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MODERN CONTROL STRATEGIES FOR UNMANNED AERIAL SYSTEMS

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Abstract: The article provides an overview of modern approaches to mathematical modelling and synthesis of control systems for rotary-wing unmanned aerial vehicles (UAVs) and fixed-wing UAVs. It considers kinematic and dynamic models describing the translational and rotational motion of the mentioned types of UAVs, taking into account aerodynamic forces, moments, and gyroscopic effects. The general principles of mathematical model development, their adaptation for various classes of aerial vehicles, and their application in the synthesis of automatic control systems are analyzed. Particular attention is given to the analysis of stabilization systems and trajectory tracking, including those synthesized using PID controllers, LQR controllers, adaptive methods, model predictive control, and intelligent control theory. The dependence of control strategy selection on the type of UAV, flight characteristics, and mission objectives is examined.

Keywords: unmanned aerial vehicles; kinematic model; dynamic model; rotary-wing UAVs; fixed-wing UAVs; automatic control systems; flight stabilization; nonlinear control.

1. Introduction

Over the past decades, unmanned aerial vehicles (UAVs) have undergone significant development and are now actively used in various domains, including military operations, agriculture, cartography, and logistics [1]. Modern sensors, such as multispectral cameras and LiDAR systems, enable UAVs to efficiently collect data during remote sensing missions. The ability to perform real-time onboard data processing, thereby implementing autonomous decision-making systems [2], has substantially expanded the functionality of UAVs and increased their effectiveness across multiple applications.

As the range of UAV applications continues to grow, so does the demand for improved control methodologies. Contemporary UAV control approaches increasingly integrate innovations such as artificial intelligence (AI), blockchain, and distributed decision-making systems [3, 4]. AI enhances trajectory planning algorithms and enables autonomous responses to environmental changes; blockchain technologies ensure secure data exchange between UAVs and ground stations; and distributed decision-making systems support effective coordination within UAV swarms. Together, these innovations significantly improve operational safety, reduce the risk of unauthorized access to control systems, and optimize navigation processes [4–6].

The primary challenges of UAV control include:.

- **Ensuring real-time operation.** UAVs are equipped with cameras, laser scanners (LiDAR), radar sensors, and other devices that generate large volumes of data, which must be processed rapidly for decision-making [7]. This challenge is particularly critical for autonomous systems, where it is necessary not only to collect data but also to analyze it on the fly for navigation and object identification [8].
- **Energy resource limitations.** The flight time of a UAV is constrained by battery capacity, which directly affects the ability to process large data streams without compromising performance. This necessitates algorithmic optimization and energy-efficient computation [8, 9].

Addressing these challenges is crucial for achieving high-precision object detection and identification, as well as for enabling fully autonomous UAV operations in diverse environments. Consideration of the UAVs' limited energy and computational resources, along with effective sensor data fusion and computational platform optimization, represent key directions for further advancement of real-time UAV control technologies [10, 11].

2. Classification of UAVs according to aerodynamic characteristics

UAVs are classified according to various criteria [12]. The generally accepted classification of unmanned aerial vehicles is based on aerodynamic characteristics (Fig. 1), which provides for three main categories: multi-rotor, fixed-wing and hybrid [3, 13, 14].

Multirotor systems are characterized by high maneuverability and the ability to operate in confined spaces, which makes them effective for tasks such as aerial photography, infrastructure inspection, as well as logistical and technically complex missions. As an example of an aircraft with a multirotor aerodynamic configuration, Fig. 2 shows the Vampire unmanned aerial system developed by the Ukrainian company **SkyFall**. The image is reproduced from the official website of the Vinnytsia Regional Military Administration [44].

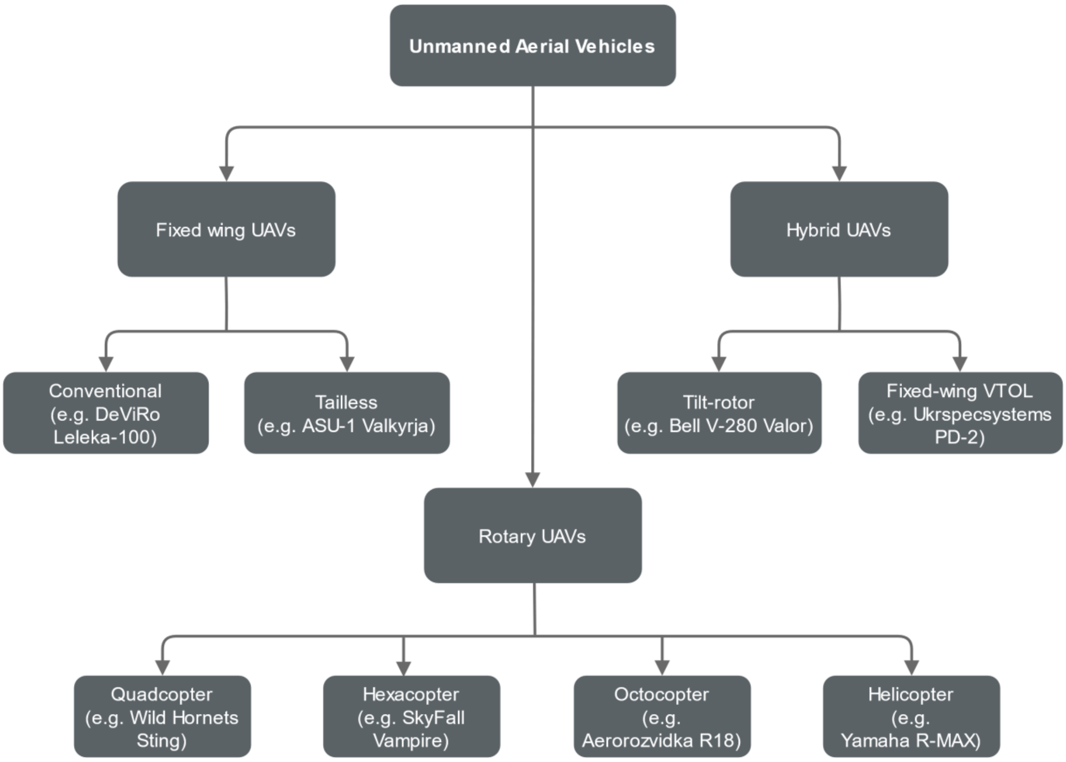

Fig. 1. Classification of UAVs according to aerodynamic characteristics

Fig. 2. Multirotor unmanned aerial vehicle 'Vampire' (Multirotor UAV) [44]

Fig. 3. External view of the fixed-wing UAV "MINI SHARK" [43]

Fig. 4. External view of the Ciconia hybrid system [42]

Fixed-wing UAVs offer longer flight endurance and higher efficiency, which is critically important for long-range missions, such as reconnaissance, mapping, or agricultural field monitoring. As an example of a fixed-wing aircraft, Fig. 3 shows the **MINI SHARK** unmanned aerial vehicle developed by the Ukrainian company **Ukrspecsystems**. The image is reproduced from the official website of the manufacturer [43].

Hybrid systems combine the advantages of both previously mentioned types, enabling their use for complex missions, such as extended monitoring with vertical take-off and landing capabilities [3]. As an example of a hybrid system, Figure 4 shows the **Ciconia** unmanned aerial system developed by the Ukrainian company **Deviro**. The image is reproduced from the official website of the manufacturer [42]. The system features vertical take-off and landing (VTOL) capabilities.

Multi-rotor and fixed-wing UAVs are the most common types, so this article will focus primarily on them.

3. Mathematical models of unmanned aerial vehicles

Mathematical models of unmanned aerial vehicles (UAVs) are essential tools for the synthesis of control systems, as they allow the evaluation of UAV characteristics under various conditions without the need for costly and time-consuming physical testing [17]. The initial stage involves modelling the physical system using nonlinear differential equations. The complexity of processes in a moving object necessitates the use of various approximations and simplifications [20]. In particular, UAVs can be represented by simplified models with three degrees of freedom (3-DOF). 3-DOF models treat the UAV as a point mass capable of moving in three spatial coordinates (along the x, y, and z axes). Such models do not account for rotational motion, mass-inertia properties, or aerodynamic moments. Despite their limited accuracy, 3-DOF models require fewer computational resources and are therefore widely used in the early stages of control system design [17] or for the development of simplified controllers.

For more accurate modelling, six degrees of freedom (6-DOF) models are employed, which fully represent the motion dynamics. A 6-DOF model is described by a system of twelve coupled first-order differential equations. This approach is significantly more precise but requires higher computational resources [19]. In 6-DOF models, the UAV is considered as a rigid body with three translational and three rotational degrees of freedom. These models account for [20]: the vehicle mass mmm; moments of inertia J_X, J_Y, J_Z; linear and angular velocities in the body-fixed coordinate system (U, V, W, P, Q, R); orientation angles (φ, θ, ψ); position in the inertial coordinate system (P_N, P_E, h); gravitational effects; and aerodynamic forces and moments.

3.1. Kinematic model of UAV

The kinematic model describes the relationship between the spatial position and orientation of a UAV and its linear and angular velocities. In the model of a micro aerial vehicle (MAV) presented in [20], the UAV is considered as a rigid body with six degrees of freedom, whose motion is formalized through a body-fixed coordinate system (body frame) and an inertial coordinate system (inertial frame).

3.1.1. Kinematics of translational motion

The position of a UAV in space is defined in the inertial coordinate system F_i by the vector $\vec{p} = [p_n, p_e, p_d]^T$, which describes the vehicle's location along the north-east-down (NED) directions. The linear velocity $\overrightarrow{v_b} = [u, v, w]^T$ is defined in the body-fixed coordinate system. The relationship between the velocity in the body-fixed frame and the change in position in the inertial frame is determined using the rotation matrix $R_{vb}(\phi, \theta, \psi)$ [15, 19, 20, 21]:

$$\dot{\vec{p}} = \begin{bmatrix} \dot{p}_n \\ \dot{p}_e \\ \dot{p}_d \end{bmatrix} = R_{vb}\left(\phi, \theta, \psi\right) \begin{bmatrix} u \\ v \\ w \end{bmatrix}, \qquad (4.1)$$

where φ, θ, ψ – Euler angles (roll, pitch, yaw).

The matrix Rυb erforms the rotational transformation between the coordinate systems and is given by [20]:

$$R_{vb} = \begin{bmatrix} c_\theta c_\psi & s_\phi s_\theta c_\psi - c_\phi s_\psi & c_\phi s_\theta c_\psi + s_\phi s_\psi \\ c_\theta s_\psi & s_\phi s_\theta s_\psi + c_\phi c_\psi & c_\phi s_\theta s_\psi - s_\phi c_\psi \\ -s_\theta & s_\phi c_\theta & c_\phi c_\theta \end{bmatrix}. \qquad (4.2)$$

3.1.2. Kinematics of rotational motion

The orientation of the vehicle in space is described by three Euler angles. The angular velocities $[p, q, r]^T$, defined in the body-fixed coordinate system, are related to the time derivatives of the orientation angles as follows [15, 19–21]:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi/\sec\theta & \cos\phi/\sec\theta \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix}, \qquad (4.3)$$

Equations (4.1) and (4.3) constitute the kinematic model of a UAV with six degrees of freedom. This model describes the changes in the vehicle's position and orientation in space under the influence of its linear and angular velocities. The presented relationships serve as the basis for the subsequent development of a dynamic model, which additionally accounts for the vehicle's mass, forces, moments, and inertia characteristics.

3.2. Dynamic model of UAV

Dynamic modelling of unmanned aerial vehicles is based on the classical equations of motion for a rigid body with six degrees of freedom. These include three translational degrees of freedom (motion along the coordinate axes) and three rotational degrees of freedom (rotation about the corresponding axes). This approach allows both rotary-wing and fixed-wing UAVs to be described using a single rigid-body motion mathematical model [20, 22].

The basis of the dynamic description is Newton's second law for translational motion and Euler's equations for rotational motion. The system of equations is given as follows [15, 20, 22]:

$$m\dot{\vec{v}}_b+\vec{\omega}_b\times\left(m\vec{v}_b\right)=\vec{F}_b, \tag{4.4}$$

$$\mathcal{J}\dot{\vec{\omega}}_b+\vec{\omega}_b\times\left(\mathcal{J}\vec{\omega}_b\right)=\vec{M}_b, \tag{4.5}$$

where m is the mass of the vehicle; $\overrightarrow{v_b}$ is the linear velocity in the body-fixed coordinate system; $\overrightarrow{\omega_b}$ is the angular velocity vector; $T_Д$ – is the differentiation time constant; $\overrightarrow{F_b}$ is the vector of forces applied to the body; $\overrightarrow{M_b}$ is the vector of moments; is the inertia tensor relative to the center of mass [20].

When developing models for control system synthesis and computational experiments, simplifications are often employed, in particular assumptions about the symmetry of the structure, the diagonal form of the inertia tensor, and the negligible effects of gyroscopic moments. These simplifications allow equations to be formulated that can be efficiently solved analytically, which is important for real-time control implementation [20, 22].

The overall structure of the UAV dynamic description is common across different configurations; however, the specific modelling of forces and moments largely depends on the type of aerial vehicle. External disturbances, such as wind and changes in air humidity, as well as interactions with sensors and control systems, significantly affect UAV behaviour. According to [15], a full dynamic model is required to ensure reliable autonomous control under dynamic conditions.

3.3. Dynamic model of multi-rotor UAVs

The dynamic model of multirotor UAVs describes the motion of a rigid body with six degrees of freedom. The most commonly used approaches for developing such a model are based on the Newton–Euler or Lagrange–Euler methods [22–25].

3.3.1. Newton-Euler general model

The translational dynamics of a quadcopter, according to the Newton–Euler model, are described by the following equations [23]:

$$\ddot{x}=\frac{U_1}{m}\left(cos\phi sin\theta cos\psi+sin\phi sin\psi\right)-k_1\dot{x}+d_1, \tag{4.6}$$

$$\ddot{y}=\frac{U_1}{m}\left(cos\phi sin\theta sin\psi-sin\phi cos\psi\right)-k_2\dot{y}+d_2, \tag{4.7}$$

$$\ddot{z}=\frac{U_1}{m}\left(cos\phi cos\theta\right)-g-k_3\dot{z}+d_3, \tag{4.8}$$

where U_1 is the total thrust force of the rotors; k_i is the velocity damping coefficients.

The rotational motion is described by the following equations [23]:

$$\ddot{\phi}=\frac{lU_2}{I_{xx}}-\frac{J_r}{I_{xx}}\dot{\theta}\omega_r+\frac{I_{yy}-I_{zz}}{I_{xx}}\dot{\theta}\dot{\psi}-k_4\dot{\phi}+M_{d\phi}, \tag{4.9}$$

$$\ddot{\theta}=\frac{lU_3}{I_{yy}}+\frac{J_r}{I_{yy}}\dot{\phi}\omega_r+\frac{I_{zz}-I_{xx}}{I_{yy}}\dot{\phi}\dot{\psi}-k_5\dot{\theta}+M_{d\theta}, \tag{4.10}$$

$$\ddot{\psi}=\frac{U_4}{I_{zz}}+\frac{I_{xx}-I_{yy}}{I_{zz}}\dot{\phi}\dot{\theta}-k_6\dot{\psi}+M_{d\psi}, \tag{4.11}$$

where U_2, U_3, U_4 are the moments produced by the difference in rotor speeds; J_r is a moment of inertia of rotors; ω_r is rotor speed; M_{d*} is disturbance.

In equations (4.6)–(4.11), forces and moments are presented in a generalized form, without detailing their physical nature. However, for a more accurate description of the real dynamics of a quadcopter, these components can be decomposed into their constituent parts.

In particular, the force acting on the vehicle in the body-fixed coordinate system includes the vertical thrust and a component accounting for aerodynamic damping [22]:

$$\vec{F}_{\text{res}}=Tz_b-D\cdot\vec{v}_b, \tag{4.12}$$

where T is the total thrust; z_b is the vertical vector; D is the damping matrix, which includes aerodynamic and induced moments; and $\overrightarrow{v_b}$ s the linear velocity vector in the body-fixed coordinate system.

Additionally, changes in rotor speeds lead to the generation of inertial moments associated with the gyroscopic effect. These moments are accounted for as a separate term in the rotational motion equation. According to [25], the gyroscopic moment is modeled as:

$$\tau_{\text{gyr}}=\omega\times\begin{bmatrix}0\\0\\J_r\omega_r\end{bmatrix}, \tag{4.13}$$

where ω is the angular velocity; J_r is the rotor's moment of inertia; ω_r is the total rotor spin rate.

This gyroscopic moment is particularly pronounced during rapid changes in rotor speeds, which are characteristic of maneuvers involving sudden increases or decreases in thrust, and can significantly affect the vehicle's rotational dynamics.

3.3.2. Lagrange–Euler model

The Lagrange–Euler method is based on an energy description of motion. As stated in [25], the dynamic model is constructed on the basis of the Lagrange function

$$L = T - V \,, \tag{4.14}$$

where T is kinetic energy; V is potential energy.

The equations of motion are derived using the classical formula:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = Q_i \,, \tag{4.15}$$

where q_i are generalised coordinates; Q_i are generalised forces including thrust, aerodynamic forces, moments and disturbances.

This approach is particularly effective for accounting for complex nonlinear effects and constructing stable control systems based on Lyapunov functions [24, 25].

3.3.3. Taking disturbances into account in a dynamic model

In real operating conditions, multi-rotor UAVs are subject to complex external influences, including wind loads, local turbulence, changes in air density, etc. These influences are difficult to model analytically, but they significantly affect the accuracy of trajectory tracking and system stability. Therefore, modern models often include explicit disturbances in the dynamics structure, which are then evaluated or compensated for at the control level. In [24], the dynamics of a quadcopter are presented taking into account disturbances that are explicitly added to the equations of motion. In particular, for vertical translational motion, the model has the following form:

$$\ddot{z} = \frac{1}{m} cos\phi cos\theta F_z - g - \frac{\xi_z}{m}\dot{z} + d_z \,, \tag{4.16}$$

where $\ddot{z}$ is the vertical acceleration of the UAV in the inertial coordinate system; m is the mass of the quadcopter; φ – is the roll angle; θ is is the pitch angle; F_z is the total vertical thrust generated by all rotors; g is the acceleration due to gravity; ξ_z is the damping coefficient; $\dot{z}$ is the vertical velocity; d_z is an external disturbance.

Disturbance compensation is implemented by incorporating disturbance observers into the control system structure. In particular, in [24], a Nonlinear Harmonic Disturbance Observer (NHDO) is implemented, designed to estimate periodic or smooth disturbances. The observer extends the dynamic model and allows disturbances to be compensated based on the estimated value $\widehat{d_\iota}$:

$$\tau_i = \tau_{i,nom} - d_i \,. \tag{4.17}$$

In contrast, [23] considers the classical Disturbance Observer (DOB), where disturbances are estimated as the error between the actual and nominal dynamics. This approach is simpler but less accurate in the case of complex or time-varying disturbances.

3.4. Dynamic model of a fixed-wing UAV

Fixed-wing unmanned aerial vehicles are modelled as rigid bodies with six degrees of freedom (6DOF) subject to aerodynamic, gravitational and traction forces, as well as moments. Unlike multi-rotor aircraft, lift in fixed-wing UAVs occurs only under conditions of steady translational motion. The structure of the dynamic model is based on Newton–Euler equations [20].

3.4.1. Translation motion

Translational motion describes the change in position and velocity of the center of mass under the action of applied forces. The position in a fixed inertial coordinate system (NED) is defined by the vector: $\vec{p} = \begin{bmatrix} p_n \\ p_e \\ p_d \end{bmatrix}$, and the linear velocity in the body-fixed coordinate system is described by the vector: $\overrightarrow{v_b} = \begin{bmatrix} u \\ v \\ \omega \end{bmatrix}$. The translational motion equation in the body-fixed coordinate system is given as [20]:

$$m\dot{\vec{v}}_b + \boldsymbol{\omega} \times \left(m\vec{v}_b\right) = \vec{F}_{\text{aero}} + \vec{F}_{\text{thrust}} + \vec{F}_{\text{gravity}} \,, \tag{4.18}$$

where m is the mass of the vehicle; $\boldsymbol{\omega} = [p, q, r]^T$ is the angular velocity vector; $\vec{F}_{\text{aero}}$, $\vec{F}_{\text{thrust}}$, $\vec{F}_{\text{gravity}}$ denote the aerodynamic force, thrust force, and gravitational force, respectively.

The aerodynamic force vector is decomposed into lift L, drag D, and side force Y which are mathematically described as [19]:

$$L = \frac{1}{2}\rho V^2 S C_L\left(\alpha\right), \tag{4.19}$$

$$D = \frac{1}{2}\rho V^2 S C_D\left(\alpha\right), \tag{4.20}$$

$$Y = \frac{1}{2}\rho V^2 S C_Y\left(\beta\right), \tag{4.21}$$

where ρ is the air density, V is the relative flow velocity, S is the wing area, α is the angle of attack, β is the sideslip angle; C_L, C_D, C_Y are the aerodynamic coefficients.

3.4.2. Rotational motion

Rotational motion is described by the equation of moments, recorded in the coordinate system associated with the centre of mass [20]:

$$J\dot{\omega}+\omega\times\left(J\omega\right)=\vec{M}_{\text{aero}}+\vec{M}_{\text{control}}, \qquad (4.22)$$

where J is the inertia tensor of the vehicle; $\vec{M}_{\text{aero}}$ is the moment due to aerodynamic forces; $\vec{M}_{\text{control}}$ is the moment generated by control surfaces (elevators, rudder, ailerons).

The mathematical description of the moments is given as [15]:

$$M=\frac{1}{2}\rho V^2 S\bar{c}C_m\left(\alpha,q,\delta_e\right), \qquad (4.23)$$

$$L=\frac{1}{2}\rho V^2 SbC_l\left(\beta,p,\delta_a\right), \qquad (4.24)$$

$$N=\frac{1}{2}\rho V^2 SbC_n\left(\beta,r,\delta_r\right), \qquad (4.25)$$

where $\bar{c}$ is the mean aerodynamic chord; b is the wingspan; δ_e, δ_a, δ_r are the deflection angles of the corresponding control surfaces; and C_m, C_l, C_n are the aerodynamic moment coefficients.

3.4.3. Thrust Effect

In general, thrust is modeled as a quadratic function of the propeller speed or approximated as a function of the thrust control signal. The analytical thrust model presented in [15] is given as:

$$F_T=\frac{1}{2}\rho D^4 C_T\left(\frac{n}{60}\right)^2, \qquad (4.25)$$

where D is the propeller diameter C_T s the thrust coefficient; and n is the rotational speed in revolutions per minute (RPM).

3.4.4. External disturbances

In the dynamic modeling of a fixed-wing UAV, external disturbances are considered as uncontrolled influences from the environment that are not included in the nominal dynamic model. Such disturbances include not only wind loads but also turbulence, variations in air density, local atmospheric disturbances, thermal updrafts, as well as uncertain or difficult-to-model external effects caused by terrain or asymmetries in the aircraft (e.g., wing icing or thrust asymmetry) [19, 21].

To account for these effects, the dynamic model is extended by adding external disturbances to the right-hand sides of the force and moment equations. The modified translational motion equation becomes:

$$\begin{aligned} &m\dot{\vec{v}}_b+\vec{\omega}\times\left(m\vec{v}_b\right)= \\ &=\vec{F}_{\text{aero}}+\vec{F}_{\text{thrust}}+\vec{F}_{\text{gravity}}+\vec{d}_f\left(t\right) \end{aligned}, \qquad (4.26)$$

where $\vec{d}_f(t)$ is the external disturbance vector, describing the force projections along the three spatial directions (in the body-fixed coordinate system).

Similarly, the rotational motion equation is extended to:

$$J\dot{\vec{\omega}}+\vec{\omega}\times\left(J\vec{\omega}\right)=\vec{M}_{\text{aero}}+\vec{M}_{\text{control}}+\vec{d}_m\left(t\right), \qquad (4.27)$$

where $\vec{d}_m(t)$ is the disturbance moment vector, representing additional rotational influences around the three axes of the vehicle.

This approach was proposed in [20], where external disturbances are included as vectorial terms in the force and moment equations. In [19], a scalar interpretation of disturbances is implemented. Additional variables, e.g., d_9, and $d_{\theta 1}$, are introduced directly into the equations of the corresponding dynamic channels to model the effects. Both approaches are compatible with modern disturbance-resistant and adaptive control methods.

4. Control System Architecture of an Unmanned Aerial Vehicle (UAV)

Modern unmanned aerial vehicles employ a **GNC (Guidance, Navigation, Control)** architecture, which serves as the basis for autonomous UAV control. It provides trajectory planning, determination of the current state of the vehicle, and adjustment of motion according to the assigned objectives [15]. The GNC architecture for a UAV is shown in Fig. 5.

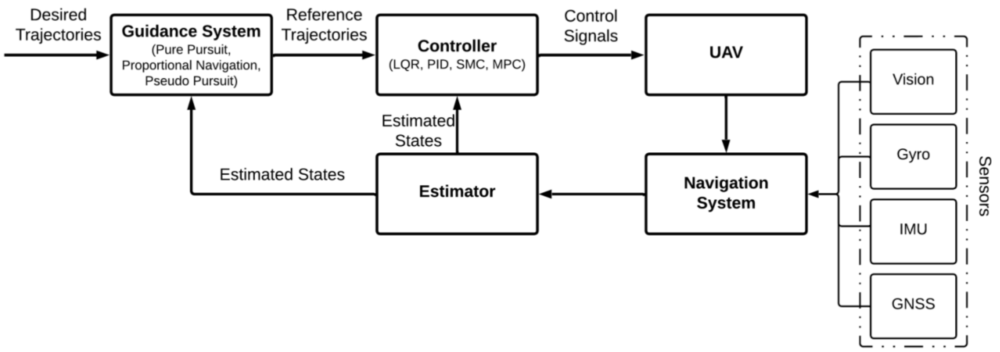

Fig. 5. GNC architecture for a UAV [15]

The three main components required to ensure the autonomous operation of unmanned aerial vehicles (UAVs) include Guidance, Navigation, and Control (GNC) systems. The Guidance subsystem is responsible for generating the flight path, taking into account the current coordinates of the UAV, target waypoints, and external conditions such as wind speed and other possible disturbances. It employs various methods, including proportional and other orientation algorithms, which help adapt the route to achieve optimal vehicle performance [15].

The Navigation subsystem determines the current position, velocity, and orientation of the UAV by analyzing data from sensors [16, 17]. The main sources of information for this process are GNSS receivers, inertial measurement units (IMUs), gyroscopes, and Pitot tubes. To improve the accuracy of navigation estimates, state estimators (e.g., Kalman filters) are often used, allowing sensor data and estimator outputs to be combined, ensuring reliability even in the presence of noise or incomplete information [17].

The Control subsystem ensures stabilization and adjustment of the UAV's motion according to the trajectory generated by the guidance system. This is achieved through control signals sent to actuators such as motors and control surfaces. Various control methods are employed in UAVs, including classical approaches based on Proportional-Integral-Derivative (PID) controllers, as well as modern approaches incorporating neural networks and fuzzy logic-based systems [18, 19]. The main objective is to maintain stable flight even in the presence of external disturbances.

5. UAV Control Systems

Development of effective control systems is one of the key tasks in the creation of unmanned aeri al vehicles (UAVs). The dynamics of multirotor UAVs are characterized by a high degree of nonlinearity, low damping of oscillations, and strong interdependence between control channels. These vehicles are capable of vertical takeoff and landing (VTOL) and can hover in place for extended periods, which imposes specific requirements for stabilization and compensation of external influences [22]. Traditionally, classical PID controllers are used for controlling such vehicles; however, as mission complexity increases, there is growing interest in nonlinear and adaptive c ontrol methods.

Fixed-wing UAVs, on the other hand, exhibit higher energy efficiency and the ability for long-endurance flight due to the lift generated by the wing. Their dynamics are closer to those of light aircraft, allowing the application of linear control methods when flying near a nominal operating regime. However, during rapid trajectory changes or under wind disturbances, the use of nonlinear or disturbance-resistant control methods becomes necessary [26].

The choice of a control strategy is determined by several factors:

- the type of vehicle (multirotor or fixed-wing);
- the complexity of the task (stabilization, trajectory tracking, coordination of group flights);
- the level of external disturbances and uncertainty in the mathematical model;
- requirements for accuracy, responsiveness, and energy consumption.

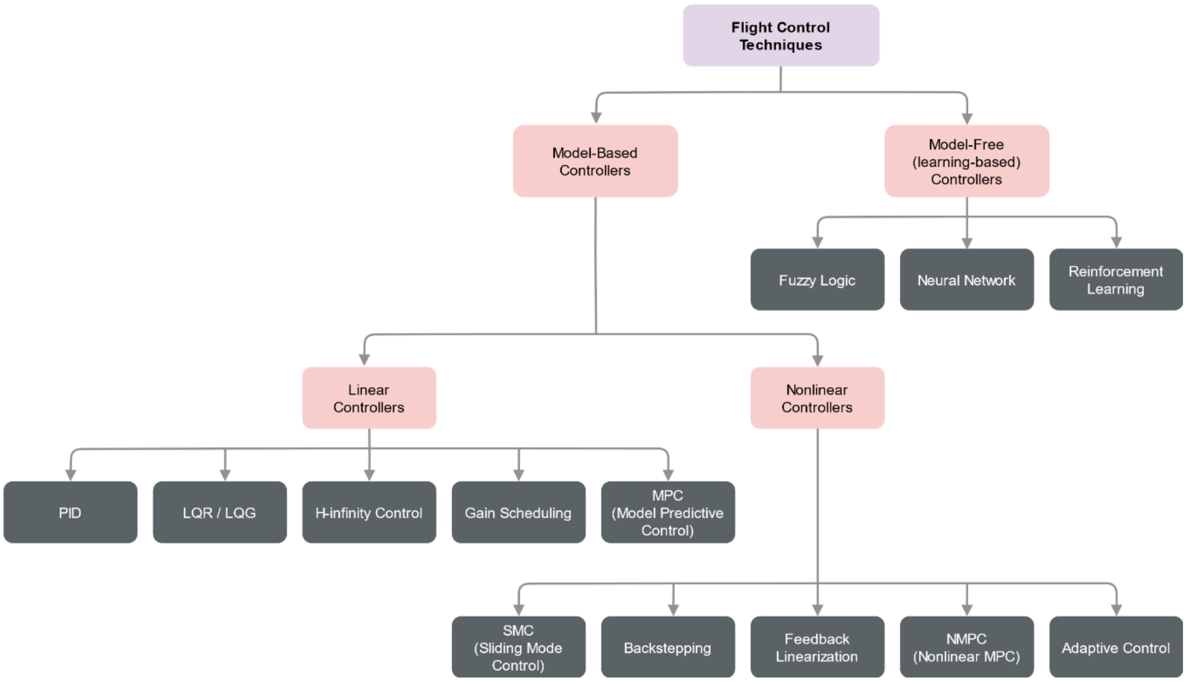

Fig. 6. Classification of modern UAV control systems

Modern UAV control methods are conventionally divided into **model-based control methods** and **learning-based methods** [15, 17, 22, 23, 25]. Fig. 6 presents a generalized structure of these approaches.

The category **"Model-Based Controllers"** encompasses systems based on the use of an analytical or empirical mathematical model of the vehicle [20]. This group includes both linear and nonlinear approaches.

Linear control systems include PID control, Linear Quadratic Regulator (LQR), Linear Quadratic Gaussian Controller (LQG), robust control with optimization based on the H∞ criterion, Gain Scheduling, and Linear Model Predictive Control (MPC) [20, 25].

Nonlinear methods are implemented through Sliding Mode Control (SMC), Feedback Linearization, Backstepping, Nonlinear Model Predictive Control (Nonlinear MPC), and Adaptive Control [22, 24].

The second category, **"Learning-Based Controllers,"** includes approaches that minimize dependence on an accurate mathematical model by using artificial intelligence and machine learning methods [23]. This group includes Fuzzy Logic systems, Neural Networks, and Reinforcement Learning algorithms.

A comparative analysis of the main UAV control systems is presented in **Table 1.**

The choice of control strategy is determined by the type of vehicle, the nature of the task, the expected level of external disturbances, as well as the available computational resources and the requirements for system stability and adaptability [20, 23, 25].

Table 1

Comparison of modern UAV control systems [17]

UAV control system	Advantages	Disadvantages
PID	Ease of implementation and setup	Sensitivity to noise and disturbances
LQR / LQG	Optimal control, guaranteed stability margin, engineering convenience	Requires a complete state vector and an accurate model
H-infinity Control	Resilience to uncertainties and disturbances	High computational cost, complexity of setup
Gain Scheduling	Efficient operation in a wide range of modes, taking into accountnonlinear properties	Stability issues during transition between modes, design complexity
Model Predictive Control (MPC)	Taking into account constraints on inputs and states, multivariate control	High dependence on the accuracy of the forecast model
Sliding Mode Control (SMC)	High resistance to uncertainties and disturbances, good tracking characteristics	Chattering or shaking effect
Backstepping	Excellent tracking and disturbance compensation capabilities, effective for under-controlled systems	Requires precise mathematical model, high computational complexity
Feedback Linearization	Efficient control of nonlinear systems, good tracking quality	The need for an accurate mathematical model, high computational cost
Nonlinear MPC (NMPC)	Ability to work with strong nonlinearities and system constraints	High computational complexity, need for powerful processors
Adaptive Control	Adaptation to variable and unknown system parameters, resistance to disturbances	Complex setup, high computational load
Fuzzy Logic	Does not require an exact mathematical model, flexibility in configuration	Complexity of rule development, dependence on expert knowledge
Neural Network	High ability to approximate complex systems, ability to learn	The need for large amounts of data for training, the complexity of validation
Reinforcement Learning	Learning optimal behavior without an explicit model	Requires a large amount of training data,instability

5.1. Proportional-integral-derivative (PID) control

Proportional-Integral-Derivative (PID) control is one of the fundamental methods used for designing stabilization and trajectory-tracking systems for unmanned aerial vehicles (UAVs).

In multirotor UAV control systems, PID controllers are most commonly applied to stabilize angular rates and attitude angles (pitch, roll, yaw), as well as to regulate altitude. Each stabilization channel has a separate PID controller, which ensures the required quality of stabilization even in the presence of moderate disturbances [22]. The error e(t) is defined as the difference between the desired and actual angle or rate (e.g., roll φ, pitch θ, yaw ψ). A key feature of using PID for multirotor UAVs is the need to coordinate control signals among multiple motors to achieve the desired torque or thrust [22, 25].

In fixed-wing aircraft, PID controllers are used to stabilize flight parameters such as altitude, airspeed, angle of attack, heading, and trajectory [20]. Unlike multirotor platforms, in fixed-wing UAVs, the control signals act on aerodynamic surfaces: ailerons (δ_a), elevator (δ_e), and rudder (δ_r). For example, altitude control is based on pitch control through a PID controller:

$$e(t) = h_{ref}(t) - h(t), \tag{5.1}$$

where $h_{ref}(t)$ is the desired altitude and h(t); $h(t)$ is the actual altitude. Similar PID structures are applied to control heading using the rudder and roll angle using the ailerons [20]. The main feature of PID application in fixed-wing

UAVs is the need to account for the coupling between control channels, which creates the necessity for using multiloop stabilization systems [20, 25].

5.2. Linear-quadratic regulator (LQR)

The Linear Quadratic Regulator (LQR) is a classical optimal control system synthesis method based on the minimization of a quadratic functional. It is effective when applied to linear or linearized system models and ensures an optimal balance between control quality and energy expenditure [20,28].

In control systems of multirotor unmanned aerial vehicles, LQR is used for stabilizing the orientation and position of the vehicle in space [27, 28]. Typically, the system is linearized around the hovering state, where angular deviations and velocities are small. The linearized dynamics of a quadcopter for the angular coordinates e.g., roll φ, pitch θ, yaw ψ are described by the following equations [28]:

$$\ddot{\varphi} = \frac{1}{I_{xx}} U_2, \quad \ddot{\theta} = \frac{1}{I_{yy}} U_3, \quad \ddot{\psi} = \frac{1}{I_{zz}} U_4, \tag{5.2}$$

are I_{xx}, I_{yy}, I_{zz} *are* the moments of inertia of the quadcopter; U_2, U_3, U_4 are the control torques around the respective axes.

The state vector is defined as:

$$x = [\varphi, \dot{\varphi}, \theta, \dot{\theta}, \psi, \dot{\psi}]^T. \tag{5.3}$$

The control vector has the form:

$$u = [U_2, U_3, U_4]^T. \tag{5.4}$$

The application of LQR ensures effective stabilization of the vehicle's orientation even under external disturbances and inaccuracies of the mathematical model [27].

In a fixed-wing aircraft, LQR is applied to stabilize altitude, velocity, heading, and navigation parameters under conditions of steady straight-line flight [20, 21]. The linearized longitudinal dynamics of the aircraft are described by the following system of equations [20]:

$$\begin{aligned}
\dot{u} &= X_u u + X_w w + Z_\vartheta \vartheta - g cos\vartheta_0 + X_{\delta_e}\delta_e, \\
\dot{w} &= Z_u u + Z_w w + Z_\vartheta \vartheta - g sin\vartheta_0 + Z_{\delta_e}\delta_e, \\
\dot{q} &= M_u u + M_w w + M_q q + M_{\delta_e}\delta_e, \\
\dot{\vartheta} &= q, \\
\dot{h} &= -u sin\vartheta + w cos\vartheta,
\end{aligned} \tag{5.5}$$

where u, w are the velocity components of the aircraft;; q is the pitch angular velocity; θ is the angle of attack; h is the flight altitude; δ_e is the elevator deflection; g is the acceleration due to gravity; X_u, X_w, Z_u, Z_w, M_u, M_w, M_q – are the coefficients obtained experimentally or through aerodynamic modeling.

The state vector has the form:

$$x = [u, w, q, \vartheta, h]^T. \tag{5.6}$$

The control input is defined by the equation:

$$u = \delta_e. \tag{5.7}$$

The use of LQR to stabilise longitudinal motion reduces altitude and angle of attack errors with minimal energy consumption [21].

5.3. Nonlinear control with predictive models (Non-linear MPC)

Nonlinear Model Predictive Control (NMPC) is an extension of the classical MPC approach that allows the full nonlinear dynamics of the system to be considered when constructing control actions. This method is viewed as an intermediate between classical and intelligent approaches since, on the one hand, it relies on a mathematical model of the system, while on the other – it enables the use of optimization methods and machine learning, in particular for modeling dynamics or generating trajectories [23].

The main idea of NMPC is to determine the optimal sequence of control actions over a finite time horizon by minimizing a cost function subject to dynamic constraints. The general mathematical formulation of the problem is as follows [23]:

$$\min_{u(\cdot)} \int_t^{t+T} \ell\,(x(\tau), u(\tau))\, d\tau \tag{5.8}$$

subject to:

$$\dot{x} = f(x, u), \quad x(t) = x_0, \quad x(\tau) \in \mathcal{X}, \quad u(\tau) \in \mathcal{U}, \quad \forall\tau \in [t, t+T]. \tag{5.9}$$

where $x(\tau)$ is the system state vector at time τ; $u(\tau)$ is the control input vector; $f(x, u)$ is the nonlinear system dynamics model; $\dot{x}$ is a derivative of the state vector with respect to time, i.e., $\dot{x} = \frac{dx}{dt}$; $x(t) = x_0$ is the initial state of the system at time t; $\mathcal{X}, \mathcal{U}$ are the admissible sets of states and controls, respectively; $\ell(x, u)$ is the cost function defining the optimization objective; T is a prediction horizon; $\forall\tau \in [t, t+T]$ indicates that the dynamic and constraint conditions for states and controls must hold at all times within the prediction horizon.

At each iteration, only the first element of the optimal control sequence is applied to the system, after which the optimization is repeated with the updated state.

In multirotor UAV control systems, NMPC is applied for stabilization, trajectory tracking, and obstacle avoidance. NMPC implementations account for the nonlinear dynamics of the vehicle, physical constraints on control signals, and the influence of external disturbances, which is critically important for performing complex maneuvers in real time [23].

The main advantages of applying NMPC in multirotor systems are: the ability to actively incorporate constraints on control inputs; adaptability to changing dynamic environmental conditions; and high trajectory accuracy even in confined spaces. NMPC is particularly effective for maneuvering in environments with high dynamic demands and limited space. The main drawbacks include the high computational complexity of the optimization algorithms, which requires the use of specialized numerical methods and powerful computational resources [23].

When applied to fixed-wing UAVs, NMPC-based approaches demonstrate a variety of implementations depending on the control objectives. In [29], a full implementation of nonlinear MPC is proposed for the task of three-dimensional tracking of a ground target using a fixed-wing UAV. The system models the full nonlinear dynamics of the UAV in space, taking into account constraints on control signals and the physical characteristics of the vehicle. To ensure closed-loop system stability, a stabilizer synthesized using the Lyapunov method is introduced. The optimization problem is solved using a global heuristic method (bat algorithm), which significantly reduces real-time computational costs. Experimental tests showed that the proposed approach provides reliable tracking of both stationary and moving targets, even in the presence of wind disturbances [29].

Another approach to using NMPC is presented in [30], where NMPC is applied to optimize a parameter within the structure of an already stable nonlinear guidance law based on Lyapunov stability theory. Specifically, a coefficient is optimized that determines prediction and compensation of trajectory tracking errors. The proposed method demonstrated advantages over fixed-parameter and fuzzy-logic approaches, particularly under crosswind conditions [30].

5.4. Adaptive Control

Adaptive control is a class of methods that enables automatic adjustment of system parameters in real time to compensate for uncertainties in the object's dynamics or changes in external conditions.

Adaptive control of multirotor UAVs allows compensation for the effects of external disturbances, changes in mass, moments of inertia, and other factors that vary during flight. One example is the use of MRAC (Model Reference Adaptive Control) with neural networks for quadcopters [27]. In this implementation, the neural network is embedded within the controller structure and approximates unknown nonlinearities of the dynamics in real time. This increases trajectory tracking accuracy in the presence of parametric uncertainties and disturbances.

To compensate for varying characteristics of the quadcopter, an Extended Classical Adaptive Approach (ECAA) has been developed, which adapts the controller parameters based on changes in mass or distribution of moments of inertia [32]. This approach ensures system stability even with significant variations in object parameters. Among adaptive control methods for multirotor UAVs, a Simple Adaptive Control (SAC) scheme with an adaptive anti-windup compensator is also used. This approach stabilizes the quadcopter's orientation in cases of control signal saturation, maintaining system stability without requiring changes to the control structure [31].

For fixed-wing UAVs, adaptive control is aimed at compensating for uncertainties in aerodynamic parameters, which may vary depending on flight mode or external conditions. Adaptive Backstepping is implemented in fixed-wing UAV control systems, ensuring stable trajectory tracking in the presence of model uncertainties. The control system is constructed based on sequential stabilization of errors relative to the desired trajectory while simultaneously adapting to unknown aerodynamic parameters. This allows maintaining control quality under changing flight conditions and performing complex maneuvers in real operational environments [19].

5.5. Fuzzy control

Fuzzy control is a class of methods based on using fuzzy rules to generate control actions in systems with uncertain or complex dynamics. The most commonly used algorithms are Mamdani and Sugeno, depending on the required precision and computational complexity.

In multirotor UAVs, fuzzy control systems are used to stabilize position and orientation under uncertainties and wind disturbances. A fuzzy PID controller is built using three input variables: position error, derivative of error, and integral of error. The implementation of fuzzy control improves trajectory tracking accuracy and enhances quadcopter stability compared to standard PID controllers [33].

Adaptability is further increased by emulating the behavior of the fuzzy PID controller using a Recurrent Neural Network (RNN), which reduces computational load while maintaining stabilization accuracy [34]. Additionally, integrating fuzzy logic with Radial Basis Function Neural Networks (RBF NN) is used to optimize PID parameters in real time, improving the system's adaptability to changes in object dynamics [35].

In fixed-wing UAVs, fuzzy control systems are applied to improve the stability and accuracy of altitude and heading stabilization, as well as to compensate for lateral-axis oscillations during flight under challenging conditions. Such systems allow the aircraft's response to adapt to changing external influences without the need to retune controller parameters.

The structure of the fuzzy controller is based on classical principles for designing stabilizers for automatic altitude and heading control. The input data are the values of altitude deviation, heading deviation, and the derivatives of these errors, which are then converted into fuzzy sets for further processing. The control rule base is formed based on the correspondence between the magnitude of deviations and the required control moments for the ailerons, elevator, and rudder. The use of fuzzy logic in the stabilization loops of fixed-wing UAVs improves system response under variable environmental conditions, increases adaptability to wind disturbances, and ensures smooth flight adjustments [20].

5.6. Neural networks in UAV control systems

Neural Networks (NN) are used in unmanned aerial vehicle (UAV) control systems as tools for approximating system dynamics, compensating for disturbances, stabilizing, and optimizing trajectories without the need for an explicit mathematical model [37]. Despite this, neural networks on their own are not classical control systems. They are considered as alternative or auxiliary intelligent controllers (Learning-Based Controllers), which complement or replace specific modules of the control system. This allows the system to adapt to complex aerodynamic characteristics of the vehicle and changing external conditions [36, 37].

Table 2 presents the main application areas and typical examples of the use of different neural network architectures in UAV control systems.

Table 2

Type of neural network	Main purpose	Features of application in UAVs	Sour-es
Feedforward Neural Networks (FNN)	Approximation of control functions or dynamics	Creating control models to stabilize the position and orientation of UAVs	[8, 37]
Radial Basis Function Networks (RBF-NN)	Compensation of local uncertainties	Robust local control in complex environments for multi-rotor UAVs	[27]
Recurrent Neural Networks (RNN), LSTM	Predicting future states	Fixed-wing UAV trajectory planning, obstacle avoidance	[34, 36]
Fractal Neural Networks	Generalization and resistance to overtraining	Use in stabilization problems in complex dynamics	[38]
Neural Networks at MRAC	Adaptive compensation control	Compensation for unknown dynamics in multi-rotor UAVs	[27]
Neural Networks in S-Plane Models	Position control in the plane	Application for stabilizing fixed-wing UAVs in windy conditions	[39]
Hybrid approaches (Fuzzy+NN)	Integrating the flexibility of fuzzy control and neural net-work training	Improving the stability and adaptability of trajectory control	[34]

Fractal Neural Networks demonstrate high resistance to overfitting and the ability to generalize complex dependencies, making them suitable for use in advanced control scenarios [38]. Integrating neural networks into MRAC-type (Model Reference Adaptive Control) adaptive control structures allows compensation for unknown dynamics by minimizing trajectory errors relative to a reference model [27].

In multirotor UAVs, neural networks are integrated to stabilize position and orientation, compensate for external disturbances, and handle variable dynamic characteristics. For mode-transition tasks in complex vehicles, particularly in ducted fan UAVs, neural networks are used to generate control moments during transitions from hovering to horizontal flight. Closed-loop system stability in these approaches is ensured using Lyapunov functions [40].

In fixed-wing UAVs, neural networks are employed for trajectory planning and flight control under variable external conditions. The use of recurrent networks, such as LSTM, enables prediction of future vehicle states, optimizing the route while accounting for wind loads and energy consumption [36]. Additionally, control signals are constructed based on a neural model in the S-plane, improving navigation accuracy of fixed-wing UAVs in challenging atmospheric conditions [39].

In more advanced implementations, hybrid strategies are considered, where neural networks are integrated with other approaches, such as fuzzy logic. The combination of a fuzzy PID controller with a recurrent neural network significantly improves the stability of trajectory tracking, even under substantial changes in environmental parameters [34].

The use of neural networks in UAV control systems opens wide opportunities to enhance adaptability, resistance to external disturbances, and flight autonomy under complex and variable conditions [37, 41].

6. Conclusions

The review found, that mathematical modelling of unmanned aerial vehicles (UAVs) is based on kinematic and dynamic models that account for both translational and rotational motion of the vehicle. For rotary-wing UAVs, modeling typically focuses on aerodynamic forces and moments, while fixed-wing aircraft are mainly modelled using aerodynamic flight models.

The analysis of existing control systems has shown that classical approaches, including proportional-integral-derivative (PID) and linear-quadratic control (LQR), remain fundamental for stabilization and implementation of simple trajectory-tracking tasks. However, under conditions of diverse disturbances and parametric uncertainty of models, the application of such approaches is relatively inefficient.

Control systems employing nonlinear model predictive control (NMPC), adaptive strategies, or artificial intelligence methods provide the capability to execute complex UAV trajectories even under significant disturbances and varying parameters.

The choice of a mathematical model and the corresponding control strategy depends on the type of UAV and the specifics of the tasks to be performed.

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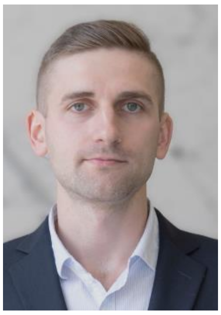
СУЧАСНІ СТРАТЕГІЇ КЕРУВАННЯ БЕЗПІЛОТНИМИ АВІАЦІЙНИМИ СИСТЕМАМИ

Максим Шепляков

Наведено сучасні підходи до математичного моделювання та синтезу систем керування роторними безпілотними літальними апаратами та безпілотними апаратами з нерухомим крилом. Розглянуто кінематичні та динамічні моделі, що описують поступальний і обертальний рух зазначених типів БПЛА, з урахуванням аеродинамічних сил, моментів та гіроскопічних ефектів. Проаналізовано загальні принципи побудови математичних моделей, їх адаптацію для різних класів літальних апаратів та використання у процесі синтезу систем автоматичного керування. Особливу увагу зосереджено аналізу систем стабілізації й відпрацювання заданої траєкторії руху, зокрема, синтезованих із застосуванням ПІД-регуляторів, LQR-регуляторів, адаптивних методів, методу model predictive control, а також теорії інтелектуального керування. Проаналізовано залежність вибору стратегії керування від типу апарата, характеристик польоту та цільових задач.



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