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Control Algorithms, Kalman Estimation and Near Actual Simulation for UAVs: State of Art Perspective

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Abstract: The pervasive use of unmanned aerial vehicles for both commercial and military operations has undergone rapid development in the recent past. When designing unmanned aerial vehicles, it is highly desirable for them to be able to complete their missions with minimal human intervention. Reaching full autonomy requires a reliable and efficient control algorithm that can handle all flight conditions. Due to the confidential nature of UAV design and development, there is a lack of comprehensive literature on the subject. When it comes to the practical application of the ideas presented in the literature, the situation is even bleaker. This research not only examines the flight phases in which controllers and estimators are used for UAVs but also provides an in-depth analysis of the most recent and state-of-the-art control and estimate techniques for UAVs. Research opportunities and challenges specific to UAVs were also examined in this study in an effort to raise the bar for UAV design as a whole and smooth the way for researchers to go from simulation-based research to practical applications. This review paper establishes a foundation that not only investigates the inherent flight dynamics, control architecture, and Kalman estimators utilized in the development of UAVs but also points out the shortcomings that currently exist in research. A number of design considerations for realistic applications and potential studies are presented in the conclusion.

Keywords: fixed-wing; near-actual simulations; unmanned aerial vehicle; control techniques; autonomous flight; state estimation

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1. Introduction

Unmanned Aerial Vehicles (UAVs), also known as drones, have become one of the most attractive branches of the aviation industry in recent years due to their versatility and capabilities for a variety of applications [1–5]. Typically, the military employs UAVs for tasks like surveillance, reconnaissance, combat/strike missions, intelligence gathering, etc. [6,7]. But as new technologies have emerged, their potential for use in the public sector has also grown. This is especially true in applications like disaster management, wireless sensor networks [8,9], surveillance and monitoring [10,11], search and rescue operations [12], Internet of Things (IoT) [13], remote sensing [14] and commodities transportation [15] etc. As the mission complexity of unmanned aerial vehicles (UAVs) increases, so does the difficulty of their development, particularly with the goal of achieving fully autonomous flight (i.e., with minimal to zero human interaction). Due to the versatility of UAVs, the mission profile will change depending on the mission's objective. Takeoff and landing are the two critical flight phases of a fully autonomous UAV flight. Furthermore, numerous applications necessitate that UAVs operate autonomously in unpredictable and changing environments, where the UAV must rely on their available sensors to perceive their surroundings and efficiently complete their mission [16]. The three fundamental subsystems necessary for UAV autonomy are guidance, navigation, and control (GNC).

An unmanned aerial vehicle's (UAV) "pilot" is its guidance system, which plans and makes decisions to carry out missions and achieve objectives. Usually, a reference trajectory for the UAV is constructed using information from both the mission planner and the present state of the vehicle. The current position and speed of the UAV are also taken into account alongside the intended location and environmental factors like wind speed that could affect the UAV's flight. UAVs utilize a variety of different types of guidance algorithms depending on their mission objectives. These algorithms developed a reference trajectory that improves the UAV's performance in accordance with user-specified goals, such as reducing travel time to the target and reducing fuel consumption. Common UAV guidance algorithms include waypoint guidance, proportional navigation, and pure pursuit.

Information regarding UAV's state and its surrounding is provided by the navigation system [17]. The UAV's location, speed, and orientation are continuously monitored by the navigation system using data collected by onboard sensors. The UAV's guidance and control systems rely on accurate state estimates provided by the navigation system. In order to estimate the UAV's current states, the navigation system frequently consists of up of a suite of sensors and algorithms. Common sensors used in UAV navigation systems include GPS, IMU, vision sensor, and pitot tube. These sensor readings are then used by State estimators within the navigation algorithms to ascertain the current states of the UAV. State estimators estimate the UAV's state using data from sensors in conjunction with the UAV's mathematical model and this estimate is more accurate than the original sensor data. In order to execute the necessary control actions, rapid and accurate state estimations are required due to the fast dynamics of the UAV. However, some system states are not observable and some measurements are unreliable because of sensor errors [18]. Efficient and precise state estimation is crucial for enabling autonomous UAV flights. Even though it's crucial for the UAV's control performance and safety, state estimate has been mainly ignored until now [19].

Unmanned Aerial Vehicles (UAVs) guidance, navigation, and control (GNC) rely heavily on the control algorithm. Actuator inputs required to produce moments and forces in accordance with guidance system commands are handled by the control system, which is comprised of control laws that take into account the current state of the UAV as determined by the navigation system (sensors) and the UAV dynamics. Maintaining stability and controllability of the UAV in the presence of exogenous inputs and wind disturbances is in the hands of the control algorithm. An unmanned aerial vehicle's trajectory is maintained via a control command calculated from the UAV's current state and the pre-planned trajectory. The ultimate objective of UAVs is to perform the required missions with minimal human assistance. Fully autonomous control of UAVs is more challenging because it does not require human support during autonomous operation. As a result, problems with flight safety and accidents are more likely to occur in unmanned aircraft compared to planes flown by humans [20]. Creating and implementing sophisticated and reliable control algorithms is crucial for preventing these failures and enhancing autonomy. Numerous control algorithms, from the more basic PID [21] controller to the more complex Neural network and fuzzy logic controllers [22], have been developed and implemented for the autonomous flight of UAVs.

UAVs quickly expanding fleet, and their increasing utility presents a significant challenge to engineers in terms of creating efficient and robust GNC algorithms. However, the development of dependable and robust systems is made possible by technological advances in the aerospace industry [9,23–25] and ground vehicles [26–36]. Figure 1 depicts the typical UAV GNC architecture. To identify and address the potential faults and errors in the designed algorithm prior to its practical implementation, model-in-loop, software-in-loop, processor-in-loop, and hardware-in-loop, along with different visualization software, are generally used. With the use of simulation and visualization tools, developers can evaluate the GNC algorithm's functionality and performance in a variety of scenarios, ensuring its robustness and dependability before committing to costly and time-consuming flight testing. Additionally, these realistic simulation techniques can be utilized to assess the GNC algorithm's robustness to complex and dynamic situations, assuring that it can deal with unforeseen changes and disruptions [37]. There is a wide variety of unmanned aerial vehicles (UAVs), each with its own set of features and capabilities to meet the desired mission requirement. Fixed-wing, rotary-wing, and Vertical Takeoff and Landing (VTOL) UAVs are the three primary types of unmanned aerial vehicles (UAVs). Like conventional airplanes, fixed-wing UAVs rely on a pair of wings to provide lift, they can carry more payload as compared to their counterparts however, they require a runway for take-off and landing. Alternatively, rotary-wing UAVs mimic the flight characteristics of helicopters by using a rotor to create lift and steer the UAV. Vertical takeoff and landing unmanned aerial vehicles (VTOL UAVs) are a hybrid of fixed-wing and rotary-wing aircraft, combining their respective strengths to provide both efficient forward flight and vertical takeoff and landing [38]. In this work, however, we shall examine only fixed-wing UAVs.

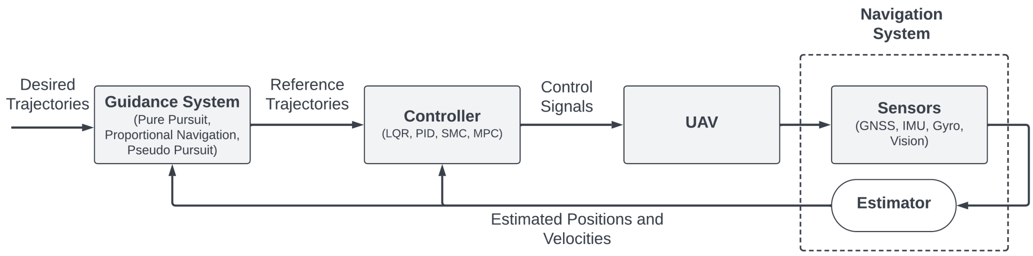

Figure 1. Generic control architecture for UAV [39].

1.1. Objective and Contents

The objective of this paper is to present an analysis of flight control algorithms utilized for the autonomous flight of fixed-wing UAVs, with a focus on landing and takeoff. Also discussed is the estimator used to compensate for inaccurate sensor data and sensor failure. It is clear from the articles consulted and the literary analysis that most UAV studies conducted by researchers have concentrated on one aspect of flight, such as takeoff or landing and the work also lacked the implementation of a state estimator. In addition, the design architecture remained simulation-based without any near-actual simulation work, such as Processor-in-the-loop or Hardware-in-the-loop simulations, which are the basis for the practical implementation of the onboard flight controller. This is an essential component for successfully implementing the control architecture to physical hardware. Due to the aforementioned highlighted observations, it is necessary to present a consolidated systematic review that summarizes and discusses all such essential components for the actual development of UAVs. Here, we provide a comprehensive overview of the simulation methods and flight simulators that have been employed by academics in their efforts to verify the efficacy of flight controllers for fixed-wing UAVs. This paper will assist both the general public and industries in moving from simulation-based work to practical implementation.

1.2. Paper Organization

In Section 2, we provide a review of the published survey papers on UAVs. Sections 3.1 and 4 respectively cover the control algorithms and state estimators utilized. Section 5 provides information and review on realistic simulation techniques and visualization software used for fixed-wing UAVs. In Section 6, we discuss the existing challenges as well as future work directions. In the final Section, 7 we sum up this manuscript.

2. Relevant Studies

Flight controller design, motion planning algorithms, traffic surveillance, communication networks, vision-based navigation, and Kalman filtering are the most studied topics when it comes to UAVs. Dadkhah et al. [40] presents an overview of motion planning techniques for unmanned aerial vehicles, focusing on their application for autonomous guidance. The authors describe the main sources of uncertainty and practical techniques to cater to these uncertainties. This review focuses mostly on algorithms that can be utilized for UAV guidance. The author also discusses the main challenges in autonomous UAV guidance. A survey on UAV's application for traffic management and the ongoing research on UAVs by the different universities is presented in [41]. The author highlighted that in the field of traffic management, unmanned air vehicles outperform other approaches due to their maneuverability and wireless network communication. Moreover, the barriers to UAV development are also discussed. The author also discusses various types of vision sensors and their types of processing.

Ollero et al. [42] presents a survey on various UAV platforms. The survey also presents control architectures, issues faced during the implementation of control algorithms, and computer vision techniques used in UAVs. Perception methods for UAVs were the primary focus of the study. The author also provided a brief overview of recent developments in multi-robot systems. Chen et al. [43] present a survey on the concept of autonomous control and the Autonomous Control Level (ACL) metrics to assess the autonomy of unmanned aerial vehicles. The architecture for autonomous control for UAVs is also discussed. Emami et al. [44] in their paper, conducted a comprehensive review of the design and development of intelligent flight control systems for UAVs, with a special emphasis on neural network-based controllers. The mathematics of neural network-based controllers is laid out in detail, and both the challenges and issues of these systems are also explored. In addition, a clear design guideline for an intelligent control system is also presented. Some of the review papers, along with their areas of research, are shown in Table 1.

Table 1. Consolidated studies: UAV.

Reference	Research Focus
[45–52]	Control algorithms
[53–56]	Motion planning techniques algorithms
[57–61]	Applications of UAV
[62,63]	Collision avoidance strategies
[64,65]	Navigation techniques
[66,67]	Guidance and Control algorithms
[68]	Kalman Filtering Techniques
[69]	6G UAV communication
[70]	Open-source Hardware and Software Flight Control Platforms

3. UAV Dynamic Modeling and Control Architecture

The mathematical models of UAVs serve as the basis for a number of different GNC algorithms. These models eradicate the need for costly and time-consuming physical testing in order to predict and assess the UAV's performance in a variety of scenarios. Unmanned aerial vehicles can be represented with either three degrees of freedom (3-DOF) or much more complex and comprehensive six degrees of freedom (6-DOF) models. A 3-degrees-of-freedom model represents the UAV as a point mass that can move in three dimensions (x, y, and z), which is computationally inexpensive but significantly inaccurate. Due to its low computational cost, the 3-DOF model has been widely used by researchers in the design of UAV control systems. Models with three degrees of freedom typically fall into one of two categories: Sach's equations of motion [71] and Zhao's equations of motion [72].

However, in the 6DoF model, UAV is considered to be a rigid body having six degrees of freedom: three translations (along the x, y, and z axis) and three rotations (i.e., roll, pitch, and yaw). A 6DoF model is more accurate than a 3DoF model and can simulate a wider range of maneuvers and flight situations since it takes into consideration aerodynamic forces and moments as well as the UAV's mass and moment of inertia. The 6DoF equation of motions for a UAV under the assumption of a flat earth model, as found in [73,74].

Where U,V and W are the translational velocities in the body axis. The body axis angular velocities are denoted by P, Q and R. Euler angles ϕ, θ and ψ define the UAV's attitude. P_E, P_N and h are the inertial position of the UAV, and m is the mass of the UAV. The moment of inertia about the x, y, and z axes are denoted by J_X, J_Y and J_Z, respectively; J represents the moment of the inertia matrix. J_{XZ} represent the product of inertia and g represents the gravitational acceleration.

These 12 coupled first-order differential Eqs accurately describe the motion of a UAV. A fixed-wing UAV has four actuators (throttle, ailerons, elevator, and rudder) to control these 12 states. The throttle (δ_t) controls the forward acceleration of the UAV, the ailerons (δ_a) control the bank angle/roll angle, the elevator (δ_e) controls the pitch angle, and the rudder (δ_r) controls the yaw of the UAV. Similarly, in the wind axis system, the states are UAV speed (V_T), angle of attack (α), and slide slip angle (β). The fixed-wing UAV is an underactuated system since it only has four control inputs and six degrees of freedom.

3.1. Flight Control Algorithms

Unmanned aerial vehicles (UAVs) rely heavily on flight control algorithms to enable precise and autonomous control throughout their flights. Several research examining various flight phases of UAVs using various control strategies have been conducted. As shown in Figure 2, control strategies can be categorized as model-based or model-free. Model-based flight control algorithms are further subdivided into linear and non-linear controllers. Common linear flight controllers include PID, LQR, H_2/H_∞, and Gain Scheduling. While Non-linear controllers include Feedback Linearization, Model Predictive Control, Backstepping, Sliding Mode Control, and Adaptive Control [49]. Because of their inherent limitations, Linear and Nonlinear flight controllers are being replaced by Learning based/Model free controllers [75], which are more complicated and intelligent. Fuzzy logic and Neural networks are types of Model-free controllers [76]. Both model-based and model-free control strategies have been employed in diverse ways to achieve desired goals [77].

Both linear and non-linear controllers have been utilized in diverse ways by researchers to achieve the desired results. In this regard, Carnes [21] has developed a low-cost flight controller based on a PID controller for the autonomous takeoff and landing of a fixed-wing UAV. Moreover, Hardware-in-Loop simulations are used to validate the efficacy of the designed controller. Similarly, Chen et al. [78] suggested a PID-based longitudinal landing control system for UAVs. The simulations were conducted using MATLAB /Simulink, and the outcomes were good. However, the complete dynamics of UAVs and the impact of wind disturbance were not investigated. Pokswat et al. [79] developed a Gain-Scheduled PID controller for a fixed-wing UAV. To determine the controller gains, an automatic tuning algorithm is used. The gain-scheduled control algorithm for the fixed-wing UAV was tested in a wind tunnel to demonstrate its effective implementation. Jetley et al. [80] designed an LQR controller for the autonomous landing of fixed-wing UAVs. The designed controller gave satisfactory performance up to 25% headwind and 10% crosswind. Similarly, Santoso et al. [81] proposed a Linear Quadratic Gaussian (LQG) controller to optimally control the longitudinal flight channel of a fixed-wing UAV. Simulation results showed that the LQG controller provides satisfactory altitude holding, takeoff, and landing performance. Manjarrez et al. [82] designed the autonomous takeoff and landing control architecture based on feedback linearization and PI controller. In the presence of winds, the performance of the developed controller is satisfactory. Similarly, Lesprier et al. [83] designed an auto-landing H_∞ based controller for UAVs.

In regards to non-linear control techniques, Qayyum et al. [84] suggested a model predictive controller (MPC) for the autonomous landing of UAV based on the Laguerre function. A comparative analysis between MPC and PID was also carried out. The results of the simulation demonstrated that the MPC controller outperformed the PID controller. However, wind disturbances and gusts were not catered. Lungu [85] Lungu proposed an auto-landing architecture for a tailless and blended-wing unmanned aerial vehicle subject to external disturbances and sensor measurement errors. The predetermined landing trajectory is tracked using a backstepping-based attitude angle controller, a dynamic inversion-based speed controller, and an adaptive disturbance observer for the estimation of wind disturbances. Similarly, Zhu et al. [86] designed an active disturbance rejection controller (ADRC) for a small fixed-wing UAV's entire flight regime and compared the simulated results to those of a PID controller. The simulation results demonstrated that ADRC offers superior anti-interference capabilities in comparison to PID. The authors also performed the flight experiments and illustrated that the ADRC controller showed satisfactory performance on stability and tracking accuracy during landing in the presence of external disturbances. However, the ADRC controller was only designed for the longitudinal UAV channel.

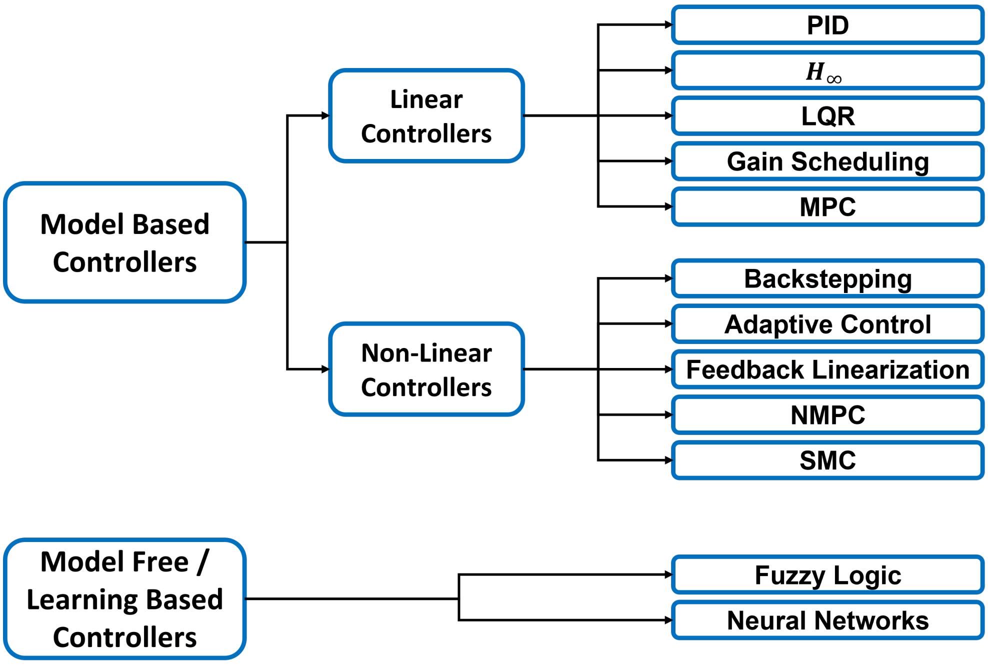

Figure 2. Model based and model free control algorithms [49].

The world is now shifting towards model-free/learning-based controllers. In contrast to traditional controllers, model-free controllers don't need any plant model. Instead, they adapt their behavior based on what they have learned through experience. In this regard, Nho et al. [87] presented a Fuzzy Logic based controller for the autonomous Landing of UAVs. The designed controller was implemented on both the linear longitudinal and 6-DOF non-linear aircraft models. The designed controller was sufficiently robust to provide excellent performance in terms of stability and low steady-state error. Similarly, Kurnaz et al. [22] proposed a Fuzzy Logic based controller for the autonomous cruise and landing of small, fixed-wing UAVs. Autonomous navigation on the pre-defined path was also achieved by fuzzy logic-based systems. However, the effects of wind disturbances were not catered for in this work. Details on the controllers utilized in autonomous UAVs are provided in Table 2, along with an indication of the stages of flight in which these controllers are utilized while Table 3 presents the advantages and disadvantages of the control algorithm.

Table 2. Control algorithms employed on fixed-wing UAV.

Flight Phase	Control Technique	Reference
Landing	PID	[78,88–96]
	Fuzzy Logic	[97]
	Sliding Mode Control	[93,98,99]
	Model Predictive Control	[84,90,100]
	LQR	[80,94,101–103]
	Backstepping	[104–106]
	Feedback Linearization	[101,105–107]
	Adaptive Controller	[108,109]
	ADRC	[86,88]
Take-off	LQR	[103]
	ADRC	[86]
	LQG	[81]
	PID	[95,96]
	Adaptive Controller	[108,109]
Cruise	LQR	[110]
	Feedback Linearization	[111]

Table 3. Advantages and disadvantages of control algorithms.

Control Algorithms	Advantages	Disadvantages
PID	Easy to implement and tune	Sensitive to noise and disturbances
LQR	Provides optimal control solutions, engineering friendly, guarantees stability margins	Full state feedback is required, requires an accurate model of the system
H_∞	Handle uncertainties and disturbances	Require accurate model of the system, computationally expensive, tuning is very time-consuming
Gain Scheduling	Handle non-linear systems effectively, coverage of a wide range of operating conditions and flight envelops is possible	Stability issues if the transition between gains is not smooth, slow and laborious design process
Adaptive Control	Can handle uncertain and time-varying systems, can handle disturbances and unmodeled system dynamics	Computationally expensive, good knowledge of system dynamics is needed, tuning of parameters requires expertise
Backstepping	Excellent tracking performance and disturbance rejection capabilities, can handle under-actuated systems effectively	Computationally expensive, requires an accurate mathematical model of the system
Model Predictive Control	Can handle systems with constraints on inputs and states, can handle multivariable control problems with multiple objectives	Performance depends heavily on the accuracy of the prediction model.
Feedback Linearization	Handle non-linear systems effectively, good tracking performance and disturbance rejection capability	Require accurate mathematical model of the system, computationally expensive

Table 3. *Cont.*

Control Algorithms	Advantages	Disadvantages
Sliding Mode Control	Can handle uncertainties and disturbances effectively, good tracking performance, disturbance rejection capability, does not require an accurate model of the plant	Chattering effect

4. Exploration of State Estimation Techniques

UAVs rely heavily on state estimators, referred to as filters, to reliably estimate the UAV's internal states from sensor data. The real-time estimations of position, velocity, orientation, and other critical variables provided by these estimators play a key part in UAV navigation, control, and guidance. The main goal of incorporating a state estimator into the GNC algorithm is to increase system dependability by mitigating noise in sensor readings and accommodating sensor failures. Additionally, state estimators are also utilized for sensor integration. A mathematical model of the plant is used by the state estimator to predict the state based on previous states and the current control inputs and then adjusts its prediction using available measurements to generate a more precise estimate of the plant states. The quality of the sensor measurement data and the accuracy of the mathematical model of the plant determine how accurate the state estimation will be. The Kalman filter (KF) is frequently employed by researchers for accurate state estimates in systems when sensor data are noisy or information about the state cannot be measured directly [68]. R.E. Kalman introduced the Kalman filter concept in his paper [112] on linear filtering. This recursive algorithm predicts the state of the plant and then uses those predictions together with data from the sensors to produce an accurate estimate. It has since been the focus of numerous academic and practical applications. The Kalman filter (KF) has multiple variants, including the extended Kalman Filter (EKF), the Unscented Kalman Filter (UKF), and the Cubature Kalman Filter (CKF). These filters are employed in numerous applications, including control systems, robotics, computer vision, and navigation [113]. In this regard, authors of [21,81,103,110,114] have employed the Kalman filter for state estimation purposes. Yang et al. [115] present an EKF to estimate the complete state of the UAV. The author's estimation of attitude, velocity, position, airspeed, and horizontal wind speed yields encouraging results. Lie et al. [116] calculated Airspeed, Angle of Attack, and Side Slip Angle using the Extended Kalman filter, with a very low RMSE between the real and estimated data. Similarly, authors of [111,117–121] used EKF for state estimation. Xiaoqian et al. [122] present the design of a Cubature Kalman Filter (CKF) and Unscented Kalman Filter (UKF) based attitude estimation algorithm for a fixed-wing unmanned aerial vehicle. The simulation outcomes showed that CKF was better than UKF in accuracy, robustness, non-linear performance, and estimation of attitude information. Similarly, authors of [123] utilize CKF in UAV's GNC algorithm.

Similarly, Marina et al. [124] proposed an AHRS based on a UKF using the Fast Optimal Attitude Matrix (FOAM) algorithm as an observer model. UKF gave suitable results for the attitude estimation of a lightweight fixed-wing UAV. In [125] author proposed an AHRS based on the UKF using the three-axis attitude determination (TRAID) algorithm as the observation model. The author also compared the performance of UKF with EKF. The results indicated that the microcontroller's real-time performance was satisfactory with low computational complexity. Authors of [125] also used UKF in their work. The various state estimators utilized in GNC of fixed-wing UAVs are summarised in Table 4. The study of the relevant literature review reveals that many GNC algorithms were developed and proposed without utilizing state estimators [22,78–80,82–84,86,89–102,105,108,109,126], Reviewing the pertinent literature, we find that many GNC algorithms were created and suggested without using state estimators, on the false premise that sensors are always present and free of noise, despite the fact that state estimators are of paramount significance in UAV's GNC algorithm.

Table 4. FlightGear and X-plane comparison.

Features	FlightGear	X-Plane
Product Price and availability	Open source software (Free)	Paid software (USD 59.99)
Operating System	Linux, Windows, and MAC	Linux, Windows, and MAC
Aircraft Catalogue	Vast selection of user-contributed aircraft models are available for free download	Compared to FlightGear, they have lesser airplanes available by default, a large collection of payware aircraft from independent developers are available
Flight dynamics model	Use JBSim model	Based on blade element theory
Co-simulation	Easy integration with MATLAB/Simulink, batch file generation is required	Easy integration with MATLAB/Simulink
Scenery Quality	High-quality graphics, use of OpenGL rendering engine, less detailed and realistic view than X-Plane, highly customizable	High-quality graphics, use of HDR and PBR rendering for realistic weather and detailed texture, excellent depiction of world and aircraft
Customization	Highly customizable	Less customizable

5. Simulation and User Adaptation Techniques

Tuning the gain of a flight controller is a laborious but essential component of its design and development. The fine-tuning of controller gains requires extensive testing. Tuning the controller's parameters during actual flight is the ideal method, but it is also quite time-consuming and costly. Model-in-loop simulations (MILS), software-in-loop simulations (SILS), processor-in-loop simulations (PILS), and hardware-in-loop simulations (HILS) are near-actual simulation techniques that can help speed up the process and reduce the number of actual flight trails [37]. Furthermore, several visualization software are employed to simulate flight conditions as close to real. The functionality and performance of an algorithm can be tested by simulating a wide range of scenarios, including varying weather and terrain variations.

5.1. Realistic Simulation Techniques

Model-in-Loop Simulation (MILS) is the first step in the design and development of any flight controller. In MILS, a mathematical model of the actual plant which is to be controlled is built in a simulation environment like MATLAB/Simulink. Next, the controller model is constructed in the same simulation environment as the plant model, and its performance (whether or not the controller is effective enough to control the plant as planned) is evaluated. The main goal of MIL simulations is to identify potential issues in the system, optimize system performance, and assess different design options before committing to hardware implementation. MIL simulation offers a low-risk testing environment, enabling engineers and researchers to test and refine system models without placing physical systems at risk. This technique can save time and money by allowing iterative design and testing cycles before the system is built. Nevertheless, MIL simulation does have some limitations and challenges, such as the simulation's accuracy is dependent on the accuracy of the model, which can be challenging to develop for complex systems and mathematical models not fully represent the actual physical model. A lot of research is based only on Model-in-loop simulation (MILS). MILS was used by the authors of [80,94] to validate the LQR controller's performance in autonomous UAV landing. Similarly, authors of [22,78,81–84,89,91–93,98–102,104–107,109–111] performed MILS simulations to simulate their controller's performance. The MILS block diagram is depicted in Figure 3.

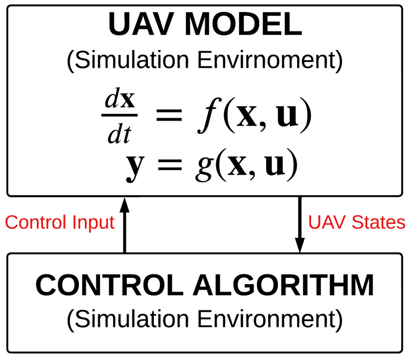

Figure 3. Model-in-loop architecture.

After achieving desirable results in MILS, the next step is to transition to Software-in-the-Loop simulation (SILS). Instead of using a controller model, SILS relies on the C-code of the controller block as depicted in Figure 4. The plant model is unaltered (same as MILS) whereas the controller model is emulated in C code for SILS. SIL simulation is typically performed to mimic the behavior of the embedded processor on which the developed algorithm will eventually be deployed. SILS's main objective is to check whether the designed algorithm is software implementable or not? In this regard, Mathisen et al. [90] used a non-linear MPC controller to achieve a precision deep-stall landing of a fixed-wing UAV, and then validated the controller's performance with Software-in-the-Loop simulations. Authors of [37,127,128] used SILS to validate their designed algorithms.

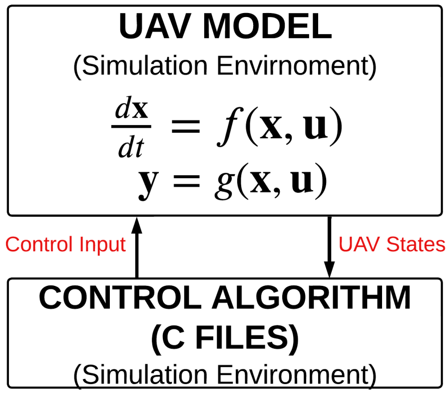

Figure 4. Software-in-loop architecture.

Processor-in-the-Loop simulations (PILS) follow SILS. Similar to SILS, PILS involves burning a controller model onto an embedded processor and then running a closed-loop simulation of the simulated plant. Figure 5 depicts the PILS setup, with the controller model code executing on hardware and plant operating in a simulated environment. PIL simulation is an effective tool for system design and development that permits engineers to assess and improve both the software as well as the hardware aspects of a system. When testing whether a processor can reliably run the controller code without errors or delays, PILS simulations prove invaluable. In this regard, You et al. [108] confirmed the controller's effectiveness during the take-off and landing of a fixed-wing UAV. Likewise, Ulker et al. [129] conducted PILS for a fixed-wing UAV in windy conditions in various flight scenarios, including straight-and-level flight, level climb, and turn. Similarly, authors of [130] used PILS to validate their flight control algorithm and microcontroller's performance.

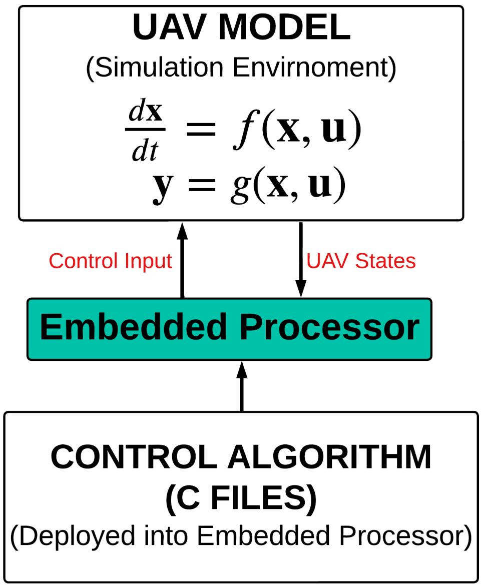

Figure 5. Processor-in-loop architecture.

Hardware-in-the-loop simulation comes after PILS has been effectively implemented. Incorporating some physical components of the actual plant into the simulation loop is the basic idea behind HILS. Actual plant hardware (servos, actuators) is employed in the simulation loop instead of a mathematical model of the plant to verify the control algorithm [131]. An example of adding a feedback servo motor in the feedback control loop of a plant during HIL simulation is shown in Figure 6. HIL simulation can be utilized to assess and verify the integration of a system's software and hardware. This can assist in identifying potential issues like different noises in the sensors and synchronization issues between the components. Figure 7 depicts the HILS system's fundamental block diagram. The autonomous takeoff and landing of a UAV were simulated using Hardware-in-the-Loop by Carnes [21]. Johnson et al. [132] utilized SILS and HILS for the verification of both hardware and software changes before the flight and after gain adjustments for system performance verification. Similarly, authors of [96,97,127,128,133,134] also performed HIL simulations.

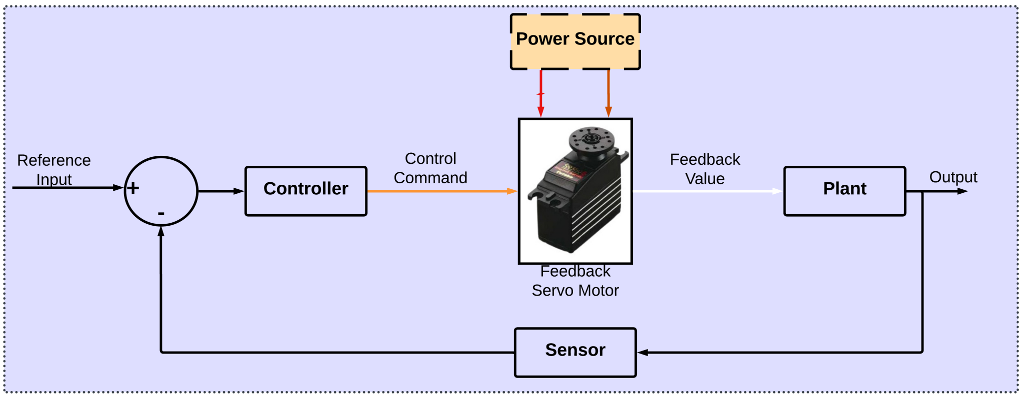

Figure 6. Feedback servo incorporated in the feedback control loop.

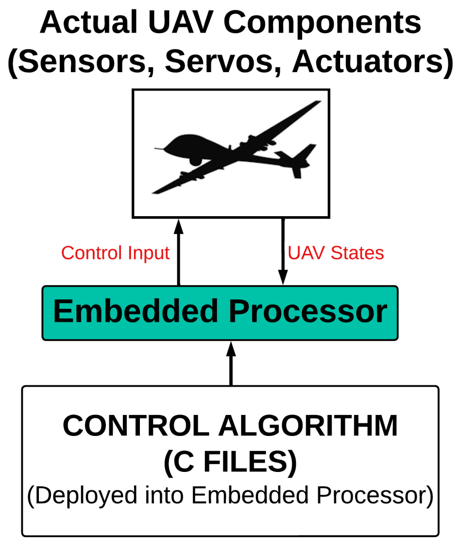

Figure 7. Hardware-in-loop architecture.

5.2. User Adaptation Techniques

In the aviation industry, visualization software is used for training, research, and development. However, actual flight testing is the most accurate method for tuning the controller gain and validating the developed algorithms. Nevertheless, it is costly and UAV flight testing can pose safety risks. In articles [86,88,95,103,108,134] the researchers validated the performance of their controllers through an actual flight of fixed-wing UAVs. However, in the majority of cases, flight testing is not a viable option. Flight testing in a 3D virtual environment is considered a safer and more cost-effective method for evaluating aircraft models and control systems. Flight simulators were initially utilized for entertainment/gaming purposes before being put to use in the realm of virtual flight testing. Matlab/Simulink has been interfaced with numerous flight simulators, including Xplane, FlightGear, and Gazebo-ROS, in order to validate the GNC algorithms of aircraft in a virtual test environment. Co-simulation combines the strengths of MATLAB/Simulink and other flight visualization software to evaluate UAV models, their GNC algorithm, and other algorithms during the design phase. These co-simulation techniques are currently used as a safe substitute for actual flight evaluations. In this regard, Arif et al. [135] proposed a simulation system using X-Plane 10, Python, and MATLAB to assess the controllability of an aircraft. Using the X-Plane simulator, numerous aircraft configurations, system failures, and environmental variables were simulated and tested. Similarly, Ribeiro et al. [136] proposed a test platform to assess the autopilot control system. MATLAB / Simulink was used to test the autopilot whereas X-Plane software was used to visualize the aircraft model. Moreover, the authors also integrated a microcontroller to drive the aircraft actuator/servos. Bulka and Nahon [134] implemented a flight controller for an agile fixed-wing UAV. The controller was initially evaluated with HILS, and the results were then displayed with an X-Plane simulator. Afterward, a successful actual flight test was carried out. Nugroho [137] compared modern and conventional landing controllers for a fixed-wing UAV. X-Plane simulator was utilized to visualize the landing of the UAV based on different controllers. Similarly, Kaviyarasu et al. [37] verified their control and navigation algorithms using SILS and X-Plane simulator.

Like Xplane, FlightGear is another extensively utilized flight simulator. The formation flight of multiple fixed-wing UAVs was presented by Yang et al. [127]. SILS and HILS are used to test the designed guidance and formation algorithms, along with Gazebo-ROS as a 3D visualization software. Priyambodo and Majid [138] build UX-6 fixed-wing flight models using analytical and empirical approaches. In this work, Simulink and FlightGear simulators are used as visualization tools. Prabowo et al. [128] designed an image-based flight control system for a fixed-wing UAV. UAV tracks the target based on the features in the image field captures by the camera. SILS and HILS were performed to validate the control algorithm. In addition, the FlightGear software is utilized to show the UAV camera view. Similarly, Sorton and Hammaker [133] tested the avionics and control system of a small fixed-wing UAV using HILS and FlightGear simulator. Using FlightGear, Zhang et al. [139] validated their designed control and navigation law. Several weather conditions and types of terrain were utilized to test the algorithm. It was found that the difference between the virtual flight and the real flight was negligible. Concluding from the above discussion, the detailed comparison between the most commonly used flight simulators is given in Table 4.

6. Existing Challenges and Way Forward

Unmanned aerial vehicles (UAVs) have been the subject of significant research for more than a century, however, fully autonomous UAV flight because of its wide spectrum and increasing complexities remains a challenging task. A lot of research work has been carried out to theoretically examine UAV performance through 6-DOF/3-DOF simulations. However, they lack the crucial analysis element of determining the algorithm's hardware implementation's feasibility and viability for usage. This is crucial since simulation-based work sometimes yields wildly different outcomes than that produced through actual hardware implementation. Software in Loop (SILS), Process in Loop (PILS), and Hardware in Loop (HILS) simulations are examples of near-real simulation techniques that help bridge the performance gap between simulated and actual controller outputs. Additionally, the use of visualization techniques such as Xplane, FlightGear and Gazebo-ROS as alternative means of flight simulators is also non-existent.

The state estimator provides an estimate of the internal state of a plant based on its input and output measurements. They're crucial in cases where the system is sensor-deficient, the sensor readings are noisy and to cater to sensor failures. Based on a review of the relevant literature, it is apparent that only a small number of studies have consolidated the estimation strategies available to the research community.

There have been several research contributions and control algorithms for autonomous UAV flight, but very little comparative analysis of controller performance for the entire flight regime has been published. This is crucial because each controller has its own pros and cons. While the PID controller is intuitive to build, it lacks robustness; the LQR approach, on the other hand, is an optimum and engineering-friendly controller but requires full-state feedback. Likewise, the feedback-linearization controller can deal with the non-linearities of the system, but at a considerable computational cost. Choosing the right controller for a UAV is a challenging and time-consuming process that requires thorough knowledge of UAV dynamics. This research shows that there is a dearth of performance comparisons in the existing literature, especially when taking into account a similar baseline in which multiple controllers are used to attain the same objective.

Based on the literature reviewed, it is evident that little research has been conducted on the entire flight regime of a UAV (takeoff, mission, and landing). Despite the fact that landing and takeoff are the most crucial phases of any autonomous fixed-wing UAV operation, these phases have been the subject of limited research. Furthermore, examination 'of' the impact of wind disturbances and other exogenous inputs is most critical in these flight phases.

Future Work Directions

This section provides a brief summary of recommendations and potential future research directions. The employment of realistic simulation techniques must be emphasized as they bring different components of the architecture within the framework of actual development. This will help validate the performance of the designed algorithm on an actual onboard processor, evaluate propagation delays, and verify the computational aspects of flight controllers [17]. Furthermore, many different flight simulators are available with user-friendly interfaces that can be used for co-simulation. Saving resources and improving flying performance are two benefits of using a flight simulator during the UAV's design phase. With these tools, researchers can analyze the UAV's performance in a number of scenarios, and they help to detect potential issues well before the development of the actual prototype. Therefore, researchers engaged in the design and development of UAVs should take advantage of available visualization software. Moreover, state estimators/observers should be employed whenever designing the GNC algorithm for a UAV. As the majority of sensors produce noisy output data in practical scenarios. Therefore, the UAV's GNC algorithm must be robust and include state estimators to handle sensor failure and noisy measurements. In this regard future work should be focused on the advancement of both model-based and data-driven estimation algorithms.

It is also recommended to investigate multiple control algorithms and compare the efficacy of various controllers. It is important to investigate the computational cost and the benefits of various control algorithms in various flight phases. In addition, the control algorithm must be sufficiently generic and robust to handle the entire flight regime of a UAV. In this regard, the exploration of artificial intelligence and machine learning algorithms will enable aerial vehicles to make complex decisions in a variety of environments. Moreover, the utilization of feedback servos for UAV applications is the most recent trend and presents major advantages over traditional servos. In comparison to traditional servos, feedback servos offer better accuracy, stability, and reliability, making them the superior choice for UAV applications.

To enable autonomous situational awareness in UAVs, more study of emerging technologies like edge computing and drone swarm data communication is required. Autonomous situational awareness is crucial for the safe operation of unmanned aerial vehicles (UAVs), especially in environments with limited or nonexistent network coverage.

Illustration for Further Work

Figure 8 depicts a graphical representation of the probable direction for future research catering to the highlighted aspects. The authors are developing an HILS-based GNC algorithm for a fixed-wing UAV covering its all flight phases in order to address the missing links. The prototype fixed-wing UAV model used has a wing span and chord length of 3 and 1.5 m, respectively. The UAV dynamics model is simulated in MATLAB/SIMULINK. As a first step, a nonlinear total energy-based guidance and control algorithm has been developed for autonomous take-off, loiter, and landing. The block diagram of the current work is shown in Figure 9.

MILS, SILS and PILS were performed to check the efficacy of the designed control algorithm. The performance of the designed controller in MILS and HILS (only feedback servos were incorporated) is shown in Figure 10. The selection of feedback servo motors depends upon the UAV dynamics/type. High-fidelity feedback servo motors were integrated with the microcontroller. Figure 10 shows the feedback servo lag that was found during the aforementioned work, providing further evidence for the necessity of employing SILS, PILS, and HILS before actual implementation/flight. In the next step, we will integrate sensors and check the performance of the designed algorithm using a 3D axis rotation table. After the completion of the work, the complete results along with the findings will be shared with the research community.

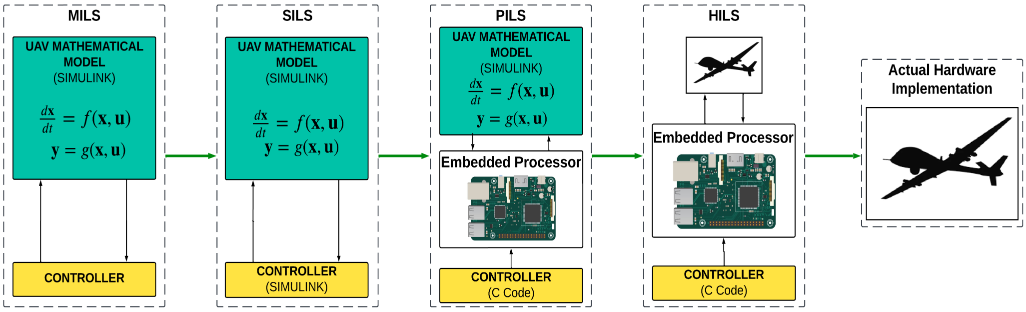

Figure 8. The proposed future work direction.

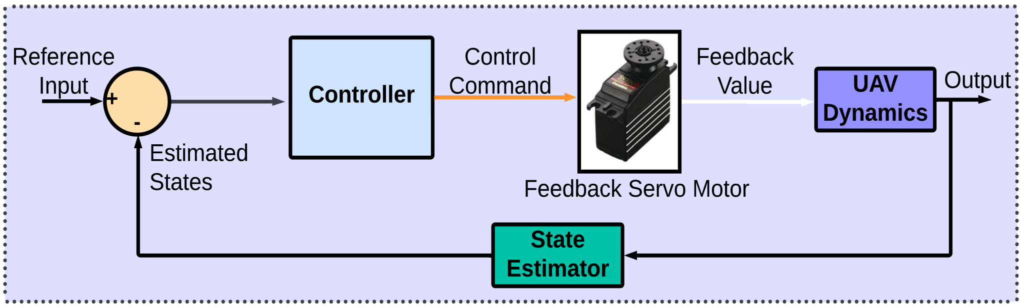

Figure 9. Current work control architecture.

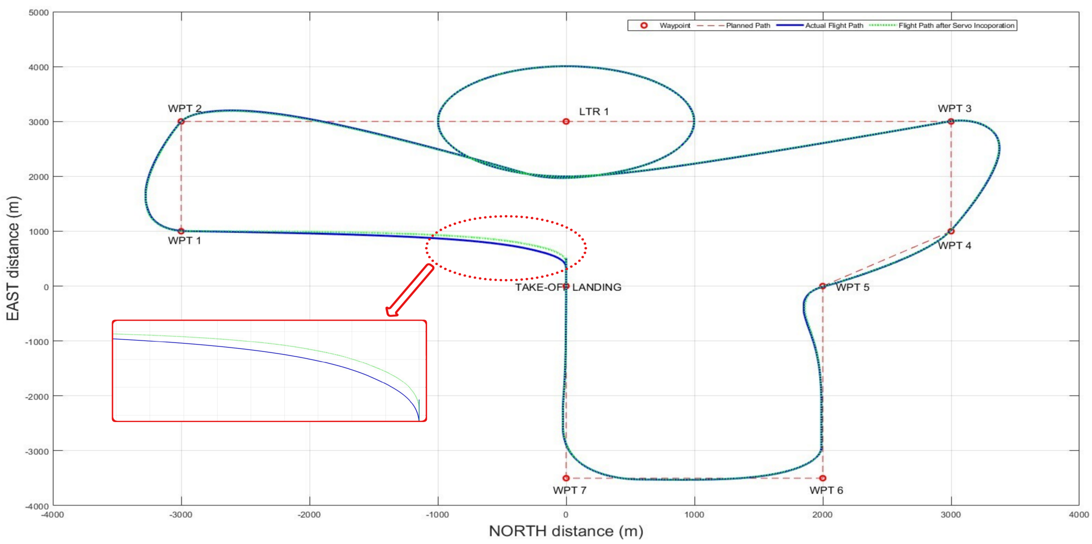

Figure 10. Flight control response with and without servos-in-loop.

7. Conclusions

All flying phases, but especially take-off and landing, are crucial for a fully autonomous UAV. The literature review and cited papers necessitated a centralized platform connecting relevant studies and filling in the missing link. Several crucial aspects need additional consideration, including the absence of a comparative analysis between controllers that can be used in different phases, a review of estimating methodologies, and a near-actual implementation of the suggested control algorithms. This research seeks to address these gaps. This review paper provides a comprehensive analysis of current research on control algorithms, estimate techniques, and simulation methodologies. The limitations are presented by consolidating the details and analyzing them separately. Additionally, we offered future research areas that can be implemented for realistic simulations utilizing SILS, PILS, and HILS before actual hardware implementation. In addition, the use of visualization software during different design phases of an unmanned aerial vehicle (UAV) can expedite the development process by allowing researchers to evaluate the UAV's behavior under various kinds of environmental effects and diagnose problems before constructing the actual prototype. Insight into future research directions for autonomous flight of fixed-wing UAVs will be provided by this study. This study will serve as a foundation for future research on UAV autonomous flight.

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References

1. Mir, I.; Gul, F.; Eisa, S.; Maqsood, A.; Mir, S. Contraction analysis of dynamic soaring. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology (AIAA SCITECH), San Diego, CA, USA, 3–7 January 2022; p. 0881.
2. Mir, I.; Gul, F.; Eisa, S.; Taha, H.E.; Mir, S. On the stability of dynamic soaring: Floquet-based investigation. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology (AIAA SCITECH), San Diego, CA, USA, 3–7 January 2022; p. 0882.
3. Mir, I.; Maqsood, A.; Eisa, S.A.; Taha, H.; Akhtar, S. Optimal morphing–Augmented dynamic soaring maneuvers for unmanned air vehicle capable of span and sweep morphologies. *Aerosp. Sci. Technol.* **2018**, *79*, 17–36. [CrossRef]
4. Mir, I.; Taha, H.; Eisa, S.A.; Maqsood, A. A controllability perspective of dynamic soaring. *Nonlinear Dyn.* **2018**, *94*, 2347–2362. [CrossRef]
5. Mir, I.; Maqsood, A.; Akhtar, S. Optimization of dynamic soaring maneuvers to enhance endurance of a versatile UAV. *Inst. Phys. Conf. Ser. Mater. Sci. Eng.* **2017**, *211*, 012010. [CrossRef]
6. Paucar, C.; Morales, L.; Pinto, K.; Sánchez, M.; Rodríguez, R.; Gutierrez, M.; Palacios, L. Use of drones for surveillance and reconnaissance of military areas. In Proceedings of the International Conference of Research Applied to Defense and Security, Salinas, Ecuador, 18–20 April 2018; Springer: Berlin/Heidelberg, Germany, 2018; pp. 119–132. [CrossRef]
7. van Lieshout, M.; Friedewald, M. Drones–dull, dirty or dangerous?: The social construction of privacy and security technologies. In *Socially Responsible Innovation in Security*; Routledge: Oxfordshire, UK, 2018; pp. 25–43. [CrossRef]
8. Li, H.; Savkin, A.V. Wireless sensor network based navigation of micro flying robots in the industrial internet of things. *IEEE Trans. Ind. Inform.* **2018**, *14*, 3524–3533. [CrossRef]
9. Mir, I.; Eisa, S.A.; Taha, H.; Maqsood, A.; Akhtar, S.; Islam, T.U. A stability perspective of bioinspired unmanned aerial vehicles performing optimal dynamic soaring. *Bioinspiration Biomim.* **2021**, *16*, 066010. [CrossRef]
10. Savkin, A.V.; Huang, H. A method for optimized deployment of a network of surveillance aerial drones. *IEEE Syst. J.* **2019**, *13*, 4474–4477. [CrossRef]
11. Huang, H.; Savkin, A.V. An algorithm of reactive collision free 3-D deployment of networked unmanned aerial vehicles for surveillance and monitoring. *IEEE Trans. Ind. Inform.* **2019**, *16*, 132–140. [CrossRef]
12. Madridano, Á.; Al-Kaff, A.; Martín, D.; de la Escalera, A. Trajectory planning for multi-robot systems: Methods and applications. *Expert Syst. Appl.* **2021**, *173*, 114660. [CrossRef]
13. Huang, H.; Savkin, A.V. Towards the internet of flying robots: A survey. *Sensors* **2018**, *18*, 4038. [CrossRef]
14. Pajares, G. Overview and current status of remote sensing applications based on unmanned aerial vehicles (UAVs). *Photogramm. Eng. Remote Sens.* **2015**, *81*, 281–330. [CrossRef]
15. Chen, Y.; Rosolia, U.; Ames, A.D. Decentralized Task and Path Planning for Multi-Robot Systems. *IEEE Robot. Autom. Lett.* **2021**, *6*, 4337–4344. [CrossRef]
16. Manchester, Z.; Peck, M. Stochastic space exploration with microscale spacecraft. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology (AIAA) Guidance, Navigation, and Control, Portland, OR, USA, 8–11 August 2011; p. 6648.

17. Louali, R.; Gacem, H.; Elouardi, A.; Bouaziz, S. Implementation of an UAV Guidance, Navigation and Control System based on the CAN data bus: Validation using a Hardware In the Loop Simulation. In Proceedings of the 2017 IEEE International Conference on Advanced Intelligent Mechatronics (AIM), Munich, Germany, 3–7 July 2017; pp. 1418–1423.
18. Jin, X.B.; Robert Jeremiah, R.J.; Su, T.L.; Bai, Y.T.; Kong, J.L. The new trend of state estimation: from model-driven to hybrid-driven methods. *Sensors* **2021**, *21*, 2085. [CrossRef]
19. Khamseh, H.B.; Janabi-Sharifi, F.; Abdessameud, A. Aerial manipulation—A literature survey. *Robot. Auton. Syst.* **2018**, *107*, 221–235. [CrossRef]
20. Raja, M.M. Extended Kalman Filter and LQR Controller Design for Quadrotor UAVs. Master's Thesis, Wright State University, Dayton, OH, USA, 2017.
21. Carnes, T. A Low Cost Implementation of Autonomous Takeoff and Landing for a Fixed Wing UAV. Master's Thesis, Virginia Commonwealth University, Richmond, VA, USA, 2014.
22. Kurnaz, S.; Çetin, O. Autonomous navigation and landing tasks for fixed wing small unmanned aerial vehicles. *Acta Polytech. Hung.* **2010**, *7*, 87–102.
23. Mir, I.; Eisa, S.A.; Maqsood, A. Review of dynamic soaring: technical aspects, nonlinear modeling perspectives and future directions. *Nonlinear Dyn.* **2018**, *94*, 3117–3144. [CrossRef]
24. Mir, I.; Maqsood, A.; Akhtar, S. Biologically inspired dynamic soaring maneuvers for an unmanned air vehicle capable of sweep morphing. *Int. J. Aeronaut. Space Sci.* **2018**, *19*, 1006–1016. [CrossRef]
25. Mir, I.; Maqsood, A.; Akhtar, S. Dynamic modeling & stability analysis of a generic UAV in glide phase. In Proceedings of the Materials science, Engineering and Chemistry (MATEC Web of Conferences). Engineering Design Process (EDP) Sciences, Sibiu, Romania, 7–9 June 2017; Volume 114, p. 01007.
26. Wadood, A.; Anavatti, S.; Hassanein, O. Robust controller design for an autonomous underwater vehicle. In Proceedings of the 2017 Ninth International Conference on Advanced Computational Intelligence (ICACI), Doha, Qatar, 4–6 February 2017; pp. 237–244.
27. Gul, F.; Rahiman, W.; Alhady, S.N.; Ali, A.; Mir, I.; Jalil, A. Meta-heuristic approach for solving multi-objective path planning for autonomous guided robot using PSO–GWO optimization algorithm with evolution ary programming. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *12*, 7873–7890. [CrossRef]
28. Gul, F.; Mir, I.; Rahiman, W.; Islam, T.U. Novel Implementation of Multi-Robot Space Exploration Utilizing Coordinated Multi-Robot Exploration and Frequency Modified Whale Optimization Algorithm. *IEEE Access* **2021**, *9*, 22774–22787. [CrossRef]
29. Gul, F.; Mir, I.; Abualigah, L.; Sumari, P.; Forestiero, A. A Consolidated Review of Path Planning and Optimization Techniques: Technical Perspectives and Future Directions. *Electronics* **2021**, *10*, 2250. [CrossRef]
30. Das, P.; Behera, H.; Panigrahi, B. Intelligent-based multi-robot path planning inspired by improved classical Q-learning and improved particle swarm optimization with perturbed velocity. *Eng. Sci. Technol. Int. J.* **2016**, *19*, 651–669. [CrossRef]
31. Gul, F.; Rahiman, W.; Nazli Alhady, S.S. A comprehensive study for robot navigation techniques. *Cogent Eng.* **2019**, *6*, 1632046. [CrossRef]
32. Gul, F.; Mir, I.; Abualigah, L.; Sumari, P. Multi-Robot Space Exploration: An Augmented Arithmetic Approach. *IEEE Access* **2021**, *9*, 107738–107750. [CrossRef]
33. Gul, F.; Mir, S.; Mir, I. Coordinated Multi-Robot Exploration: Hybrid Stochastic Optimization Approach. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology (AIAA SCITECH Forum), San Diego, CA, USA, 3–7 January 2022; p. 1414.
34. Gul, F.; Mir, S.; Mir, I. Multi Robot Space Exploration: A Modified Frequency Whale Optimization Approach. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology (AIAA SCITECH Forum), San Diego, CA, USA, 3–7 January 2022; p. 1416.
35. Szczepanski, R.; Bereit, A.; Tarczewski, T. Efficient Local Path Planning Algorithm Using Artificial Potential Field Supported by Augmented Reality. *Energies* **2021**, *14*, 6642. [CrossRef]
36. Szczepanski, R.; Tarczewski, T. Global path planning for mobile robot based on Artificial Bee Colony and Dijkstra's algorithms. In Proceedings of the 2021 IEEE 19th International Power Electronics and Motion Control Conference (PEMC), Gliwice, Poland, 25–29 April 2021; pp. 724–730.
37. Kaviyarasu, A.; Saravanakumar, A.; Logavenkatesh, M. Software in Loop Simulation based Waypoint Navigation for Fixed Wing UAV. *Def. Sci. J.* **2021**, *71*, 448–455. [CrossRef]
38. ud Din, A.F.; Mir, I.; Gul, F.; Mir, S.; Saeed, N.; Althobaiti, T.; Abbas, S.M.; Abualigah, L. Deep Reinforcement Learning for integrated non-linear control of autonomous UAVs. *Processes* **2022**, *10*, 1307. [CrossRef]
39. Vidal Morató, J.; Gomáriz Castro, S.; Manuel Lázaro, A. Autonomous Underwater Vehicle control. *Instrum. Viewp.* **2005**, *4*, 10.
40. Dadkhah, N.; Mettler, B. Survey of motion planning literature in the presence of uncertainty: Considerations for UAV guidance. *J. Intell. Robot. Syst.* **2012**, *65*, 233–246. [CrossRef]
41. Puri, A. *A Survey of Unmanned Aerial Vehicles (UAV) for Traffic Surveillance*; Department of Computer Science and Engineering, University of South Florida: Tampa, FL, USA, 2005; pp. 1–29.
42. Ollero, A.; Merino, L. Control and perception techniques for aerial robotics. *Annu. Rev. Control* **2004**, *28*, 167–178. [CrossRef]
43. Chen, H.; Wang, X.M.; Li, Y. A survey of autonomous control for UAV. In Proceedings of the 2009 International Conference on Artificial Intelligence and Computational Intelligence, Shanghai, China, 7–8 November 2009; Volume 2, pp. 267–271.

44. Emami, S.A.; Castaldi, P.; Banazadeh, A. Neural network-based flight control systems: Present and future. *Annu. Rev. Control.* **2022**, *53*, 97–137. [CrossRef]
45. Budiyono, A. Recent advances in control and instrumentation of unmanned aerial vehicles. In Proceedings of the Conference on Instrumentation and Control, Bandung, Bandung, Indonesia, 19 February 2007; pp. 19–20.
46. Chao, H.; Cao, Y.; Chen, Y. Autopilots for small unmanned aerial vehicles: A survey. *Int. J. Control. Autom. Syst.* **2010**, *8*, 36–44. [CrossRef]
47. Gautam, A.; Sujit, P.; Saripalli, S. A survey of autonomous landing techniques for UAVs. In Proceedings of the 2014 International Conference on Unmanned Aircraft Systems (ICUAS), Orlando, FL, USA, 27–30 May 2014; pp. 1210–1218.
48. Nguyen, H.T.; Quyen, T.V.; Nguyen, C.V.; Le, A.M.; Tran, H.T.; Nguyen, M.T. Control algorithms for UAVs: A comprehensive survey. *EAI Endorsed Trans. Ind. Networks Intell. Syst.* **2020**, *7*, e5. [CrossRef]
49. Gu, W.; Valavanis, K.P.; Rutherford, M.J.; Rizzo, A. UAV model-based flight control with artificial neural networks: A survey. *J. Intell. Robot. Syst.* **2020**, *100*, 1469–1491. [CrossRef]
50. Michailidis, M.G.; Rutherford, M.J.; Valavanis, K.P. A survey of controller designs for new generation UAVs: The challenge of uncertain aerodynamic parameters. *Int. J. Control Autom. Syst.* **2020**, *18*, 801–816. [CrossRef]
51. Zuo, Z.; Liu, C.; Han, Q.L.; Song, J. Unmanned aerial vehicles: Control methods and future challenges. *IEEE/CAA J. Autom. Sin.* **2022**, *9*, 601–614. [CrossRef]
52. Chandar, E.A.S. A Review on Longitudinal Control Law Design for a Small Fixed-Wing UAV. *Int. Res. J. Eng. Technol. (IRJET)* **2022**, *9*, 197–202.
53. Goerzen, C.; Kong, Z.; Mettler, B. A survey of motion planning algorithms from the perspective of autonomous UAV guidance. *J. Intell. Robot. Syst.* **2010**, *57*, 65–100. [CrossRef]
54. Quan, L.; Han, L.; Zhou, B.; Shen, S.; Gao, F. Survey of UAV motion planning. *IET Cyber-Syst. Robot.* **2020**, *2*, 14–21. [CrossRef]
55. Israr, A.; Ali, Z.A.; Alkhammash, E.H.; Jussila, J.J. Optimization methods applied to motion planning of unmanned aerial vehicles: A review. *Drones* **2022**, *6*, 126. [CrossRef]
56. Iqbal, M.M.; Ali, Z.A.; Khan, R.; Shafiq, M. Motion Planning of UAV Swarm: Recent Challenges and Approaches. In *Aeronautics-New Advances*; IntechOpen: Vienna, Austria, 2022. [CrossRef]
57. Adams, S.M.; Friedland, C.J. A survey of unmanned aerial vehicle (UAV) usage for imagery collection in disaster research and management. In Proceedings of the 9th International Workshop on Remote Sensing for Disaster Response, Stanford, CA, USA, 15–16 September 2011; Volume 8, pp. 1–8.
58. Nex, F.; Remondino, F. UAV for 3D mapping applications: A review. *Appl. Geomat.* **2014**, *6*, 1–15. [CrossRef]
59. Cai, G.; Dias, J.; Seneviratne, L. A survey of small-scale unmanned aerial vehicles: Recent advances and future development trends. *Unmanned Syst.* **2014**, *2*, 175–199. [CrossRef]
60. Menouar, H.; Guvenc, I.; Akkaya, K.; Uluagac, A.S.; Kadri, A.; Tuncer, A. UAV-enabled intelligent transportation systems for the smart city: Applications and challenges. *IEEE Commun. Mag.* **2017**, *55*, 22–28. [CrossRef]
61. Srivastava, S.; Narayan, S.; Mittal, S. A survey of deep learning techniques for vehicle detection from UAV images. *J. Syst. Archit.* **2021**, *117*, 102152. [CrossRef]
62. Albaker, B.; Rahim, N. A survey of collision avoidance approaches for unmanned aerial vehicles. In Proceedings of the 2009 International Conference for Technical Postgraduates (TECHPOS), Kuala Lumpur, Malaysia, 14–15 December 2009; pp. 1–7.
63. Pham, H.; Smolka, S.A.; Stoller, S.D.; Phan, D.; Yang, J. A survey on unmanned aerial vehicle collision avoidance systems. *arXiv* **2015**, arXiv:1508.07723.
64. Lu, Y.; Xue, Z.; Xia, G.S.; Zhang, L. A survey on vision-based UAV navigation. *Geo-Spat. Inf. Sci.* **2018**, *21*, 21–32. [CrossRef]
65. Elmokadem, T.; Savkin, A.V. Towards fully autonomous UAVs: A survey. *Sensors* **2021**, *21*, 6223. [CrossRef]
66. Santoso, F.; Garratt, M.A.; Anavatti, S.G. State-of-the-art integrated guidance and control systems in unmanned vehicles: A review. *IEEE Syst. J.* **2020**, *15*, 3312–3323. [CrossRef]
67. Chai, R.; Tsourdos, A.; Savvaris, A.; Chai, S.; Xia, Y.; Chen, C.P. Review of advanced guidance and control algorithms for space/aerospace vehicles. *Prog. Aerosp. Sci.* **2021**, *122*, 100696. [CrossRef]
68. Emer, N.; Özbek, N. A survey on Kalman Filtering for Unmanned Aerial Vehicles: Recent Trends, Applications, and Challenges. In Proceedings of the International Conference on Engineering Technologies (ICENTE'20), Konya, Turkey, 19–21 November 2020.
69. Vaigandla, K.K.; Thatipamula, S.; Karne, R.K. Investigation on Unmanned Aerial Vehicle (UAV): An Overview. *IRO J. Sustain. Wirel. Syst.* **2022**, *4*, 130–148. [CrossRef]
70. Ebeid, E.; Skriver, M.; Jin, J. A survey on open-source flight control platforms of unmanned aerial vehicle. In Proceedings of the 2017 Euromicro Conference on Digital System Design (DSD), Vienna, Austria, 30 August–1 September 2017; pp. 396–402.
71. Sachs, G.; Traugott, J.; Nesterova, A.P.; Dell'Omo, G.; Kümmeth, F.; Heidrich, W.; Vyssotski, A.L.; Bonadonna, F. Flying at no mechanical energy cost: disclosing the secret of wandering albatrosses. *PLoS ONE* **2012**, *7*, e41449. [CrossRef]
72. Zhao, Y.J. Optimal patterns of glider dynamic soaring. *Optim. Control. Appl. Methods* **2004**, *25*, 67–89. [CrossRef]
73. Beard, R.W.; McLain, T.W. *Small Unmanned Aircraft: Theory and Practice*; Princeton University Press: Princeton, NJ, USA, 2012.
74. Stevens, B.L.; Lewis, F.L.; Johnson, E.N. *Aircraft Control and Simulation: Dynamics, Controls Design, and Autonomous Systems*; John Wiley & Sons: Hoboken, NJ, USA, 2015.
75. Din, A.F.U.; Mir, I.; Gul, F.; Nasar, A.; Rustom, M.; Abualigah, L. Reinforced Learning-Based Robust Control Design for Unmanned Aerial Vehicle. *Arab. J. Sci. Eng.* **2022**, *48*, 1221–1236. [CrossRef]

76. Szczepanski, R.; Tarczewski, T.; Grzesiak, L.M. Adaptive state feedback speed controller for PMSM based on Artificial Bee Colony algorithm. *Appl. Soft Comput.* **2019**, *83*, 105644. [CrossRef]
77. Mir, I.; Maqsood, A.; Taha, H.E.; Eisa, S.A. Soaring Energetics for a Nature Inspired Unmanned Aerial Vehicle. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology (AIAA SCITECH Forum), San Diego, CA, USA, 7–11 January 2019; p. 1622.
78. Chen, K. The design of longitudinal autonomous landing control for a fixed wing Unmanned Aerial vehicle. In Proceedings of the 2021 4th World Conference on Mechanical Engineering and Intelligent Manufacturing (WCMEIM), Shanghai, China, 12–14 November 2021; pp. 120–127.
79. Poksawat, P.; Wang, L.; Mohamed, A. Gain scheduled attitude control of fixed-wing UAV with automatic controller tuning. *IEEE Trans. Control. Syst. Technol.* **2017**, *26*, 1192–1203. [CrossRef]
80. Jetley, P.; Sujit, P.; Saripalli, S. Safe landing of fixed wing UAVs. In Proceedings of the 2017 47th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W), Denver, CO, USA, 26–29 June 2017; pp. 2–9.
81. Santoso, F.; Liu, M.; Egan, G. Linear quadratic optimal control synthesis for a uav. In Proceedings of the 12th Australian International Aerospace Congress, AIAC12, Melbourne, Australia, 19–22 March 2007.
82. Manjarrez, H.; Davila, J.; Lozano, R. Low level control architecture for automatic takeoff and landing of fixed wing UAV. In Proceedings of the 2018 Annual American Control Conference (ACC), Milwaukee, WI, USA, 27–29 June 2018; pp. 6737–6742.
83. Lesprier, J.; Biannic, J.M.; Roos, C. Nonlinear structured H∞ controllers for parameter-dependent uncertain systems with application to aircraft landing. In Proceedings of the 2014 IEEE Conference on Control Applications (CCA), Juan Les Antibes, France, 8–10 October 2014; pp. 433–438.
84. Qayyum, N.; Bhatti, A.I.; Liaquat, M. Landing control of unmanned aerial vehicle using continuous model predictive control. In Proceedings of the 2017 29th Chinese Control And Decision Conference (CCDC), Chongqing, China, 28–30 May 2017; pp. 1804–1808.
85. Lungu, M. Backstepping and dynamic inversion control techniques for automatic landing of fixed wing unmanned aerial vehicles. *Aerosp. Sci. Technol.* **2022**, *120*, 107261. [CrossRef]
86. Zhu, G.; Qi, J.; Wu, C. Landing control of fixed-wing uav based on adrc. In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019; pp. 8020–8025.
87. Nho, K.; Agarwal, R.K. Automatic landing system design using fuzzy logic. *J. Guid. Control Dyn.* **2000**, *23*, 298–304. [CrossRef]
88. Zhang, D.; Wang, X. Autonomous landing control of fixed-wing uavs: from theory to field experiment. *J. Intell. Robot. Syst.* **2017**, *88*, 619–634. [CrossRef]
89. Jantawong, J.; Deelertpaiboon, C. Automatic landing control based on GPS for fixed-wing aircraft. In Proceedings of the 2018 15th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Chiang Rai, Thailand, 18–21 July 2018; pp. 313–316.
90. Mathisen, S.; Gryte, K.; Gros, S.; Johansen, T.A. Precision deep-stall landing of fixed-wing UAVs using nonlinear model predictive control. *J. Intell. Robot. Syst.* **2021**, *101*, 1–15. [CrossRef]
91. Hsiao, F.B.; Chan, W.L.; Lai, Y.C.; Tseng, L.C.; Hsieh, S.Y.; Tenn, H.K. Landing longitudinal control system design for a fixed wing UAV. In Proceedings of the 45th AIAA Aerospace Sciences Meeting and Exhibit, Reno, NV, USA, 8–11 January 2007; p. 868. [CrossRef]
92. Prach, A.; Gürsoy, G.; Yavrucuk, L. Nonlinear Controller for a Fixed-Wing Aircraft Landing. In Proceedings of the 2019 American Control Conference (ACC), Philadelphia, PA, USA, 10–12 July 2019; pp. 2897–2902.
93. Rao, D.V.; Go, T.H. Automatic landing system design using sliding mode control. *Aerosp. Sci. Technol.* **2014**, *32*, 180–187.
94. de Sousa Pereira, J.J.V.; Automatic Landing Control Design for Unmanned Aerial Vehicles. Master's Thesis, Universidade do Porto, Porto, Portugal, 2016. Available online: https://repositorio-aberto.up.pt/bitstream/10216/85551/2/146173.pdf (accessed on 20 May 2023).
95. Daibing, Z.; Xun, W.; Weiwei, K. Autonomous control of running takeoff and landing for a fixed-wing unmanned aerial vehicle. In Proceedings of the 2012 12th International Conference on Control Automation Robotics & Vision (ICARCV), Guangzhou, China, 5–7 December 2012; pp. 990–994.
96. Carnes, T.W.; Bakker, T.M.; Klenke, R.H. A fully parameterizable implementation of autonomous take-off and landing for a fixed wing UAV. Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology Guidance, Navigation, and Control Conference, Kissimmee, FL, USA, 5–9 January 2015; p. 0603.
97. Lai, Y.C.; Chan, K.C.; Liu, Y.C.; Hsiao, F.B. Development of an automatic landing system based on adaptive fuzzy logic control for fixed-wing unmanned aerial vehicles. *J. Aeronaut. Astronaut. Aviat.* **2016**, *48*, 183–194.
98. Zheng, Z.; Jin, Z.; Sun, L.; Zhu, M. Adaptive sliding mode relative motion control for autonomous carrier landing of fixed-wing unmanned aerial vehicles. *IEEE Access* **2017**, *5*, 5556–5565. [CrossRef]
99. Mahmood, A.; Bhatti, A.I.; Siddique, B.A. Landing of Aircraft Using Integral State Feedback Sliding Mode Control. In Proceedings of the 2019 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), Swat, Pakistan, 24–25 July 2019; pp. 1–6.
100. Mathisen, S.H.; Fossen, T.I.; Johansen, T.A. Non-linear model predictive control for guidance of a fixed-wing UAV in precision deep stall landing. In Proceedings of the 2015 International Conference on Unmanned Aircraft Systems (ICUAS), Denver, CO, USA, 9–12 June 2015, pp. 356–365.
101. Ishioka, S.; Uchiyama, K.; Masuda, K. Landing System Using Extended Dynamic Window Approach For Fixed-Wing UAV. In Proceedings of the 32nd Congress of the International Council of the Aeronautical Sciences, Shanghai, China, 6–10 September 2021.

102. Xu, J.; Keshmiri, S. Dubins-Based Autolanding Procedure for Fixed-Wing UAS. In Proceedings of the 2021 International Conference on Unmanned Aircraft Systems (ICUAS), Athens, Greece, 15–18 June 2021; pp. 146–154.
103. Cho, A.; Kim, J.; Lee, S.; Kim, B.; Park, N.; Kim, D.; Kee, C. Fully automatic taxiing, takeoff and landing of a UAV based on a single-antenna GNSS receiver. *IFAC Proc. Vol.* **2008**, *41*, 4719–4724. [CrossRef]
104. Yoon, S.H.; Kim, Y.D.; Park, S.H. Constrained adaptive backstepping controller design for aircraft landing in wind disturbance and actuator stuck. *Int. J. Aeronaut. Space Sci.* **2012**, *13*, 74–89. [CrossRef]
105. Lungu, M. Auto-landing of fixed wing unmanned aerial vehicles using the backstepping control. *ISA Trans.* **2019**, *95*, 194–210. [CrossRef] [PubMed]
106. Lungu, M. Backstepping and dynamic inversion combined controller for auto-landing of fixed wing UAVs. *Aerosp. Sci. Technol.* **2020**, *96*, 105526. [CrossRef]
107. prasad B, B.; Pradeep, S. Automatic landing system design using feedback linearization method. In Proceedings of the AIAA infotech@ Aerospace 2007 Conference and Exhibit, Rohnert Park, CA, USA, 7–10 May 2007; p. 2733.
108. You, D.I.; Jung, Y.D.; Cho, S.W.; Shin, H.M.; Lee, S.H.; Shim, D.H. A guidance and control law design for precision automatic take-off and landing of fixed-wing UAVs. In Proceedings of the American Institute of Aeronautics and Astronautics Science and Technology Guidance, Navigation, and Control Conference, Minneapolis, Minnesota, 13–16 August 2012; p. 4674.
109. Chunlei, D.; Qingbo, G.; Qing, F. High performance L 1 adaptive take-off and landing controller design for fixed-wing UAV. In Proceedings of the 2015 34th Chinese Control Conference (CCC), Hangzhou, China, 28–30 July 2015; pp. 3091–3096.
110. Hajiyev, C.; Vural, S.Y. LQR controller with Kalman estimator applied to UAV longitudinal dynamics. *Positioning* **2013**, *4*, 36–41. [CrossRef]
111. Homayouni Amlashi, A.; Mojed Gharamaleki, R.; Hamidi Nejad, M.H.; Mirzaei, M. Design of estimator-based nonlinear dynamic inversion controller and nonlinear regulator for robust trajectory tracking with aerial vehicles. *Int. J. Dyn. Control* **2018**, *6*, 707–725. [CrossRef]
112. Kalman, R.E. A new approach to linear filtering and prediction problems. *J. Basic Eng.* **1960**, *82*, 35–45. [CrossRef]
113. Khodarahmi, M.; Maihami, V. A Review on Kalman Filter Models. *Arch. Comput. Methods Eng.* **2022**, *30*, 727–747. [CrossRef]
114. Borup, K.T.; Stovner, B.N.; Fossen, T.I.; Johansen, T.A. Kalman filters for air data system bias correction for a fixed-wing UAV. *IEEE Trans. Control Syst. Technol.* **2019**, *28*, 2164–2176. [CrossRef]
115. Yang, Y.; Liu, X.; Liu, X.; Guo, Y.; Zhang, W. Model-Free Integrated Navigation of Small Fixed-Wing UAVs Full State Estimation in Wind Disturbance. *IEEE Sens. J.* **2022**, *22*, 2771–2781. [CrossRef]
116. Lie, F.A.P.; Gebre-Egziabher, D. Synthetic air data system. *J. Aircr.* **2013**, *50*, 1234–1249. [CrossRef]
117. Warsi, F.A.; Hazry, D.; Ahmed, S.F.; Joyo, M.K.; Tanveer, M.H.; Kamarudin, H.; Razlan, Z.M. Yaw, Pitch and Roll controller design for fixed-wing UAV under uncertainty and perturbed condition. In Proceedings of the 2014 IEEE 10th International Colloquium on Signal Processing and Its Applications, Kuala Lumpur, Malaysia, 7–9 March 2014; pp. 151–156.
118. Pettersson, M. Extended Kalman Filter for Robust UAV Attitude Estimation. Master's Thesis, Department of Electrical Engineering, Linköping University, Linkoping, Sweden, 2015; p. 86.
119. Magnusson, T. State Estimation of Uav Using Extended Kalman Filter. Master's Thesis, Department of Electrical Engineering, Automatic Control, The Institute of Technology, Linköping University, Linkoping, Sweden, 2013, p. 76.
120. Hervas, J.R.; Reyhanoglu, M.; Tang, H.; Kayacan, E. Nonlinear control of fixed-wing UAVs in presence of stochastic winds. *Commun. Nonlinear Sci. Numer. Simul.* **2016**, *33*, 57–69. [CrossRef]
121. Yin, X.; Peng, X.; Zhang, G.; Che, B.; Tang, M. Research on Attitude Control System Design and Flight Experiments of Small-scale Unmanned Aerial Vehicle. In Proceedings of the 2022 34th Chinese Control and Decision Conference (CCDC), Hefei, China, 15–17 August 2022; pp. 5866–5871.
122. Xiaoqian, T.; Feicheng, Z.; Zhengbing, T.; Hongying, W. Nonlinear Extended Kalman Filter for Attitude Estimation of the Fixed-Wing UAV. *Int. J. Opt.* **2022**, *2022*, 7883851. [CrossRef]
123. Yu, Y.j.; Zhang, X.; Khan, M.S.A. Attitude heading reference algorithm based on transformed cubature Kalman filter. *Meas. Control* **2020**, *53*, 1446–1453. [CrossRef]
124. De Marina, H.G.; Espinosa, F.; Santos, C. Adaptive UAV attitude estimation employing unscented Kalman filter, FOAM and low-cost MEMS sensors. *Sensors* **2012**, *12*, 9566–9585. [CrossRef]
125. De Marina, H.G.; Pereda, F.J.; Giron-Sierra, J.M.; Espinosa, F. UAV attitude estimation using unscented Kalman filter and TRIAD. *IEEE Trans. Ind. Electron.* **2011**, *59*, 4465–4474. [CrossRef]
126. Burchett, B.T. Feedback linearization guidance for approach and landing of reusable launch vehicles. In Proceedings of the 2005, American Control Conference, Portland, OR, USA, 8–10 June 2005; pp. 2093–2097.
127. Yang, J.; Thomas, A.G.; Singh, S.; Baldi, S.; Wang, X. A semi-physical platform for guidance and formations of fixed-wing unmanned aerial vehicles. *Sensors* **2020**, *20*, 1136. [CrossRef]
128. Prabowo, Y.A.; Trilaksono, B.R.; Triputra, F.R. Hardware in-the-loop simulation for visual servoing of fixed wing UAV. In Proceedings of the 2015 international conference on electrical engineering and informatics (ICEEI), Denpasar, Indonesia, 10–11 August 2015; pp. 247–252.
129. Ülker, H.; Baykara, C.; Özsoy, C. PIL simulations of an FWUAV under windy conditions. *Aircr. Eng. Aerosp. Technol.* **2018**, *90*, 461–470. [CrossRef]

130. Santos, M.H.; Oliveira, N.M.; D'Amore, R. From Control Requirements to PIL Test: Development of a Structure to Autopilot Implementation. *IEEE Access* **2021**, *9*, 154788–154803. [CrossRef]
131. Bacic, M. On hardware-in-the-loop simulation. In Proceedings of the Proceedings of the 44th IEEE Conference on Decision and Control, Seville, Spain, 12–15 December 2005; pp. 3194–3198.
132. Johnson, E.N.; Fontaine, S. Use of flight simulation to complement flight testing of low-cost UAVs. In Proceedings of the AIAA Modeling and Simulation Technologies Conference, Montreal, QC, Canada, 6–9 August 2001.
133. Sorton, E.; Hammaker, S. Simulated flight testing of an autonomous unmanned aerial vehicle using flightgear. In Proceedings of the Infotech@ Aerospace, , Arlington, VA, USA, 26–29 September 2005; p. 7083.
134. Bulka, E.; Nahon, M. Autonomous fixed-wing aerobatics: from theory to flight. In Proceedings of the 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, Australia, 21–25 May 2018; pp. 6573–6580.
135. Arif, A.; Sasongko, R.; Stepen. Numerical Simulation Platform for a Generic Aircraft Flight Dynamic Simulation. In Proceedings of the International Conference on Aviation Technology and Management 2018 (ICATeM 2018), Kuala Lumpur, Malaysia, 12–14 September 2018. [CrossRef]
136. Ribeiro, L.R.; Oliveira, N.M.F. UAV autopilot controllers test platform using Matlab/Simulink and X-Plane. In Proceedings of the 2010 IEEE Frontiers in Education Conference (FIE), Arlington, VA, USA, 27–30 October 2010; Session: S2H.
137. Nugroho, L. Comparison of classical and modern landing control system for a small unmanned aerial vehicle. In Proceedings of the 2014 International Conference on Computer, Control, Informatics and Its Applications (IC3INA), Bandung, Indonesia, 21–23 October 2014; pp. 187–192.
138. Priyambodo, T.K.; Majid, A. Modeling and simulation of the UX-6 fixed-wing Unmanned Aerial Vehicle. *J. Control Autom. Electr. Syst.* **2021**, *32*, 1344–1355. [CrossRef]
139. Zhang, J.; Geng, Q.; Fei, Q. UAV flight control system modeling and simulation based on FlightGear. In Proceedings of the International Conference on Automatic Control and Artificial Intelligence (ACAI 2012), Xiamen, China, 3–5 March 2012; pp. 2231–2234.