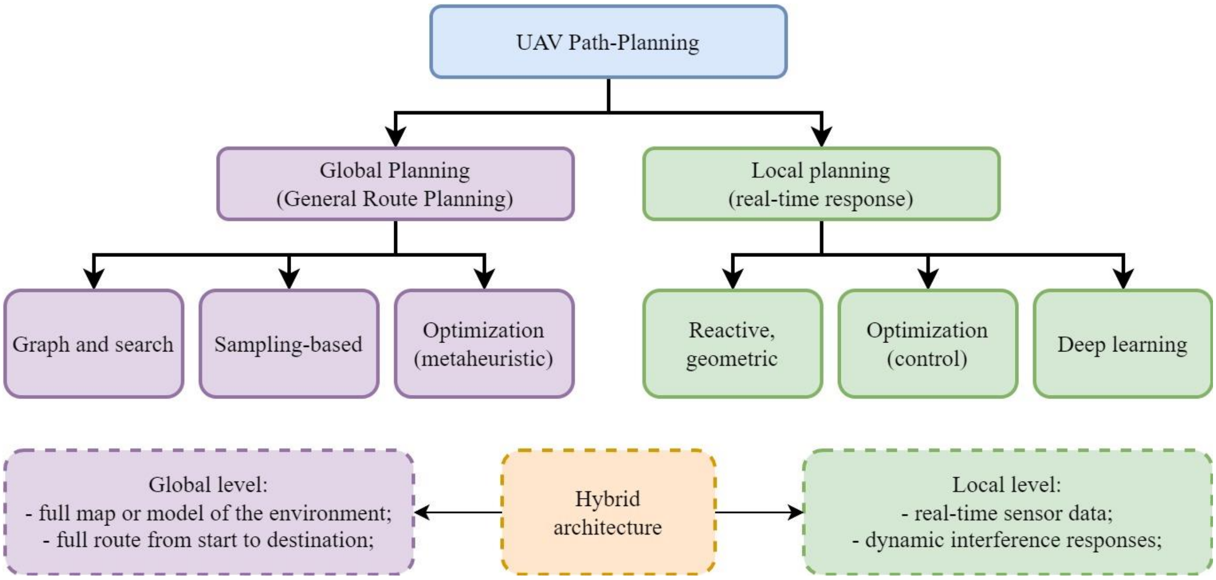

Fig. 1. Generalized classification of UAV trajectory planners

Unlike global planners, local planners operate at the level of real-time motion adaptation. Their purpose is to adjust the current UAV trajectory in response to changes in the surrounding environment, particularly when sudden or dynamic obstacles appear, localization errors occur, or unforeseen environmental changes arise. Local planners provide a somewhat lower level of flight control and, in fact, directly align the vehicle's current motion with the actual situation. This group includes reactive and geometric approaches, among which Artificial Potential Field and Vector Field Histogram are widely used. A separate subgroup comprises optimization-based and control-oriented local planning methods, in particular the Dynamic Window Approach, Model Predictive Control, and related collision-avoidance methods. In modern research and practical systems, learning-based and hybrid approaches are also receiving increasing attention, including algorithms based on Reinforcement Learning and Deep Reinforcement Learning.

Global and local planners should not be considered as alternative solutions that exclude one another. On the contrary, most modern onboard autonomous flight systems function jointly as complementary components of a single control hierarchy. The global planner defines the overall route or motion corridor toward the target. In contrast, the local planner provides adaptive refinement of this route in the real environment based on current sensor data. It is precisely this two-level planning organization that is most characteristic of modern UAV trajectory control systems with obstacle avoidance, since it combines the strategic expediency of route generation with tactical flexibility and flight safety.

The main classes and groups of modern automatic UAV trajectory control systems with obstacle avoidance are presented below. These include reactive systems, geometric and field-based methods, graph-based methods, optimization-based and predictive systems, SLAM and VIO systems, and computer-vision-based systems. The above-mentioned systems, methods, and approaches have specific features, which are discussed below.

Reactive sensor-based systems are the simplest implementation option for a UAV control system with obstacle avoidance. Such systems are based on responding to the surrounding environment, in which the UAV control system does not «construct» a new fully optimal flight trajectory, that is, essentially a new route, but instead directly limits speed or changes the direction of motion based on current sensor measurements. This is an approach involving stopping and avoidance: when an obstacle approaches, the system either brakes, «slides» along it, or deflects the vehicle to the side. For example, an implementation exists in the open-source PX4 autopilot platform, namely «Collision Prevention», which automatically slows down or stops a multicopter in front of an obstacle and can use data from onboard sensors and from external devices [17]. In the ArduPilot software, a similar system is implemented under the name «Simple Object Avoidance», which operates with various sensors, such as LiDAR, rangefinders, depth cameras, and others [18].

The advantages of reactive systems are minimal response latency, ease of configuration, and high practical reliability at low speeds. Their main disadvantages are the locality of technical decisions, the absence of global optimality, and limited capability to operate in complex, dynamically changing environments. Therefore, such systems are useful as a basic safety layer but are rarely sufficient for fully autonomous flight in complex environments.

The next group comprises geometric methods: Artificial Potential Field, Vector Field Histogram, local vector fields, and geometric obstacle avoidance based on free-space directions.. The operating principle of these methods is that the final target, that is, the end of the route, «attracts» the UAV, while obstacles conditionally «repel» it [3]. These systems operate faster than optimization-based approaches and account for the local geometry of the environmental scene better than reactive methods. In modern scientific reviews, such systems are considered flexible and suitable for group UAV motion. However, a common problem with local minima occurs when the vehicle becomes «trapped» between the values of «attraction» and «repulsion». For Vector-Field approaches, the quality and accuracy of onboard sensor data are also critical.

Graph-based, search-based, and sampling-based methods also constitute a large group within trajectory planners. Here, the environment is represented as a graph, a grid, a free-space map, or a set of alternatives in the configuration space. Their operating principle is as follows: first, a traversability model is constructed; then the algorithm finds a path from the start to the target, accounting for transitions, restricted zones, and kinematic constraints. Such methods are particularly effective when the environment map is known in advance or can be reconstructed with sufficient accuracy.

Optimization-based and predictive systems are currently among the best approaches for complex scenarios, especially MPC (Model Predictive Control) and gradient-based local planners. The operating principle of this group of systems is that control is computed not only for the current instant, but over a prediction horizon; that is, the system predicts the future state of the UAV and the possible motion of obstacles along the route, and accordingly calculates the trajectory of further motion. MPC-based approaches can use predictions to operate even when obstacles are outside the sensor systems' instantaneous field of view. Such approaches are also compatible with other methods, such as gradient-based methods, in which predicting the future motion of dynamic objects is not an auxiliary addition but a central part of the entire trajectory control system. In practice, this group of approaches is best suited for urban, warehouse, forest, and other densely cluttered environmental scenes where a static map is insufficient. However, despite its effectiveness, an obvious drawback is the high computational load on the onboard control system, the need for high-quality state estimation, and sensitivity to model errors. That is, MPC is almost always more powerful than reactive avoidance, but more expensive to implement.

When the global navigation satellite system is unstable or unavailable, visual SLAM (Simultaneous Localization and Mapping), Visual-Inertial Odometry, and their hybrids become key elements. Localization and onboard sensor-based perception form the foundation of autonomous unmanned applications, and visual SLAM is a critical technology. Its operating principle is to use sensor data, usually from a camera, together with specialized algorithms (particle filters, Graph SLAM) to update the environmental model and the vehicle's position. The specific features of these systems make real-time operation more difficult; operation in homogeneous environments without clear markers is also challenging, and dynamic environments where markers and scenes change frequently are likewise problematic.

Special attention should also be paid to computer-vision-based systems, YOLO, and DRL. In modern research directions and engineering developments, YOLO-like detection systems have become a dominant tool for environmental perception. A systematic review published in [19] in 2024 showed that more than 39,5 % of studies in the field of DL-based Computer Vision for UAVs use the YOLO family. This can be explained by the fact that, for real-time operation, fast single-stage detectors are most often used for environmental scene perception. However, it is important to note that YOLO itself is not a trajectory control system. It solves the problem of object detection and classification in the image frame. To transform scene detection into flight with obstacle-avoidance trajectories, a local trajectory planner is required. For this reason, the most engineering-effective solutions are hybrid; for example, the computer vision module provides semantics, SLAM/VIO determines the UAV's position and map, and the planner transforms this information into safe routes and trajectories.

Summarizing the above-described approaches, Table 1 below presents a general comparison based on recent reviews and real-world autopilot stacks.

Table 1

General comparison of systems

System class	**Operating principle**	**Advantages**	**Disadvantages**	**Usage scenario**
Reactive, sensor-based	Direct response to the distance to an obstacle	Very fast, simple, reliable	No global optimization, local decisions	Low-speed flight, basic collision protection
Geometric methods (APF, VFH, Vector Field)	Local field of directions or potentials	Fast, perform well in unknown local scenes	Local minima, dependence on sensors	Corridors, simple local traversals
Graph, search and sampling methods	Pathfinding on a map or in state space	Better global route quality	Difficult for dynamic real-time operation	Known maps, static obstacles
MPC, Gradient-based	Optimization on the forecast horizon	Efficient for dynamic obstacles and constraints	High computational and model requirements	Urban and dense dynamic scenes
SLAM with a local planner	Simultaneous localization, mapping and local planning	Works without GNSS, suitable for complex environments	Sensitivity to texture, lighting, «drift»	Forests, rooms, underground or closed objects
YOLO, deep learning	Semantic perception or learned policy	High adaptability, strong semantics	Data and GPU-intensive	Complex scenes, semantic objects

The analysis of modern automatic UAV trajectory control systems with real-time obstacle avoidance shows that hybrid architectures are the most promising ones (Fig. 1), in which different algorithmic modules perform specialized functions and interact within a unified closed-loop control framework. This approach represents a further development of multi-level autonomous navigation systems, since no single algorithm, including an object detector, a local planner, or a localization method, can by itself simultaneously provide semantic scene understanding, reliable positioning, hazard prediction, and the generation of a safe control action.

In a typical hybrid architecture, a computer vision module based on YOLO or related detectors performs semantic perception of the environment. Its main task is the detection, classification, and initial localization of potentially hazardous objects in the frame, such as buildings, trees, vehicles, other UAVs, people, or dynamic obstacles. The advantage of this approach lies in the high speed of single-stage detectors and the ability to obtain not only geometric but also semantic information about objects. At the same time, semantic detection alone does not yet ensure the generation of a safe trajectory, as it does not form a complete model of the UAV's spatial position relative to the scene or perform predictive selection of control actions. For this reason, the computer vision module in engineering-complete systems is considered not an autonomous control means but a perception subsystem.

The next critical level is formed by SLAM or VIO modules, which provide estimates of position, velocity, and orientation, and, if necessary, construct a local map of the environment. It is these modules that transform fragmented sensor information from cameras, IMU, and other sensors into a consistent spatial model suitable for motion planning. Under GNSS-denied or GNSS-degraded conditions, such a subsystem becomes a key source of navigation information. The interaction between semantic vision modules and SLAM/VIO enables the integration of scene content recognition and spatial geometry estimation, significantly improving decision-making quality for obstacle avoidance.

At the upper level of tactical response, there is a local planner or a safe control module, which transforms information from perception and localization into a direct trajectory or control command. The above is illustrated in the block diagram (Fig. 2).

The block diagram presents a generalized hybrid architecture of an automatic UAV trajectory control system with obstacle avoidance. Onboard sensors, which may include a camera, IMU, LiDAR, depth sensors, or radar, generate the primary data flow about the surrounding environment and the UAV state. These data are then sent to the preprocessing and synchronization block, where temporal and spatial alignment of measurements, noise filtering, and data preparation for further analysis are performed.

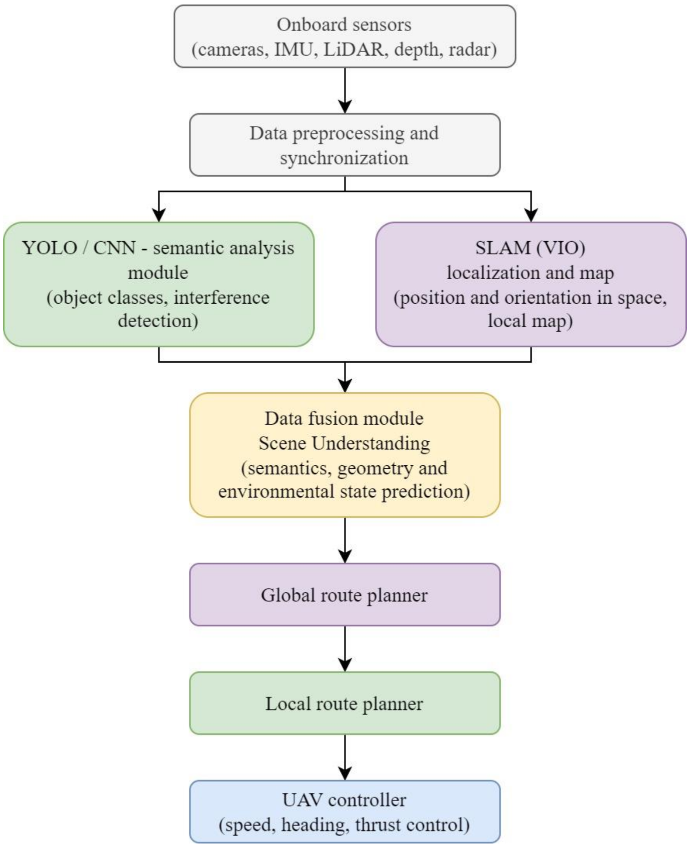

Fig. 2. Generalized block diagram of the hybrid architecture of the UAV trajectory control system with obstacle avoidance

After that, the information flow branches into two main directions. The first direction is represented by the YOLO/CNN semantic analysis module, which performs object detection and classification within the scene, thereby providing semantic understanding of the environment and enabling the identification of potential obstacles. The second direction is formed by the SLAM/VIO block, which is responsible for UAV localization, estimation of its position and orientation, and the construction of a local map of the environment. Thus, the system simultaneously obtains both semantic information about object types and geometric information about the scene's spatial structure.

At the next stage, the outputs of the computer vision and localization modules are sent to the data fusion module (Scene Understanding). In this block, semantic information, environmental geometry, and, if necessary, scene-state prediction are integrated. It is this level that forms a holistic representation of the surrounding environment, which serves as the basis for further motion planning.

After the generalized environmental model has been formed, the information is passed to the global route planner, which operates at the strategic level and constructs the overall path to the goal. In this block, algorithms such as the A*, D*, or RRT* algorithms may be used. They ensure the construction of a feasible route while taking into account the overall map of the environment, restricted zones, and the available free space for movement.

The generated global route is then refined in the local planner block, where MPC may be used. This block operates in real time and adapts the trajectory in response to the current situation, the appearance of dynamic obstacles, environmental changes, or localization errors.

At the final stage, the control signals are transmitted to the UAV controller, which controls speed, heading, thrust, and orientation. Through this block, direct influence is exerted on the aircraft's actuating mechanisms. The result is the UAV motion that realizes the selected trajectory in the real environment.

An important feature of the scheme is the presence of feedback, through which the actual UAV state and new sensor data are repeatedly fed back into the system. It ensures a closed-loop control process in which the trajectory is continuously adjusted in accordance with environmental changes.

Summarizing the above, it can be stated that a hybrid architecture is not merely a sum of separate modules, but a functionally coordinated system in which YOLO-like models provide scene semantics, SLAM/VIO provides spatial localization and the map, and MPC, DWA, CBF, or other local planners transform this information into a safe flight trajectory. It is precisely such a structure that best meets the requirements of modern UAVs operating in dynamic, uncertain, and partially known environments.

Conclusions and future research directions. The article generalizes modern approaches to automatic UAV trajectory control with obstacle avoidance. It establishes that the effectiveness of autonomous flight is determined not by a single algorithm, but by the coordinated interaction among the sensor subsystem, localization modules, mapping, global and local planning, and motion controllers. It is shown that reactive and geometric methods provide high speed, but have limited global optimality. In contrast, graph-based and sampling-based approaches are effective in known environments, but are less suitable for rapidly changing scenes. It is established that optimization-based and predictive methods demonstrate high potential under dynamic conditions, but require significant computational resources and high-quality state estimation. It is further substantiated that computer vision systems, in particular YOLO-like detectors, do not replace the trajectory planner, but serve as an effective semantic module within a hybrid architecture together with SLAM/VIO and local planning. Summarizing the above, the most promising solutions for practical implementation are multi-level hybrid systems combining global and local planning, multi-sensor perception, and predictive control methods. Further research should be directed toward reducing the computational demands of onboard algorithms, increasing robustness to environmental uncertainties, integrating semantic computer vision with guaranteed-safe control methods, and conducting experimental validation of such systems under real field conditions.

References:

1. Debnath, D., Vanegas, F., Sandino, J. et al. (2024), «A Review of UAV Path-Planning Algorithms and Obstacle Avoidance Methods for Remote Sensing Applications», *Remote Sensing*, Vol. 16, No. 21, doi: 10.3390/rs16214019.
2. Zhou, Y., Yan, L., Han, Y. et al. (2025), «A Survey on the Key Technologies of UAV Motion Planning», *Drones*,Vol. 9, No. 3, doi: 10.3390/drones9030194.
3. Merei, A., Mcheick, H., Ghaddar, A. and Rebaine, D. (2025), «A Survey on Obstacle Detection and Avoidance Methods for UAVs», *Drones*, Vol. 9, No. 3, doi: 10.3390/drones9030203.
4. Randieri, C. et al. (2025), «Aerial Autonomy Under Adversity: Advances in Obstacle and Aircraft Detection Techniques for Unmanned Aerial Vehicles», *Drones*, Vol. 9, No. 8, doi: 10.3390/drones9080549.
5. Xia, W., Song, F. and Peng, Z. (2025), «Dynamic Obstacle Perception Technology for UAVs Based on LiDAR», *Drones*, Vol. 9, No. 8, doi: 10.3390/drones9080540.
6. Wang, D., Mu, L., Wang, B. et al. (2025), «UAV Obstacle Avoidance Algorithm Based on Model Predictive Control and Control Barrier Functions», *IFAC-PapersOnLine*, Vol. 59, No. 20, pp. 405–410, doi: 10.1016/j.ifacol.2025.11.184.
7. Shi, J., Zhou, Y., Wang, L. et al. (2026), «Trajectory Planning and Tracking for UAVs with Deep Reinforcement Learning and Adaptive Nonlinear MPC», *Expert Systems with Applications*, Vol. 289, doi: 10.1016/j.eswa.2025.129158.
8. Akanbi, I., Ngqondi, T. and Ismail, Y. (2025), «Event-Based Vision Application on Autonomous Unmanned Aerial Vehicle: A Systematic Review of Prospects and Challenges», *Sensors*, Vol. 26, No. 1, doi: 10.3390/s26010081.
9. Liao, Y., Wu, Y., Zhao, S. and Zhang, D. (2024), «Unmanned Aerial Vehicle Obstacle Avoidance Based Custom Elliptic Domain», *Drones*, Vol. 8, No. 8, doi: 10.3390/drones8080397.
10. Li, Y., Zhang, P., Wang, Z. et al. (2024), «Multi-UAV Obstacle Avoidance and Formation Control in Unknown Environments», *Drones*, Vol. 8, No. 12, doi: 10.3390/drones8120714.
11. Zhang, P. et al. (2024), «Enhanced Multi-UAV Formation Control and Obstacle Avoidance through an Improved Adaptive Artificial Potential Field», *Drones*, Vol. 8, No. 9, doi: 10.3390/drones8090514.
12. Ahmadi, B. et al. (2025), «Enhanced Dynamic Obstacle Avoidance for UAVs Using Event Camera and Ego-Motion Compensation», *Drones*, Vol. 9, No. 11, doi: 10.3390/drones9110745.
13. Cocoma-Ortega, J.A. and Martinez-Carranza, J. (2019), «A CNN-based Drone Localisation Approach for Autonomous Drone Racing», *11th International Micro Air Vehicle Competition and Conference*.
14. Arshad, M.A., Khan, S.H., Qamar, S. et al. (2022), «Drone Navigation Using Region and Edge Exploitation-Based Deep CNN», *IEEE Access*, Vol. 10, pp. 95441–95450.
15. Habash, R.I. et al. (2025), «Recent Real-Time Aerial Object Detection Approaches, Performance, Optimization, and Efficient Design Trends for Onboard Performance: A Survey», *Drones*.
16. Meng, W. et al. (2025), «Advances in UAV Path Planning: A Comprehensive Review of Methods, Challenges, and Future Directions», *Drones*, Vol. 9, No. 5, doi: 10.3390/drones9050376.
17. «Collision Prevention», *PX4 Guide*, [Online], available at: https://docs.px4.io/main/en/computer_vision/collision_prevention
18. ArduPilot Flight Features, «Simple Object Avoidance», [Online], available at: https://ardupilot.org/copter/docs/common-simple-object-avoidance.html
19. Katkuri, A.V.R., Madan, H., Khatri, N. et al. (2024), «Autonomous UAV navigation using deep learning-based computer vision frameworks: A systematic literature review», *Array*, Vol. 23, doi: 10.1016/j.array.2024.100361.
20. Reid, I., «Discrete-time Kalman filter», *Estimation II*, University of Oxford, [Online], available at: https://www.robots.ox.ac.uk/~ian/Teaching/Estimation/LectureNotes2.pdf
21. Tedrake, R., «Underactuated Robotics: Trajectory Optimization», *MIT*, [Online], available at: https://underactuated.mit.edu/trajopt.html
22. Kravchuk, A., Tkachuk, A., Dobrzhanskyi, O. et al. (2025), «Analysis of autonomous UAV navigation methods in GPS dead zones», *Technical Engineering*, No. 1 (95), pp. 235–242, doi: 10.26642/ten-2025-1(95)-235-242.

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- БПЛА та авіація;
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Системи автоматичного керування траєкторією БПЛА з уникненням перешкод

У статті розглянуто сучасні підходи побудови систем автоматичного керування траєкторією безпілотних літальних апаратів з уникненням перешкод. Обґрунтовано актуальність теми в умовах розширення сфер застосування БПЛА та зростання вимог до безпечної автономної навігації в середовищах із неповною апріорною інформацією, динамічними перешкодами та часовими обмеженнями на прийняття рішень. Узагальнено архітектурні, алгоритмічні та сенсорні особливості сучасних систем керування, які поєднують сприйняття середовища, локалізацію, картографування, глобальне й локальне планування, генерацію безпечної траєкторії та регулювання руху. Проаналізовано реактивні, геометричні, графові, вибіркові, оптимізаційні та прогнозні підходи, а також системи на основі SLAM/VIO і комп’ютерного зору. Показано, що реактивні та геометричні методи характеризуються високою швидкодією, але мають обмежену глобальну оптимальність. Графові та вибіркові алгоритми є ефективними у відомому середовищі, однак менш придатними до швидкозмінних сцен. Оптимізаційні та прогнозні методи забезпечують високий рівень адаптивності, проте вимагають значних обчислювальних ресурсів. Окрему увагу приділено системам комп’ютерного зору, зокрема YOLO-подібним детекторам, які розглянуто як ефективний модуль семантичного сприйняття у складі гібридних архітектур, але не як самодостатній засіб керування траєкторією. Встановлено, що найбільш перспективними для практичного впровадження є багаторівневі гібридні системи, які поєднують мультисенсорне сприйняття, SLAM/VIO, глобальне і локальне планування та методи прогнозного безпечного керування.

Ключові слова: БПЛА; автоматичне керування; планування траєкторії; уникнення перешкод; комп’ютерний зір; багатосенсорна інтеграція; автономна навігація; інтелектуальні системи.

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