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A Survey of Controller Designs for New Generation UAVs: The Challenge of Uncertain Aerodynamic Parameters

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Abstract: This paper presents a survey of controller design techniques aimed at autonomous navigation and control of Unmanned Aerial Vehicles (UAVs), focusing on the challenge of aerodynamic uncertainty. Although many roadblocks exist, the most significant and challenging task for UAV navigation and control is the one of aerodynamic/model uncertainty. Current autopilots and controller designs for autonomous airplanes are mainly concerned with the feature of constant, unknown aerodynamic parameters, i.e., control and stability derivatives of the platform. This research focuses on a thorough investigation of the related theory and its applicability, centering on specific techniques that are able to control UAVs with rapidly changing, time-varying aerodynamic characteristics during flight. The scientific merit of this work is the comprehensive overview provided and the technical study that is performed, highlighting the advantages and disadvantages for each technique with respect to its efficiency and performance.

Keywords: Flight control, model uncertainty, robust control, unmanned aerial vehicle (UAV).

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are typically highly nonlinear underactuated systems; controller design presents challenges that need to be addressed and tackled. Challenges relate, among others, to problematic nonlinearities, coupling between lateral and longitudinal motions and uncertainty in aerodynamic parameters in the model (control and stability derivatives). When dealing with non-conventional UAV designs, such inherent uncertainties either limit or prohibit applicability of known controller design techniques. Viewed from this perspective, controller design for non-conventional UAVs (i.e., new generation UAVs) requires consideration of unstructured parameters, model uncertainty and an advanced controller design framework.

As mentioned in [1], modeling of the aircraft aerodynamic coefficients raises the fundamental question of what the mathematical structure of the model should be. Although a complicated model structure can be justified for accurate description of the aerodynamic forces and moments, it is not always clear what the relationship between model complexity and information in the measured data should be. If too many model parameters are sought for a limited amount of data, reduced accuracy of estimated parameters is expected, or the attempts to estimate all the parameters in the model might fail. Aircraft system identification is a complex process and the final values for the estimated aerodynamic parameters are usually within some certain error bounds. Therefore, even in the classical, conventional UAV case, aerodynamic/model uncertainty should be taken into consideration for flight control and navigation purposes.

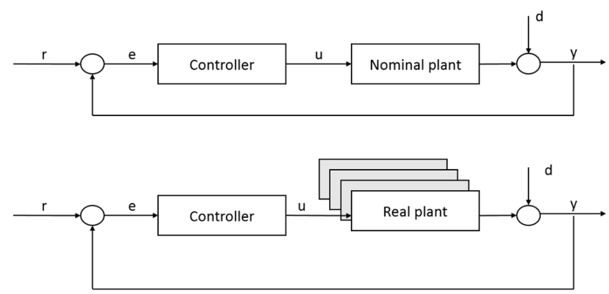

Fig. 1. Nominal versus real plant control system.

Regardless of the nature of the system to be controlled, a candidate controller cannot be designed solely on the basis of nominal plant and performance requirements. The true plant is (partially) unknown and it must belong to an admissible family of plants as Fig. 1 shows.

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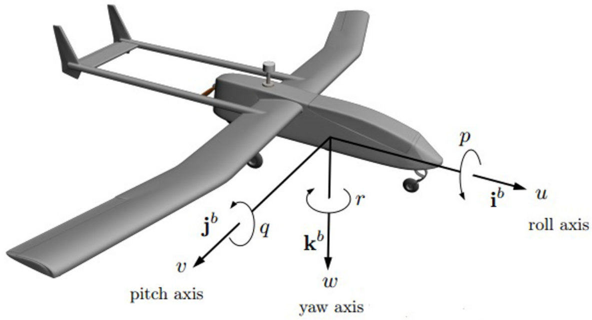

Fig. 2. UAV axes of motion [2].

Model uncertainty must be addressed and tackled. Robust controller design ensures that closed-loop stability holds for any plant within this family and that performance specifications are met. In real-life problems, a nominal model is an intentional approximation to reality. However, if model uncertainty is not accounted for and if the nominal plant model is exclusively used, the nominal feedback design might not be stable and only strict performance specifications will be met.

In what follows, the fundamental question of what is the source of aerodynamic uncertainty is answered through the aircraft equations of motion and the detailed breakdown of the aerodynamic coefficients. The UAV main axes of motion (roll, pitch and yaw) are shown in Fig. 2, which also defines the UAV body frame F^b (i^b, j^b, k^b).

The complete set of the navigation, force, kinematic and moment equations that govern the dynamic behavior of the UAV during flight, as found in [2, 3], is given in (1). Parameters p_n, p_e, p_d refer to inertial north, east and down (altitude) position of the UAV, variables u, v, w are the linear velocities, ϕ, θ, ψ are the attitude (pitch, roll and heading) angles and p, q, r correspond to pitch, roll and heading rates (angular rates).

Navigation equations

$$\begin{aligned}
\dot{p}_n &= (\cos\theta\cos\psi)u + (\sin\phi\sin\theta\cos\psi - \cos\phi\sin\psi)v \\
&\quad + (\cos\phi\sin\theta\cos\psi + \sin\phi\sin\psi)w, \\
\dot{p}_e &= (\cos\theta\sin\psi)u + (\sin\phi\sin\theta\sin\psi + \cos\phi\cos\psi)v \\
&\quad + (\cos\phi\sin\theta\sin\psi - \sin\phi\cos\psi)w, \\
\dot{p}_d &= u\sin\theta - v\sin\phi\cos\theta - w\cos\phi\cos\theta.
\end{aligned}$$

Force equations

$$\begin{aligned}
\dot{u} &= rv - qw - g\sin\theta + F_{i^b}/m, \\
\dot{v} &= pw - ru + g\cos\theta\sin\phi + F_{j^b}/m, \\
\dot{w} &= qu - pv + g\cos\theta\cos\phi + F_{k^b}/m.
\end{aligned}$$

Kinematic equations

$$\begin{aligned}
\dot{\phi} &= p + q\sin\phi\tan\theta + r\cos\phi\tan\theta, \\
\dot{\theta} &= q\cos\phi - r\sin\phi, \\
\dot{\psi} &= q\sin\phi\sec\theta + r\cos\phi\sec\theta.
\end{aligned}$$

Moment equations

$$\begin{aligned}
\dot{p} &= \Gamma_1 pq - \Gamma_2 qr + \Gamma_3 \ell + \Gamma_4 \mathscr{n}, \\
\dot{q} &= \Gamma_5 pr - \Gamma_6 (p^2 - r^2) + \mathscr{m}/J_y, \\
\dot{r} &= \Gamma_7 pq - \Gamma_1 qr + \Gamma_4 \ell + \Gamma_8 \mathscr{n}. \qquad (1)
\end{aligned}$$

A UAV is a nonlinear underactuated dynamic system, with its motion mathematically described by a set of 12 coupled, first-order, ordinary differential equations. The aerodynamic forces and moments and their respective coefficients have a complex dependence on a large number of variables and this creates both modeling and measurement challenges. Therefore, it is advantageous to build an aerodynamic coefficient from a sum of components that provide physical insight and are convenient to handle mathematically. The actual nonlinear dependence between the forces ($F_{i^b}, F_{j^b}, F_{k^b}$) and moments ($l, m, n$) acting on the airframe and the aerodynamic coefficients and the control surfaces (δ_e, δ_a, δ_r) is established in (2).

$$\begin{aligned}
F_{i^b} &= F_{i^b}(C_L, C_D, \delta_e), \\
F_{j^b} &= F_{j^b}(C_Y, \delta_\alpha, \delta_r), \\
F_{k^b} &= F_{k^b}(C_L, C_D, \delta_e), \\
\ell &= \ell(C_l, \delta_\alpha, \delta_r), \\
\mathscr{m} &= \mathscr{m}(C_m, \delta_e), \\
\mathscr{n} &= \mathscr{n}(C_n, \delta_\alpha, \delta_r). \qquad (2)
\end{aligned}$$

Aircraft lift C_L, drag C_D, sideforce C_Y, pitching C_m, rolling C_l and heading (yawing) C_n moment coefficients are typically nonlinear functions of the system states. These models can be linearized and simplified about a trim flight condition by utilizing Taylor series expansion, small perturbation theory and motion decoupling as in [1, 4]. Making use of this approach, the coefficients can be simplified as in (3), introducing the control and stability derivatives of the platform.

$$\begin{aligned}
C_L &= C_L(C_{L_0}, C_{L_\alpha}, C_{L_q}, C_{L_{\delta_e}}), \\
C_D &= C_D(C_{D_0}, C_{D_\alpha}, C_{D_q}, C_{D_{\delta_e}}), \\
C_Y &= C_Y(C_{Y_0}, C_{Y_\beta}, C_{Y_p}, C_{Y_r}, C_{Y_{\delta_\alpha}}, C_{Y_{\delta_r}}), \\
C_l &= C_l(C_{l_0}, C_{l_\beta}, C_{l_p}, C_{l_r}, C_{l_{\delta_\alpha}}, C_{l_{\delta_r}}), \\
C_m &= C_m(C_{m_0}, C_{m_\alpha}, C_{m_q}, C_{m_{\delta_e}}), \\
C_n &= C_n(C_{n_0}, C_{n_\beta}, C_{n_p}, C_{n_r}, C_{n_{\delta_\alpha}}, C_{n_{\delta_r}}), \qquad (3)
\end{aligned}$$

where the subscript 0 is the value of the respective coefficient when the linearizing variables are set to 0. The terms inside the parentheses on the right hand side of (3) are dimensionless quantities called control and stability derivatives. The label *derivative* comes from the fact that the coefficients originated as partial derivatives in the Taylor series approximation.

Having established (2) and (3), the connection between aerodynamic changes/uncertainty and the impact on the UAV model is clear. Aerodynamic uncertainty is by default present in the UAV model for controller design purposes due to the challenging task of accurate estimation of the control and stability derivatives. In addition to that, any aerodynamic changes on the UAV can be reflected on the aircraft control and stability derivatives. In this context, the term "new generation UAV" refers to fixed-wing unmanned aircraft with inherent time-varying, rapidly changing control and stability derivatives during flight.

Unlike existing work in the field of navigation and control of UAVs, this survey is specific to controller design techniques for non-conventional aircraft subject to aerodynamic uncertainty, with time-varying aerodynamic parameters during flight. To the best of the authors' knowledge, this is the first technical, comprehensive study of its kind, laying the foundation for autonomous navigation of UAVs in the presence of aerodynamic uncertainty, providing a basis for comparison for all the control design approaches and their related applications.

The remainder of the paper is organized as follows: Section 2 presents existing applications of new generation UAVs and section 3 provides a summary of published surveys. Section 4 gives a detailed literature review for fixed-wing UAV controllers, followed by a comprehensive summary in section 5. Section 6 concludes the paper.

2. NEW GENERATION UAVS

Focusing on the control and stability derivatives, this section presents potential or existing applications of new generation UAVs, where the results of this study might be immediately helpful for researchers.

2.1. Circulation control UAVs

This research is motivated by the challenge to design, build, model, control and test a small-scale Unmanned Circulation Control Aerial Vehicle (UC^2AV), which is the first of its kind with proven flight capability [5]. Circulation Control (CC) is an active flow control technique that is proven to be an efficient method for lift augmentation resulting in improved aerodynamic efficiency, runway reduction during takeoff/landing, smoother landing, enhanced payload capabilities and delayed stall.

For experimentation, validation and verification, a stock RMRC Anaconda has been integrated with a CC system on-board, which operates on demand according to the ongoing mission. The UC^2AV has been designed to perform missions with different flight requirements and mission adaptation gives the ability to the end user to operate a single UAV for multiple applications. Operating the CC-system on demand results in direct changes of the aircraft control and stability derivatives during flight (primarily C_L in (3)). Preliminary research has shown a reduction in take-off distance by 54% compared to the conventional UAV as depicted in Fig. 3.

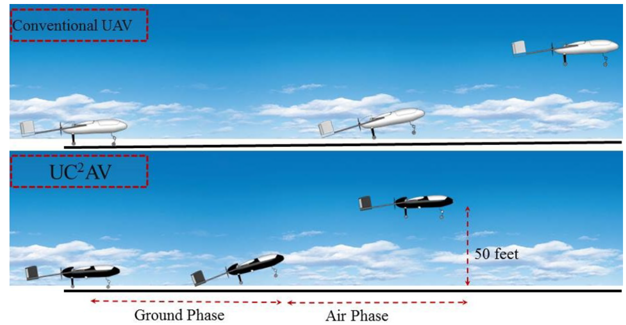

Fig. 3. Take-off performance behavior of the UC^2AV compared to a conventional UAV [5].

After a thorough literature review, a UC^2AV-based controller design has been proposed in [6], and validated for the longitudinal motion of the UC^2AV in [7]. The overall control system architecture is a hybrid structure, consisting of a dynamic inversion inner-loop and a μ-synthesis outer-loop controller, aimed at tackling the challenge of time-varying aerodynamic characteristics during flight.

2.2. Morphing UAVs

It is always fascinating when technology mimics nature. Motivated by the Greek word "*morpho*," which means to transform, morphing technology seeks to emulate the biological structure of a bird [8]. This new class of UAVs will be able to control itself like a bird, with wings that twist, fold and transform [9, 10]. Morphing research projects such as the MFX-1 developed by NextGen Aeronautics [11] will revolutionize the costs of building and operating aircraft.

The objective of morphing technologies is to develop high performance aircraft with wings designed to change shape and performance substantially during flight to create multiple-regime, aerodynamically-efficient, shape-changing aircraft. The morphing wing change of shape can occur either in-plane (Fig. 4), or out-of-plane as shown in Fig. 5.

For a detailed definition of the airfoil characteristics the reader is referred to [13]. Morphing technologies will be used to improve aircraft performance, make them more efficient and enable the vehicles to operate under a wide range of flight conditions. Morphing UAVs belong to the general class of active wing shaping UAVs which enable complex trailing-edge shapes that could contribute to aerodynamic, structural, and control advantages. An example can be seen in Fig. 6, which shows a UAV with segmented control surfaces for improved aerodynamic efficiency. Changing shape during flight implies an on-demand alteration of all the aircraft aerodynamic coeffi-

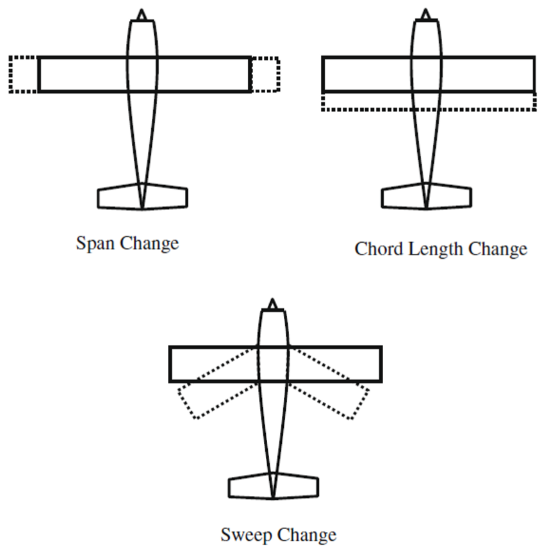

Fig. 4. In-plane shape morphing [12].

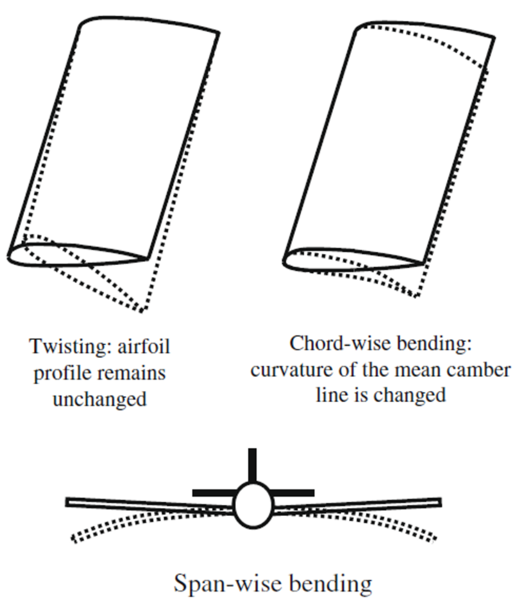

Fig. 5. Out-of-plane shape morphing [12].

cients in (3). Therefore, this survey will be a useful tool for those conducting research in the field of navigation and control of morphing and active wing shaping UAVs.

2.3. Delivery UAVs

Interest in small flying machines as means of delivering payloads has been continuously increasing and the idea of turning UAVs into a commercialized delivery mechanism has sparked a lot of debate. Some of the numerous applications include delivery of food products, providing assistance in the agricultural and farming industry, supply chain applications, package delivering and last but

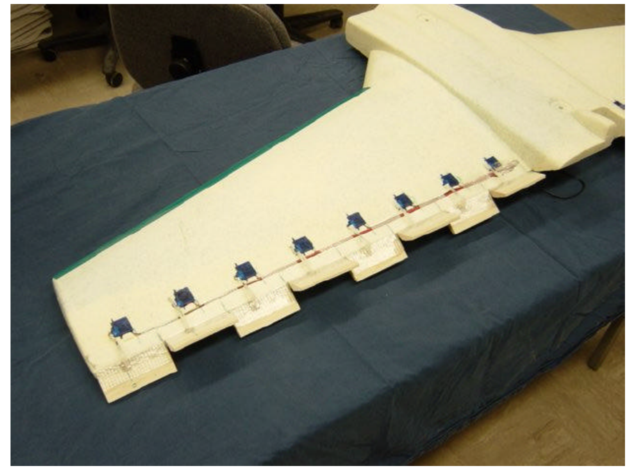

Fig. 6. Segmented left wing deflected to induce heading moment [14].

not least, the use of UAVs for medical purposes [15, 16]. Amazon, Google and UPS are some of the industry leaders that have initiated research on new, UAV-assisted product-delivery methods.

For a technical justification of the importance of this study when it comes to UAVs as delivery mechanisms, the relation between the control and stability derivatives and the vehicle's mass must be identified. The traditional approach for aircraft system identification is the derivation of a linear model based on motion decoupling [1]. For the UAV lateral and longitudinal motion, a state-space model $\dot{x} = Ax + Bu$ is derived through flight testing. The elements of matrix A are functions of the aircraft's control and stability derivatives and trim flight conditions. An example can be seen in (4), which gives the actual mathematical expression for the lateral state-space model coefficient Y_r (C_Y and C_{Y_r} in (3)) as a function of the aircraft's mass m.

$$Y_r = -u^* + \frac{\rho V_\alpha^* S b}{4m} C_{Y_r}. \tag{4}$$

Nomenclature and the complete tables of the lateral and longitudinal state-space model coefficients can be found in [2]. Assuming changing mass due to a delivery scenario means that the UAV control and stability derivatives will have time-varying values during flight as (4) dictates. Hence, the controller design methodology that will be applied on a delivery UAV, will inevitably be one of the techniques investigated in this paper.

3. PUBLISHED SURVEYS REVIEW

Eleven surveys have been published to date, exploring research in the areas of autopilot hardware and software, control techniques, motion planning, collision avoidance, traffic surveillance, imagery collection, communication networks and vision-based navigation. This section presents a summary of contributions of existing surveys.

Published in 2004, "*Control and Perception Techniques for Aerial Robotics*" [17], is mostly focused on perception techniques, reviewing methods that have been applied to aerial robotics including different vehicle platforms and flight control hardware. It provides a brief survey of control architectures and computer vision techniques. It covers a broad range of UAVs, but little emphasis is placed on controller design methodologies.

Published in 2005, "*A Survey of Unmanned Aerial Vehicles (UAV) for Traffic Surveillance*" [18], presents a survey of research activities in several universities around the world in the area of application of UAVs in traffic surveillance. A summary of research projects, vehicle platforms and research objectives is provided with respect to traffic sensing and management.

Published in 2009, "*A Survey of Autonomous Control for UAV*" [19], surveys the autonomous control concept and Autonomous Control Level (ACL) metrics that can measure autonomy of UAVs. The constraint conditions and realizations of the three basic levels of UAV system autonomy (execution, coordination and organization) are studied comprehensively. The key hardware and software technologies for multi-tasking are modularized depending on mission requirements.

Published in 2009, "*A Survey of Collision Avoidance Approaches for Unmanned Aerial Vehicles*" [20], focuses on collision avoidance approaches deployed for unmanned aerial vehicles. The collision avoidance concept is introduced together with proposing generic functions carried by collision avoidance systems. The design factors of the sense and avoid system are explained in detail and based on these, several typical approaches are categorized.

Published in 2010, "*A Survey of Motion Planning Algorithms from the Perspective of Autonomous UAV Guidance*" [21], provides an overview of existing motion planning algorithms while adding perspectives and practical examples from UAV guidance approaches. It emphasizes practical methods and provides a general perspective on the particular problems arising with UAVs.

Published in 2010 in the IJCAS journal, "*Autopilots for Small Unmanned Aerial Vehicles: A Survey*" [22], contains a survey of autopilot systems intended for use with small or micro UAVs. Several typical commercial off-the-shelf autopilot packages are compared in detail and some research autopilot systems are introduced. Concluding remarks are made with a summary of the autopilot market and a discussion on the future directions.

Published in 2011, "*A Survey of Unmanned Aerial Vehicle (UAV) Usage for Imagery Collection in Disaster Research and Management*" [23], provides a review of utilization of UAVs for imagery collection for disaster monitoring and management. A review of papers regarding data acquisition and assessment prior, during and after disaster events is presented.

Published in 2012, "*Survey of Motion Planning Literature in the Presence of Uncertainty: Considerations for UAV Guidance*" [24], surveys motion planning algorithms that can be applied on UAVs and that can deal with the primary sources of uncertainty arising in real world missions. Emphasis is placed on uncertainties in vehicle dynamics and environment knowledge, investigating optimal, model predictive and Lyapunov techniques for the first as well as A^* and D^* planning techniques for the second.

Published in 2014, "*A Survey of Small-Scale Unmanned Aerial Vehicles: Recent Advances and Future Development Trends*" [25], provides a detailed overview of advances of small-scale UAVs including platforms and scientific research areas. The evolution of the key elements, including on-board processing units, navigation sensors, mission-oriented sensors, communication modules, and ground control station is presented and analyzed. Finally, the future of small-scale UAV research, civil and military applications are forecasted.

Published in 2016, "*Survey of Important Issues in UAV Communication Networks*" [26], focuses on the issues of routing, seamless handover and energy efficiency in UAV networks. A categorization of UAV networks and an examination of important characteristics like topology, control, and client server behavior is carried out. Requirements from the routing protocols unique to UAV networks and the need for disruption tolerant networking are also discussed.

Published in 2018, "*A survey on vision-based UAV navigation*" [27], presents a comprehensive literature review of the vision-based methods for UAV navigation. Specifically, it focuses on visual localization and mapping, obstacle avoidance and path planning, which compose the essential parts of visual navigation. Furthermore, an insight into the prospect of UAV navigation and the challenges to be faced is given.

There is no existing technical and detailed study, evaluating the control techniques for navigation and control of the family of new generation aircraft. This article aims to establish the foundational methodology to design controllers for complex, uncertain UAV systems with a particular focus on the significant challenge of aerodynamic uncertainty.

4. FIXED-WING UAV CONTROLLERS

This section provides a technical overview and the necessary background for existing controller synthesis methods that have been applied for navigation and control of UAVs. These include linear controllers (PID, LQR, LQG, etc.), backstepping, sliding mode, nonlinear model predictive, adaptive, dynamic inversion, fuzzy logic, neural networks, learning, gain scheduling, H_∞ and μ-synthesis. The distinctive advantages and drawbacks for each technique are investigated with respect to applicability to the family of new generation UAVs.

4.1. Linear control

PID controllers are a type of single-input/single-output (SISO) control structure. A great advantage of PID controllers is that they can be easily implemented and they require low computational effort on-board the UAV [22]. It is also relatively easy to build on top of PIDs, in cascaded loops as in [28], meaning that they can be effectively combined with other synthesis methods. On the other hand, as stated in [22], PID techniques are non-model based and they lack robustness. Their non-model based characteristic can be considered as an advantage, but in the case of a UAV with time-varying aerodynamic uncertainties, tuning the PID gains can become a rather difficult task due to model uncertainty.

Linear Quadratic Gaussian (LQG) and Linear Quadratic Regulator (LQR) are optimal feedback controllers based on minimizing predefined cost functions and can be used both for SISO and MIMO (multi-input/multi-output) structures. LQG control can also operate in the presence of white noise. These techniques can be used for multivariable systems but due to their iterative nature, the control input vector may be hard to determine [29]. Additionally, input constraints of the system are not taken into consideration. An application of LQR for UAV flight control can be seen in [30], presenting a 3D LQR based landing controller that accurately lands the vehicle on a runway.

Every linear technique is based on the fact that the studied system model is linear. This means that even if the actual system behaves in a nonlinear way, in order to apply linear methods, one has to linearize the given model around some specific operating condition. Linearization can be convenient but it has local validity, only in a certain neighborhood around the specified condition. State of the art in linear controller design for fixed-wing UAV tackles the challenges of PID auto-tuning [31] and model uncertainty and robustness by using gain-scheduling [32]. Studies comparing PID, LQR, adaptive, neural, fuzzy and backstepping designs can be found in [33, 34]. Adaptive neuro-fuzzy techniques are proven to be more efficient, indicating that linear controllers cannot provide robust performance guarantees in presence of large-scale aerodynamic uncertainties.

4.2. Backstepping

Backstepping has been widely used for UAV control due to its recursive nature; its foundation lies in Lyapunov analysis [35]. One requirement for backstepping to be applied is the system to be put in strict feedback form [36], see (5). Virtual control inputs are generated in order to account for the deficit between the number of system states and the number of actual control inputs. The design can benefit from useful nonlinearities by appropriately choosing these virtual control inputs.

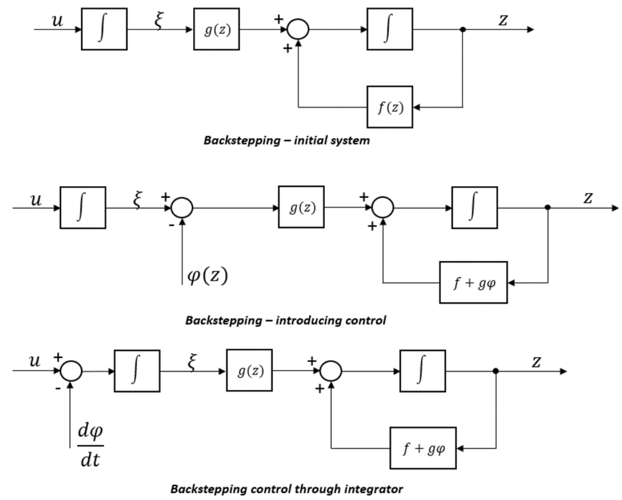

Fig. 7. The backstepping concept.

$$\begin{aligned}
\dot{x} &= f(x) + g(x)\xi_1,\\
\dot{\xi}_1 &= f_1(x,\xi_1,\xi_2),\\
\dot{\xi}_2 &= f_2(x,\xi_1,\xi_2,\xi_3),\\
&\vdots\\
\dot{\xi}_{k-1} &= f_{k-1}(x,\xi_1,\dots,\xi_k),\\
\dot{\xi}_k &= f_k(x,\xi_1,\dots,\xi_k,u).
\end{aligned} \tag{5}$$

The general concept of backstepping can be seen in Fig. 7, for the simplest system $\dot{z} = f(z) + g(z)\xi$, $\dot{\xi} = u$. The asymptotically stabilizing control law $\phi(z)$ is "backstepped" through the integrator. The primary challenge for backstepping control designs is finding a potential Lyapunov candidate function.

Putting (1) into (5) i.e., the UAV equations of motion into a strict feedback form requires a set of a-priori assumptions related to the aircraft aerodynamics [37]. As far as new generation UAVs are concerned, this is acceptable but not preferable. Furthermore, backstepping is a robust technique but it is sensitive to aerodynamic parameter variation. Researchers have employed more sophisticated control architectures such as adaptive, for trajectory tracking [38] and disturbance rejection/observer [39–41], or incremental (sensor-based) backstepping [42] to robustify the technique and make it more versatile. An interesting comparison of backstepping, PID and fuzzy PID can be found in [43] for UAV path planning, concluding that fuzzy PID provides superior performance.

4.3. Sliding mode

Sliding mode is a nonlinear control method designed to constrain the system states to a certain manifold or sliding surface. In its ideal setup, sliding mode requires the control input to oscillate with very high frequency but this may not be achievable for every dynamic system [44]. The trajectory of the system states does not always stay on the sliding surface but instead, it may oscillate around the surface due to delays in control switching in what is called chattering [45, 46]. Sliding mode generates discontinuous control laws, raising questions about the existence and uniqueness of solutions and the validity of Lyapunov analysis.

The mathematical objective of sliding mode control is to transform a system of the form $\dot{x} = f(x) + B(x)(G(x)u + \delta(t,x,u))$ into a system in a regular form as in (6) by utilizing an appropriate change of variables.

$$\begin{aligned} \dot{\eta} &= f_\alpha(\eta,\xi), \\ \dot{\xi} &= f_b(\eta,\xi) + G(x)u + \delta(t,x,u). \end{aligned} \tag{6}$$

Parameter x is the state vector, u is the control input vector, f and B are sufficiently smooth functions and G, δ are uncertain functions. The sliding manifold $s = \xi - \phi(\eta) = 0$ is then designed so that when the motion is restricted to the manifold, the reduced-order model $\dot{\eta} = f_\alpha(\phi(\eta))$ has an asymptotically stable equilibrium point at the origin. This is achievable for attitude control of a new generation UAV because sliding mode guarantees robustness against aerodynamic/model uncertainty with a given upper bound.

Applications of adaptive sliding mode control for fixed-wing UAVs can be found in [47–49], where disturbance observer and adaptation are employed to deal with disturbances, the effect of chattering and to optimize robustness against model uncertainty. In [50], an adaptive PD controller is designed with the adjustment mechanism following the gradient-based MIT rule. Recent advances in the field of continuous sliding mode control of UAVs are established in [51–54], proposing a technique that eliminates the effect of chattering. Finally, a study comparing backstepping, sliding mode and backstepping with sliding mode control can be found in [55], concluding that backstepping with high order sliding mode achieves superior performance with a better minimization of the chattering effect.

4.4. Nonlinear model predictive

Nonlinear model predictive control is a technique that can predict the future behavior of the system and allows for on-line implementation. It is based on the concept of repetitively solving an optimization problem involving a finite time horizon and a dynamic mathematical model [56]. The goal is to minimize a cost function of the form

$$J[u(t),x(t)] = \int_0^T l(x(t),u(t),t)dt + S(x(T),T), \tag{7}$$

where T is the time horizon, function l denotes the stage cost and function S represents the terminal cost, subject to the physical constraints

$$u_{min} \leq u(t) \leq u_{max}, \quad g(x(t),u(t),t) \leq 0 \tag{8}$$

with the dynamic mathematical model described by the ordinary differential equation $\frac{d}{dt}x(t) = f(x(t),u(t),t)$. Solving this differential equation for a new generation UAV, either analytically or numerically, is a challenging task. The UAV control and stability derivatives (function f) will be uncertain and time-varying, so the process will be computationally intensive for on-board implementation. Nonlinear optimization of the cost function (7) requires accurate sensor measurement of the state vector $x(t)$, or alternatively, employment of linear model predictive control approaches [57, 58].

However, the feature that prohibits applicability of nonlinear model predictive on a new generation UAV is dependence on system knowledge. In principle, nonlinear model predictive designs cannot handle large scale, time-varying uncertainties because system knowledge is required for model prediction. A low-level kinematic model of the UAV dynamics is utilized in [59] to design a high-level controller for path following. An adaptive nonlinear model predictive approach that varies the conventional fixed horizon according to the path curvature profile is proposed in [60].

A large body of literature, including recent advances such as [61–64], utilizes a UAV kinematic model to achieve trajectory tracking with a nonlinear model predictive design due to its ability to explicitly handle the control input and system state constraints highlighted in (8). Although this approach is generally applicable for a new generation UAV, the controller will be non-model based, meaning that the time-varying control and stability derivatives will not be taken into consideration. An advanced architecture that guarantees stability properties in presence of time-varying uncertainties would be more suitable.

4.5. Adaptive

The design of a controller that can alter or modify the behavior and response of an unknown plant to meet certain performance requirements can be a tedious and challenging problem in many control applications. By definition, to adapt means to change (oneself) so that one's behavior will conform to new or changed circumstances. Adaptive control seeks to address issues of parametric or environmental uncertainties based on the Lyapunov concept of stability [65, 66].

Unknown parameter vectors are defined and estimated so that Lyapunov stability is guaranteed, following two main approaches, the indirect (Fig. 8) and the direct adaptive control (Fig. 9). Adaptive control enables a wide operation range during flight as demonstrated in [67–71], where adaptive is used to robustify backstepping, neural and fuzzy designs against model uncertainty and unmodeled dynamics.

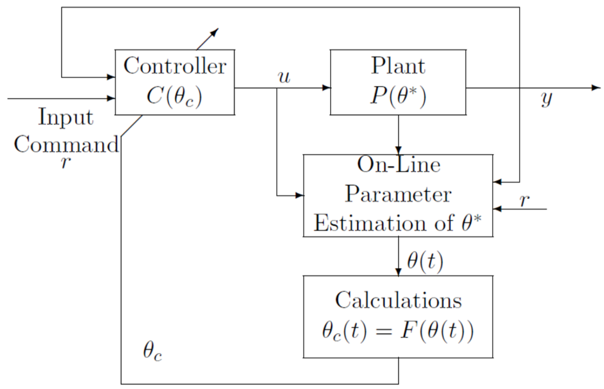

Fig. 8. Indirect adaptive control [72].

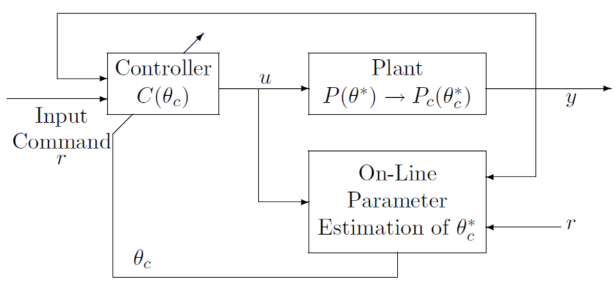

Fig. 9. Direct adaptive control [72].

Adaptive control strategies can be categorized according to whether the controller parameters are tuned continuously in time or switched between discrete values at specified instants. The first category refers to the classical, deterministic adaptive control and has some inherent limitations due to dependence on an identified plant model. This issue becomes severe if robustness and high performance is sought. In the second case, switching can be performed among controllers of different structures, resulting in a design that is independent of plant identification accuracy and other prior assumptions [73]. A major setback for the applicability of traditional adaptive control for a new generation UAV is limited flexibility of the unknown parameter vector for robust controller design purposes.

Switching multi-model adaptive control provides a more robust alternative compared to the classical adaptive control approach. The idea lies behind switching between stabilizing and destabilizing controllers from a predefined set to achieve asymptotic stability. Switching among candidate controllers is orchestrated by a high-level decision maker called a supervisor. The supervisor updates controller parameters when a new estimate of the process parameters becomes available, similarly to the adaptive control paradigm, but these events occur at discrete instants of time [74, 75]. This results in a hybrid closed-loop system. The general view of a switching adaptive control system, in which the control action is based on the learned characteristics of the process (plant) is depicted in Fig. 10.

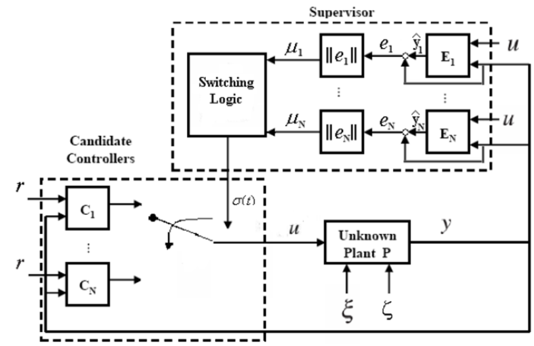

Fig. 10. Adaptive control architecture consisting of a switching controller and a supervisory controller block [74].

If the parametric uncertainty is described by a continuum, one has the choice of working with a continuous or a discrete family of controllers. In this case, one needs to ensure that every admissible process model is satisfactorily controlled by at least one of these controllers. The switching algorithms that seem to be the most promising are those that evaluate the potential performance of each candidate controller on-line and use this to direct their search. Comprehensive examples of fuzzy adaptive control for switched systems can be found in [76–78].

The mathematical foundation and the ground for the design of switched adaptive control systems has been well established in numerous works over the last two decades. A recent application for robotic manipulators can be seen in [79]. Nevertheless, real-life aerospace applications of the switching adaptive control strategy are yet to be seen. The supervisory control system framework requires thorough analysis and understanding, not to mention the potential computational burden the control systems engineer might have to face for a real-time application. One last limitation of this approach is the speed of switching between candidate controllers, occurring based on observed system data. For instance, designing a switched adaptive controller for a fighter aircraft, or a morphing aircraft with on-demand configuration, might prove to be a significant challenge.

4.6. Dynamic inversion

Dynamic inversion or feedback linearization is a method seeking to transform the nonlinear system dynamics into an equivalent, fully or partially linear form through some algebraic transformation. Given a system of the form $\dot{x} = f(x) + g(x)u$, if the control law $u = g^{-1}(x)[-f(x) + ax]$ is applied for some constant a, the initial nonlinear system can transform into a linear one. This simple idea summarizes the concept behind dynamic inversion. Linear transformation can be achieved by somehow inverting the nonlinear UAV dynamics and solving the puzzle of motion decoupling [80]. By applying dynamic inversion, one controller is capable of handling the entire flight regime.

Recent applications of dynamic inversion for unmanned aircraft systems can be found in [81–85], where observer-based dynamic inversion is used to account for input constraints and inaccurate sensor measurements. Dynamic inversion can be used in cascaded designs for performance tuning. For instance, dynamic inversion is robustified by the use of gain scheduling in [86] after linearizing the system to handle the complex UAV system dynamics. Additionally, dynamic inversion can efficiently serve as an inner-loop control law for H_∞ and μ-synthesis designs that will be analyzed in a subsequent section. However, the control law u is implementable only if the system is precisely known, which is a significant limitation for application on a new generation UAV. This would require accurate measurement of the UAV attitude angles, linear velocities and angular rates, as well as a precise feedback of the time-varying control and stability derivatives during flight.

4.7. Fuzzy, neural networks and learning

Fuzzy logic control is a model-free, knowledge based technique which tries to mimic the way humans think and make decisions by creating a set of rules that are used by the controller to analyze the input and to determine the appropriate output. The basic concept of a fuzzy control system is depicted in Fig. 11 and the main steps for a fuzzy logic control algorithm are given below.

1) Define the linguistic variables and terms (initialization).
2) Construct the membership functions (initialization).
3) Construct the rule base (initialization).
4) Convert crisp input data to fuzzy values using the membership functions (fuzzification).
5) Evaluate the rules in the rule base (inference).
6) Combine the results of each rule (inference).
7) Convert the output data to non-fuzzy values (defuzzification).

Membership functions in fuzzy logic control systems are used in the fuzzification and defuzzification process to convert non-fuzzy input values to linguistic terms and vice versa. Fuzzy logic is a model-free, intuitive design that can be built up and trained for specific applications. The fuzzy logic UAV controller follows a (if event A, then event B) framework based on the rule base, meaning that it indirectly deals with aerodynamic uncertainties in the UAV model [87, 88]. In the case of new generation aircraft however, where aerodynamic uncertainties have time-varying structure, several simulation or flight tests

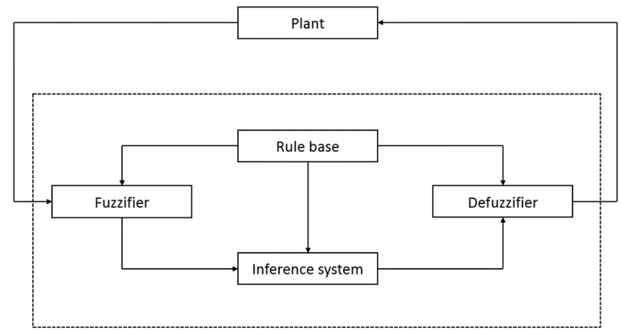

Fig. 11. Architecture of fuzzy logic control system.

will be needed to train the system and the designed controller to achieve robust performance for every on-demand change of the aerodynamic coefficients (event A). Consistency of rules and system tuning parameters (inference, fuzzification and defuzzification) have to be investigated because system stability and optimization can only occur experimentally.

Unlike fuzzy, neural networks are a learning based method that seeks to mimic the human central nervous system by utilizing input-output data to program the neurons in a network. A three-layer neural network structure to account for aerodynamic uncertainties in the UAV model can be found in [89]. Recent genetic neuro-fuzzy applications on fixed-wing aircraft are reported in [90, 91] to deal with lack of modeling and flight uncertainties. State of the art in intelligent (fuzzy, neural network and learning) flight control systems for small aerial vehicles is discussed in [92–95]. The challenges of computational demand, online learning and uncertainty in data representation are highlighted for the still growing field of intelligent aerial robotics. Applications of learning-based control for robotic arm and UAV attitude control can be found in [96] and [97, 98] respectively.

4.8. Gain scheduling

Gain scheduling is a switching strategy between a finite number of linear controllers each corresponding to a linear model of the aircraft dynamics near a design trim condition. The idea behind designing a gain scheduled controller for a nonlinear plant, illustrated in Fig. 12 and taken from [99], can be described as a four step procedure as follows:

1) The first step is to compute a linear-parameter-varying (LPV) model for the aircraft. The traditional approach in this area is based on Jacobian linearization of the nonlinear plant about a family of equilibrium points, also called operating points or set points. This yields a parametrized family of linearized plants and forms the basis for linearization scheduling. A detailed comparative study can be found in [100], where LPV models for the Boeing 747-100/200 are derived and evaluated.

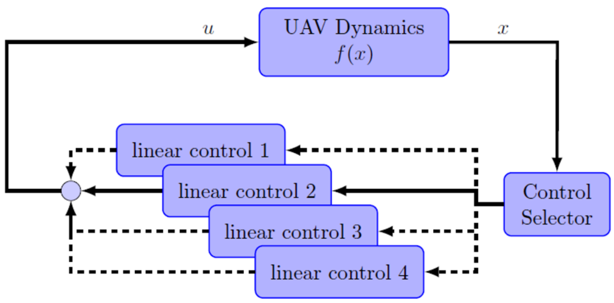

Fig. 12. Functionality of gain scheduling [101].

2) The second step is to use linear design methods to design linear controllers for the linear parameter-varying plant model that arises. This design process results in a family of linear controllers corresponding to the linear-parameter-dependent plant. Traditionally, the designs are such that for each fixed value of the parameter, the linear closed-loop system exhibits desirable performance.

3) The third step includes the actual gain scheduling. A family of linear controllers is implemented so that the controller coefficients (gains) are varied (scheduled) according to the current value of the scheduling variables.

4) Performance assessment is the final step. Desired performance guarantees might be part of the design process but typically, the local stability and performance properties of the gain scheduled controller might be subject to analytical investigation, while the nonlocal performance evaluation might require simulation studies.

Gain scheduling employs powerful linear design tools on difficult nonlinear problems. Gain scheduled controllers preserve well-understood linear intuition, in contrast to nonlinear control approaches that involve coordinate transformations. Moreover, gain scheduling enables the controlled system to respond rapidly to changing operating conditions. Last but not least, the computational burden of linearization scheduling approaches is often much less than other nonlinear design approaches. Applications of gain-scheduling for morphing aircraft can be found in [102,103] whereas a detailed gain-scheduled flight control design is performed in [104].

Limitations of gain scheduling for control of a new generation UAV include the large number of flight conditions that need to be considered and also the need for the transition between the models to be smooth. Stability can be assured only locally and in a slow-variation setting and usually there are no performance guarantees. This presents a bottleneck in the case of a UAV with rapidly changing aerodynamic parameters.

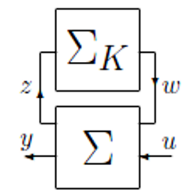

Fig. 13. H_∞ control system [106].

4.9. H_∞ and μ-synthesis

Linear H_∞ is a type of multi-variable, robust, model-based control and its major advantage over linear techniques is its robustness in presence of model uncertainties. Given a linear, time-invariant system Σ as depicted in Fig. 13, with w being the exogenous input, z being the corresponding output and u, y representing regular inputs and outputs, a control law $u = F_1 x + F_2 w$ is sought that will minimize the H_∞ norm of the overall transfer matrix over parametric uncertainties Σ_K [105, 106].

Nonlinear H_∞ is based on the same optimization concept and it is transformed into a nonlinear technique through the use of a dynamic inversion inner-loop control law for linearization of the dynamics [107–109]. The Hamilton-Jacobi partial differential inequality (HJPDI) that can be found in [110, 111] is another alternative. In a nutshell, given a nonlinear system $\dot{x} = f(x) + g_1(x)d + g_2(x)u$, the HJPDI approach attempts to solve the differential inequality shown in (9).

$$\left(\frac{\partial E}{\partial x}\right)^T f + \frac{1}{2}\left(\frac{\partial E}{\partial x}\right)^T \left(\frac{1}{\gamma_1^2} g_1 g_1^T - g_2 W_E^{-2} g_2^T\right)\left(\frac{\partial E}{\partial x}\right) + \frac{1}{2} h_1^T h_1 < 0, \tag{9}$$

for some positive C^1 function E, output signal h_1 and weighting function W_E, and then make use of the nonlinear bounded real lemma. The μ-synthesis method is an extension to the H_∞ design because it is a doubly-iterative optimization process with respect to:

1) the H_∞ compensator $K(s)$,
2) the $D(s)$ scales.

An optimal H_∞ compensator $K(s)$ is designed and the scales $D(s)$ are optimized so that the robust complex-μ test shown in (10) is satisfied, for the system's overall transfer matrix M [112].

$$\mu(M) = \mu(DMD^{-1}) \leq \sigma_{max}(DMD^{-1}) \leq 1, \ \ \forall \omega \in \mathbb{R}. \tag{10}$$

The μ-synthesis framework allows model uncertainties and system perturbations to enter the design in a multiplicative or additive fashion [113]. For instance, the authors have implemented a novel, nominal plant with additive uncertainty in [7, 114] (Fig. 14), where an uncertainty

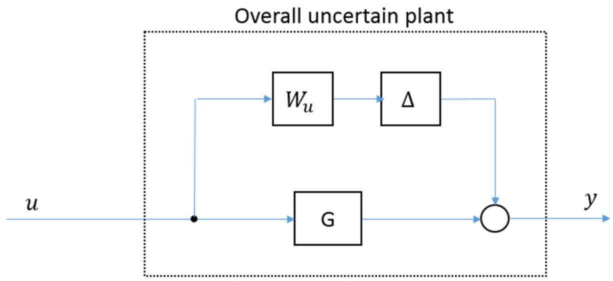

Fig. 14. Nominal plant with additive uncertainty [114].

range such as $C_{L_1} \leq C_L \leq C_{L_2}$ is utilized to compensate for time-varying, lift coefficient, aerodynamic uncertainties of a new generation aircraft. The approach was based on research reported in [115, 116], where a μ-synthesis controller is designed for a 4-wheel vehicle and then extended for application on fixed-wing aircraft.

Both H_∞ and μ-synthesis can deal with nonlinear, multi-variable systems and can also handle UAV time-varying aerodynamic uncertainties through an off-line definition of the uncertainty interval. Performance specifications, disturbances in several locations in the feedback loop and actuator models are also considered. The entire μ-synthesis controller design can be simplified, validated and supported by existing MATLAB software such as [112, 113]. A possible increase of the complexity is anticipated as the model dimension increases and the controller will only be optimal with respect to a predefined cost function and not to other common measures such as settling time.

5. RESULTS

This section gives a comprehensive summary of the literature review performed in Section 4, providing a basis for comparison for researchers that is divided into two concise tables. Table 1 gives a general overview of the non-qualifying techniques, containing the advantages and disadvantages for each method evaluated in Section 4. Table 2 summarizes the promising and applicable control architectures for new generation UAVs, highlighting potential challenges as well as the respective references used to justify our claim.

6. CONCLUSION

Unmanned Aviation has expanded significantly in recent years and research and development in the field of navigation and control have advanced beyond expectations. However, it is worth mentioning that conventional and commercially available small-scale UAVs have limited utilization and applicability to executing specific short-duration missions because of limitations in size, payload, power supply and endurance. And this fact has already marked the dawn of a new era of more powerful and versatile UAVs (e.g. morphing aircraft), able to perform a variety of missions.

This survey provides a technical, comprehensive study of existing controller design methodologies, highlighting the techniques that qualify for design and implementation on new generation UAVs i.e., UAVs with rapidly changing, time-varying aerodynamic characteristics during flight. The stated arguments are supported both by theoretical and application results, providing researchers with a useful tool in the promising field of navigation and control of new generation unmanned aircraft.

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Table 1. Summary of non-qualifying control techniques.

Method	Advantages	Disadvantages	References
Linear control	Straightforward design, low computational effort, cascaded loops	Local validity, robustness issues	[28–34]
Backstepping	Efficient for underactuated systems	Strict feedback form, sensitive to parameter variation	[35–43]
Sliding mode	Sliding manifold, robust against model uncertainty	Discontinuous control law, effect of chattering	[44–50, 55]
Nonlinear model predictive	Can predict future behavior of the system, can handle system and input constraints	Dependent on the system knowledge	[56–64]
Adaptive	Can handle unknown parameters, wide operation range available	Limited flexibility of the unknown parameter vector	[65–72]
Dynamic inversion	One control law needed, no motion decoupling required	Highly dependent on the system knowledge	[80–86]

Table 2. Summary of proposed controller design frameworks.

Method	Advantages	Challenges	References
Continuous sliding mode	Robust against model uncertainty, minimization of chattering	Smoothness of control inputs	[51–54]
Switching adaptive control	Learning-based supervisory control algorithm, direct performance evaluation of candidate controllers, asymptotic stability guaranteed	Potential computational burden, no existing real-life applications, speed of switching	[73–79]
Fuzzy, neural networks, learning	Model free method, intuitive design, can be built up and trained	Intensive simulation or flight tests needed to be trained	[87–98]
Gain scheduling	Simplification of controller design, rapid response to changing parameters, computationally efficient	Large number of flight conditions need to be considered, smooth transition	[99–104]
H_∞ and μ-synthesis	Robust in presence of uncertainties, performance specs and actuator models are considered	Increase of complexity as dimension increases, controller is optimal with respect to a predefined cost function	[105–116]

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