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Review of Advanced Guidance and Control Algorithms for Space/Aerospace Vehicles

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Abstract

The design of advanced guidance and control (G&C) systems for space/aerospace vehicles has received a large amount of attention worldwide during the last few decades and will continue to be a main focus of the aerospace industry. Not surprisingly, due to the existence of various model uncertainties and environmental disturbances, robust and stochastic control-based methods have played a key role in G&C system design, and numerous effective algorithms have been successfully constructed to guide and steer the motion of space/aerospace vehicles. Apart from these stability theory-oriented techniques, in recent years, we have witnessed a growing trend of designing optimisation theory-based and artificial intelligence (AI)-based controllers for space/aerospace vehicles to meet the growing demand for better system performance. Related studies have shown that these newly developed strategies can bring many benefits from an application point of view, and they may be considered to drive the onboard decision-making system. In this paper, we provide a systematic survey of state-of-the-art algorithms that are capable of generating reliable guidance and control commands for space/aerospace vehicles. The paper first provides a brief overview of space/aerospace vehicle guidance and control problems. Following that, a broad collection of academic works concerning stability theory-based G&C methods is discussed. Some potential issues and challenges inherent in these methods are reviewed and discussed. Then, an overview is given of various recently developed optimisation theory-based methods that have the ability to produce optimal guidance and control commands, including dynamic programming-based methods, model predictive control-based methods, and other enhanced versions. The key aspects of applying these approaches, such as their main advantages and inherent challenges, are also discussed. Subsequently, a particular focus is given to recent attempts to explore the possible uses of AI techniques in connection with the optimal control of the vehicle systems. The highlights of the discussion illustrate how space/aerospace vehicle control problems may benefit from these AI models. Finally, some practical implementation considerations, together with a number of future research topics, are summarised.

Keywords: Guidance and control, Space/Aerospace vehicles, Stability theory, Optimisation theory, Artificial intelligence.

1. Introduction

1.1. Background

The impact of space and aerospace activities on our modern world is becoming more apparent than ever. In the past decades, a number of remarkable achievements have been made in space/aerospace flight missions, including deep space exploration [1], satellite surveillance [2], interplanetary travel [3], Mars landings [4], space debris removal [5], atmospheric reentry or hopping [6], missile-target engagement [7], spacecraft rendezvous and docking [8], spacecraft or unmanned aerial vehicle (UAV) swarms [9], and multi-spacecraft formation flying [10]. Figure 1 provides a graphical depiction of some typical examples. Behind these success stories, the development of advanced guidance and control (G&C) methods has made significant contributions and is of particular importance [11]. A promising guidance and control system can effectively output instructions and execute operations for a space/aerospace vehicle, thereby enabling the vehicle to fulfil the mission targets in a reliable way [12].

By investigating the literature, two popular trends in the development of advanced guidance and control methods can be identified. The first mainstream development was the development of robust or stochastic control-based methods. In recent years, numerous effective robust and stochastic control algorithms have been successfully constructed to guide and steer space/aerospace vehicle motion in a variety of missions [13–15]. Improving the system robustness as well as the fault tolerance ability should always be a crucial design requirement. This is mainly because various model uncertainty, environmental disturbances, sensor measurement noise, and actuator faults frequently exist in real-world practice. If certain treatments with respect to these negative effects are not performed, the entire system is likely to become unstable, resulting in a failure of the flight mission. Since most of the robust and stochastic control algorithms originate from stability theory, it is natural to classify them into stability theory-based methods.

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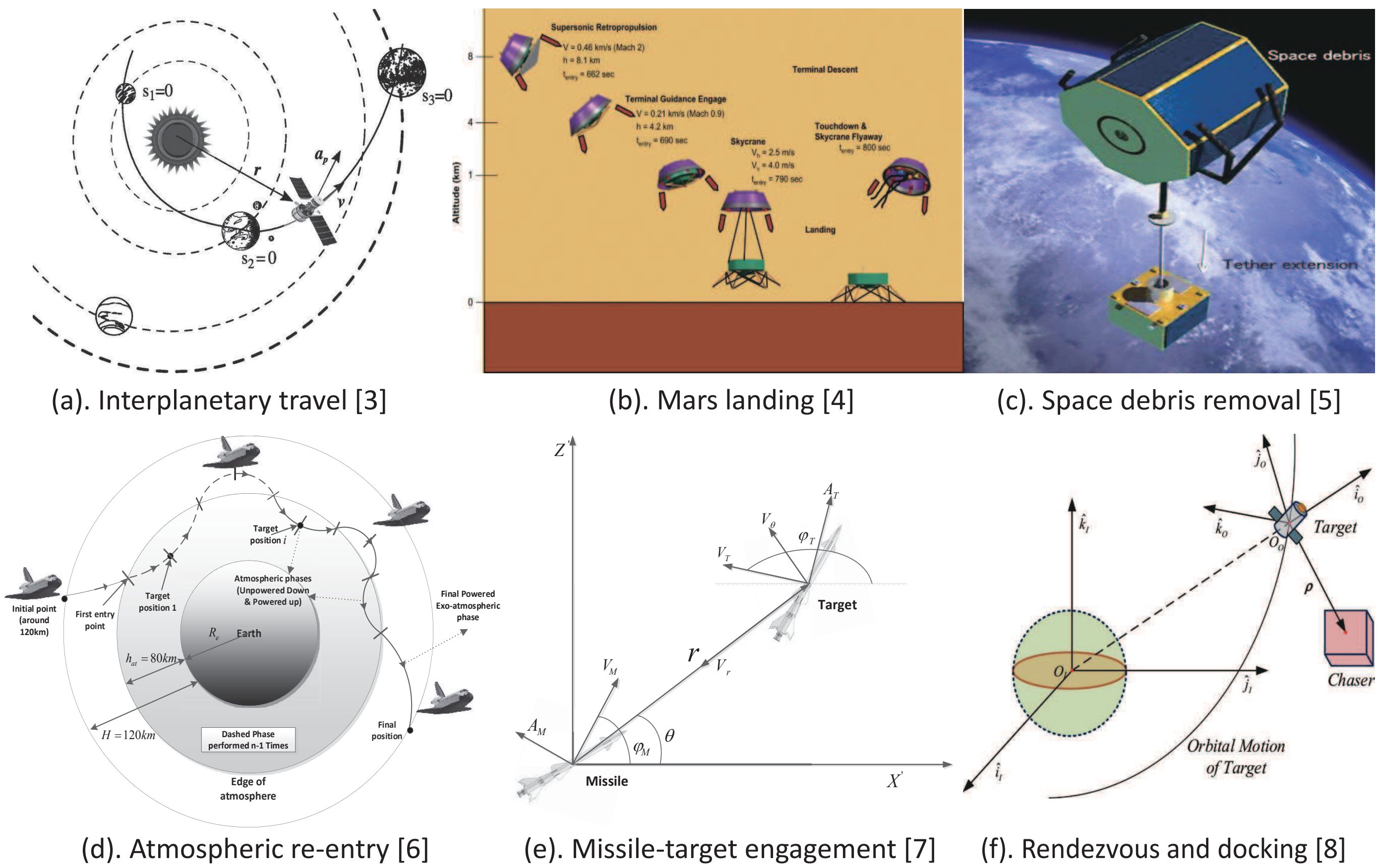

Figure 1: Typical examples: (a). Interplanetary travel [3]; (b). Mars landings [4]; (c). Space debris removal [5]; (d). Atmospheric re-entry or hopping [6]; (e). Missile-target engagement [7]; (f). Spacecraft rendezvous and docking [8]

In addition to the stability theory-based guidance and control methods, the second mainstream approach is to apply optimisation theory-based methods to guide and steer the motion of space/aerospace vehicles [16, 17]. This type of approach can be viewed as a direct result of merging the concepts of control and optimisation, and it has become increasingly popular in recent years. It is worth noting that this merge can bring advantages for the design of guidance and control algorithms. This is primarily reflected in the following characteristics:

- Improved system performance: As the control problem is reformulated for an optimisation task, a certain performance index can be optimised to some extent during the control process. This can meet the growing demand for better system performance.
- Enhanced algorithm flexibility and functionality: Tools such as artificial neural networks (ANNs) [18], adaptive methods [19], and disturbance observers [20] can be easily combined with optimisation theory-based control methods, thereby enhancing the controller's ability to identify system uncertainties and reject disturbances. In addition, this type of algorithm has the capability of handling variable and process constraints.

Recently, many effective optimisation theory-based control methods have been reported in the literature, such as (heuristic) dynamic programming-based methods, model predictive control-based methods, and other enhanced versions. In addition, researchers have devoted a large amount of effort to exploring the conditions that can provide theoretical guarantees with respect to the system stability as well as the feasibility of the optimisation process [21, 22]. This further improves the reliability of using these optimisation theory-based methods for space/aerospace vehicle guidance and control problems.

Benefiting from remarkable advances in machine learning (ML), artificial intelligence (AI), and deep learning technology, a new interest can be found in the literature toward applying ANNs or deep neural networks (DNNs) to achieve the online guidance and control of space/aerospace vehicles. One important feature of using these models is that they have the ability to preserve the obvious advantages of optimisation theory-based control methods while simultaneously maintaining an acceptable computational burden in real time [23, 24]. Specifically, this type of algorithm aims to train some neural network models that are able to generate optimal guidance and control commands, thus forming the onboard decision-making system for different mission profiles. Over the past decade, efforts have been made to develop and investigate different network models, and successful explorations of these types of method can be found in a number of space-related or aerospace-related applications, including low-thrust orbital transfer [25], spacecraft atmospheric re-entry [26], and planetary pinpoint landing [27]. Although differences can be found in the applied network models and training strategies, they all share a similar design philosophy. As a consequence, these kinds of method are denoted as AI-based G&C methods throughout this paper for the sake of simplicity.

1.2. Motivation

Perhaps there is no single method capable of achieving a generally acceptable guidance and control performance for all space/aerospace vehicle guidance and control problems. However, designing reliable guidance and control algorithms is a fast-developing field, and each method has unique advantages and disadvantages in various aspects, such as efficiency, flexibility, functionality, and complexity. This indicates that selecting a proper guidance and control algorithm is usually problem-dependent.

The central objective of this article is to present a detailed survey covering the latest research results as well as the potential follow-up research directions in this field. Moreover, it is vital to understand the key features of different approaches and to be aware of the potential issues and challenges of applying these algorithms. More precisely, we intend to:

- classify the existing approaches published in recent years according to their design philosophies;
- summarise the advantages and disadvantages of different guidance and control approaches;
- analyse the current challenges of using different methods for spaceflight and aerospace applications; and
- provide some guidelines for the development of stability theory-based, optimisation theory-based and AI-oriented guidance and control methods.

1.3. Organisation of the Article

This review article is organised as follows: In Section 2, a brief overview of space/aerospace vehicle guidance and control systems is provided. Section 3 describes a broad collection of academic works researching stability theory-based guidance and control methods. Next, various recently developed optimisation theory-based guidance and control methods, including dynamic programming-based methods, model predictive control-based methods, and other enhanced versions, are reviewed in Section 4. Key aspects such as the main advantages and inherent challenges of applying these approaches are also discussed in detail. Following that, Section 5 has a particular focus on recent attempts to explore the possible uses of AI-oriented techniques in connection with the guidance and control of different space/aerospace vehicles. Finally, some concluding remarks, together with future research topics, are provided in Section 6. We understand that it is relatively difficult to study, comment on, and summarise all the important works existing in this field. Hence, we mainly restrict our attention to works that have been published since the beginning of this century. Moreover, the works that have been published in the recent ten years are prioritized.

2. Types of Guidance and Control Systems

Early development on the guidance and control systems may heavily rely on the separation principle [28, 29]. To be more specific, the central idea behind a so-called separate guidance and control (SGC) system for space/aerospace vehicles can be demonstrated via the conceptual diagram shown in Figure 2(a).

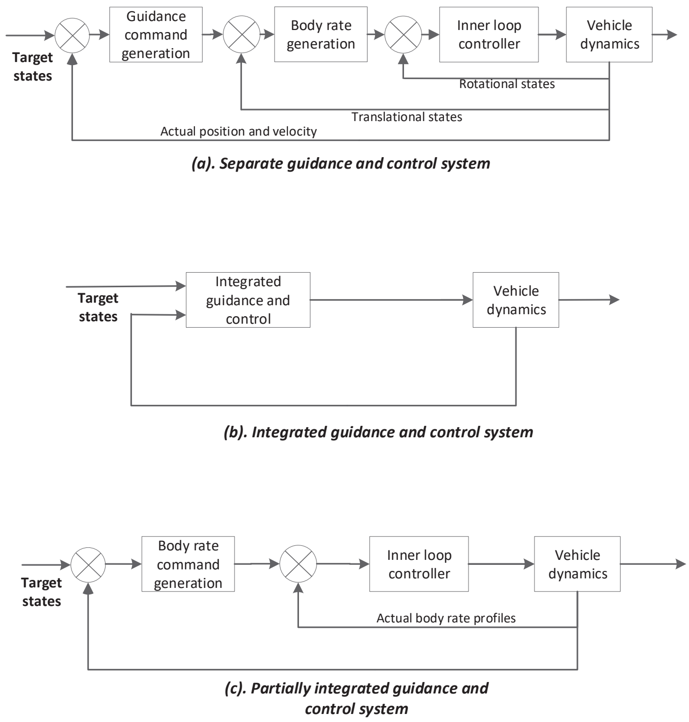

Figure 2: Typical space/aerospace vehicle guidance and control systems

In an SGC framework, the guidance and control systems are separated as two loops, thereby allowing both loops can be independently designed. In fact, researchers and engineers still prefer to consider the guidance and control problems separately, and research works reported to contribute the development of SGC can be found in a number of literature [29, 30]. However, according to some investigations [31–33], an SGC scheme may suffer from various issues such as high-frequency oscillations, expensive parameter tuning process, and large time lags. These issues are usually undesirable for practical applications, and this stimulates the development of integrated guidance and control (IGC) systems [34–36] and partially integrated guidance and control (PIGC) systems [31–33].

2.1. Integrated Guidance and Control System

In the past ten years, researchers have devoted significant effort to contribute the development of IGC systems, in applications ranging from space autonomous vehicles to guided missiles [34–36]. Different from the SGC, the IGC aims to synthesize the guidance and control loops together (e.g., as indicated in Figure 2(b)). An important advantage of the IGC design is that such an integrated system can fully exploit the rich information of the six-degree-of-freedom (6-DOF) vehicle dynamics, thereby alleviating the time lag problem to some extent. As more published works on developing IGC systems are becoming available in the existing body of literature, we briefly discuss some progresses in the this field and highlight some features of existing IGC designs.

In the work presented by Luo et al.[34], an IGC system was established for an air-to-air autonomous attack mission. The nonlinear dynamics of the unmanned combat aerial vehicles and the guided missile were firstly introduced by the authors. Following that, a robust control algorithm, along with a parameter adaptive strategy, was proposed to serve as the main controller. According to simulation results carried out by the authors, certain advantages can be obtained by applying the proposed IGC in comparison to the traditional SGC. For example, the proposed IGC is able to save about 25% of the control effort while achieving a high attack precision.

Similarly, in [35], a rapid and robust IGC system was proposed for the problem of 3-D interception of hypersonic vehicles. A compound control law was derived with signal compensation such that the speed of the system response can be increased. Numerical simulations, together with a number of comparative studies, were carried out and presented. Based on the obtained results, it was verified that the proposed IGC system can simultaneously enhance the robustness of the interceptor as well as the response ability.

2.2. Partially Integrated Guidance and Control System

The concept of PIGC has been recently introduced in the development of advanced guidance and control systems [31–33]. This concept aims to combine the merits of SGC and IGC, thereby dealing with the limitations of the one-loop IGC systems such as the insufficient capability of exploiting time scale separation and the relatively expensive parameter tuning process [31]. Similar to that of SGC, the PIGC system formulates the problem by applying an inner-outer loop structure. Each loop will manipulate a part of the 6-DOF dynamics. More precisely, an graphical depiction of the PIGC is shown in Figure 2(c), from where it is obvious that in the outer loop, the body rate commands will be generated and provided to the inner loop. Subsequently, the inner loop will track the body rate command profiles utilizing the nonlinear body rate equations of the 6-DOF dynamics.

In the context of PIGC, the works reported by Padhi et al.[31, 32] are of particular importance. Specifically, in [31], the authors proposed a PIGC scheme for a missile-target engagement mission, while in the work reported in [32], a PIGC scheme was successfully developed for a UAV formation flying mission. According to the reported simulation results, the developed PIGC successfully inherited the advantages of the IGC and the conventional SGC. As for the missile-target engagement mission, it was shown that PIGC can lead smaller miss distance values than that of IGC. In terms of the UAV formation flying mission, the PIGC is able to bring multiple UAVs into pre-specified formation quickly and maintain the formation. More importantly, it was shown that negative effects caused by time scale separation between the translational and rotational vehicle dynamics were successfully addressed.

It is worth noting that some interesting branches such as cost-effective IGC/PIGC systems, adaptive IGC/PIGC systems, networked IGC/PIGC systems start appearing in the literature [37]. Detailed classification and discussion of these guidance and control systems are beyond the scope of this article. Interested readers are referred to [37] for such a comprehensive review. Alternatively, in this paper, we focus on reviewing the latest developments of guidance and control algorithms that are effective and available for different space/aerospace vehicle guidance and control systems.

3. Review of Stability Theory-based G&C Methods

Most of the newly developed guidance and control methods for space/ aerospace vehicles are constructed based on stability theory. This can be attributed to the increasing theoretical advances in branches of control theory, including robust control, adaptive control, stochastic system theory, and data-driven control, since the beginning of this century. However, both theoretical and practical challenges remain open for this type of method, which has stimulated further research on this subject.

3.1. Design and Applications of Robust G&C Algorithms

Not surprisingly, due to the existence of various model uncertainties or environmental disturbances, using deterministic guidance and control policies may fail to achieve the desired control performance. Therefore, dealing with or rejecting these negative effects is one of the primary objectives in the design of robust guidance and control systems [13, 14]. In the recently published literature, numerous robust guidance and control algorithms have been successfully constructed to guide and steer the motion of various space/aerospace vehicles.

In the following subsections, we provide a summary of the applications of several typical techniques in the design of guidance and control systems. These techniques include: finite-time sliding mode control (SMC) theory-based schemes, fractional-order control-based schemes, dynamic inversion-based schemes, backstepping-based schemes, and other robust methods.

3.1.1. Finite-Time SMC Theory-based Scheme

Among various methods, one popular option is the variable structure control method based on SMC [38]. Benefiting from its insensitivity to disturbances and uncertainties, it has been widely used for space/aerospace vehicle guidance and control systems [38, 39]. Note that for the linear hyperplane-based SMC designs presented in [38] and [39], the asymptotic stability and convergence may only hold true on the sliding manifold. That is, the system errors might not converge to an equilibrium point in finite-time. Hence, to deal with this issue, the development of guidance and control methods based on finite-time SMC theory has been stimulated [40–42].

As a variant of conventional SMC, the terminal sliding mode control (TSMC) strategy is able to achieve the finite-time stability. It is worth noting that in recent years TSMC-based algorithms have been extensively researched, especially in the field of space/aerospace vehicle guidance and control systems. For example, the authors of [40] established a TSMC algorithm to generate the guidance commands for the Mars atmospheric entry problem. In their work, TSMC was combined with a second-order differentiator responsible for estimating the total external disturbance, thus creating a hybrid structure. Simulation results were provided to illustrate the higher control precision obtained by applying their proposal. Also, it was confirmed that the proposed approach can effectively steer the tracking error between the actual spacecraft state trajectories and the desired references to a small neighbourhood of zero in finite time.

However, it was highlighted in [41] and [42] that the TSMC-based guidance and control algorithms may suffer from the singularity issue. Therefore, the authors of these two works have devoted efforts on developing non-singular TSMC (NTSMC) approaches to overcome this drawback. Specifically, in [41], an NTSMC scheme was developed to produce control commands in real time for a small satellite. More precisely, bounded external disturbances were considered in the problem formulation, and the inherited singularity problem of using traditional TSMC was successfully avoided by applying the authors' design.

Moreover, a non-singular fast TSMC (NFTSMC) control strategy was developed in [43], wherein a flexible spacecraft attitude tracking problem was addressed. In addition, an adaptive strategy was proposed such that the boundary of the unknown external disturbances could be estimated. The motivation for the design of NFTSMC is to combine the advantage of NTSMC and the conventional SMC, thereby accelerating the algorithm convergence speed. Based on the reported simulation results, a faster convergence speed can be achieved while simultaneously guaranteeing the finite-time stability of the controlled system.

On the other hand, in the design of SMC guidance and control laws, an important problem that needs to be carefully considered is the chattering phenomenon. This phenomenon can stimulate the high-frequency dynamic characteristics of the system and is not conducive to the realisation of the guidance and control system. To effectively address this problem, a number of finite-time SMC theory-based guidance and control algorithms have been studied to extend and generalise standard SMC [44–48]. For example, in [44], an higher-order SMC (HOSMC) scheme was proposed to address a rigid spacecraft attitude tracking control problem. By increasing the order of the sliding mode (e.g., setting it higher than the relative degree of the spacecraft system), the chattering phenomenon was effectively eliminated. Simulation studies were provided to support the main argument discussed in this work.

The authors of [45] proposed a two-layer control structure incorporating a TSMC manifold and an HOSMC to achieve the robust attitude synchronisation of spacecraft in finite-time while simultaneously reducing the communication burden to some extent. The validity of this hybrid design as well as the chattering-free performance were confirmed by executing a number of numerical simulations.

Apart from the HOSMC, some integral SMC (ISMC)-based guidance and control systems have been successfully proposed to alleviate the chattering problem. For example, in [46], the authors proposed an integral TSMC (ITSMC) scheme for the rigid spacecraft attitude tracking problem in the presence of actuator uncertainties. The main theoretical conclusion, along with the obtained simulation results, suggested that by adding an integral term in the design of the sliding surface, the steady-state error can be reduced and the chattering problem can be alleviated while the finite-time stability is simultaneously maintained.

In [47], a modified ISMC approach was applied to obtain a spacecraft attitude control system that considered actuator saturation and external disturbances. By applying this approach, a robust tracking performance could be achieved, and the trajectory tracking error could be driven to zero in finite time. In addition, the authors of [48] advocated a composite spacecraft attitude stabilisation system combining a disturbance observer and an ISMC controller. Simulation examples were carried out to illustrate the effectiveness as well as the enhanced disturbance rejection performance of their proposal.

3.1.2. *Fractional-Order Control-based Schemes*

In recent years, a growing trend has been witnessed in terms of designing fractional-order control (FOC)-based strategies for space/aerospace vehicle guidance and control problems [49, 50]. Fractional order control methods take advantage of their flexibility in meeting desired performance specifications and tuning the closed-loop response. In such a method, fractional-order derivatives and integrals of the state are usually applied for feedback, thus allowing a greater freedom to fit the desired behaviour of the controlled plant. Note that some fractional-order control-based methods have been successfully developed and applied [35, 49–51]. For example, two fractional-order proportional integral derivative (FOPID) methods were proposed in [49] in order to stabilize the rigid spacecraft rotational dynamics. Compared with integer feedback control schemes, one important feature of these two proposed FOPID controllers is that they all apply the fractional derivative and integral feedback terms with adjustable fractional orders. According to the experimental simulations, it was confirmed that by tuning the integral orders and fractional derivative, both the settling time and control effort can be simultaneously reduced.

In [50], the authors proposed a fractional-order control scheme to stabilise a spacecraft attitude system. The central idea of this work is to combine the advantage of fractional feedback control and ISMC, thereby constructing a fractional-order integral sliding mode control (FOISMC) algorithm for the considered problem. By analyzing the reported comparative results, the main advantage of applying FOISMC over pure ISMC was appreciated. Actually, the ISMC scheme may suffer from problems such as integral saturation and a low convergence rate. The reasons are mainly due to the existence of integral action, and the control performance can be significantly affected.

Similarly, in [35], the authors suggested a FOISMC scheme and eliminated the disturbances by establishing robust compensation signals. In addition, they designed a parallel control structure to execute the sliding phases, thus enhancing the system response velocity. It was shown that this approach had the potential to be applied in the design of space vehicle guidance and control systems.

In addition, a FOISMC scheme was developed in [51], wherein a small satellite attitude control problem was considered. Theoretical results, along with numerical simulations, were obtained to demonstrate the effectiveness and advantage of using their proposal to achieve an enhanced steady-state performance.

3.1.3. Dynamic Inversion-based Scheme

Nonlinear dynamic inversion (NDI)-based algorithms have long been recognized as an effective guidance and control strategy for various space/aerospace vehicles [52, 53]. This type of approach usually cancels the system nonlinearity by transforming the original nonlinear dynamics into an entirely or partly linear version, thus enabling the use of conventional linear control techniques. Although some attempts of applying NDI methods for flight control were reported in the literature [52, 53], one critical problem is that exact dynamic inversion may inherently suffer from lack of robustness. Hence, researchers have devoted efforts to address this issue and an enhanced version, named incremental NDI (INDI) control, has been successfully proposed [54–57].

The authors of [55] applied an INDI-based method to serve as the trajectory tracking controller of an aircraft. In their work, both actuator faults and model uncertainties were considered and tackled by incrementally applying control inputs. According to the simulation tests, it was verified that the proposed design is able to fulfill the tracking mission in the presence of uncertainties and actuator faults. Moreover, comparative studies against NDI method further confirmed the advantage of using INDI.

In [56], a rigours robustness and stability analysis for INDI was provided by using the nonlinear system perturbation theory as well as the Lyapunov method. The main theoretical conclusion was validated by performing a large number of Monte-Carlo simulation tests on an aircraft command tracking task with the consideration of model uncertainties and external disturbances.

In addition, a cascaded INDI scheme was structured in [57] to serve as a robust hovering controller for the quadcopters. Based on the reported experimental results, it was demonstrated that significant improvements over a conventional PID controller can be achieved in terms of the control accuracy and the disturbance rejection performance.

3.1.4. Backstepping-based Scheme

Backstepping-based (BS) techniques is also a popular option for the design of robust guidance and control algorithms [15, 58]. This type of method usually contains two steps. In the first step, a virtual subsystem control signal is designed. Subsequently, this virtual input will be provided to the controller to compute the control command of the actual subsystem. Typical examples of designing or applying backstepping-based guidance and control algorithms for various space/aerospace systems can be found in a number of published works [15, 59, 60]. For instance, Hu and Meng [15] suggested an adaptive BS control scheme to address the air-breathing hypersonic vehicle trajectory tracking problem. In their work, both input saturations and aerodynamic uncertainties were considered when designing the controller. To avoid repeated differentiations of the virtual control variables, an attempt was made to merge the advantage of dynamic surface control and conventional BS. The effectiveness of their proposal was confirmed by performing numerical simulations.

In 2019, a novel BS-based guidance algorithm was proposed in [59] for the missile-target engagement system. One important feature of the proposed BS guidance law is that it can satisfy the the seeker's field-of-view limits while simultaneously achieving the desired impact time. Numerical simulation results revealed that by applying the proposed BS-based guidance method, the interception mission can be successfully fulfilled at the desired impact time.

3.1.5. Other Robust Control Schemes

In addition to the aforementioned robust algorithms, other robust control schemes have also been applied in the design of spacecraft guidance and control systems [49, 61–63]. Examples include the fault tolerant control-based guidance scheme proposed in [64] and the H_∞-based guidance algorithm developed in [61]. Besides, in 2016, Bandyopadhyay et al.[62] developed an attitude control strategy, together with a nonlinear tracking controller, for spacecrafts carrying a large object. One important feature of the proposed design is that both bounded tracking errors in the presence of uncertainties and the global exponential convergence to the reference attitude trajectory can be ensured. By executing case studies, the possibility of applying this robust control scheme in future asteroid capture missions was confirmed.

Similarly, in [63], a robust ordinary differential equation (ODE) – partial differential equation (PDE) feedback controller was constructed for precise attitude trajectory tracking and slewing in the presence of bounded disturbances. In this work, the unique equations of motion capable of describing the one-degree-of-freedom rotation of spacecrafts equipped with strain-actuated solar arrays were established. Detailed stability analysis and proofs were provided to further demonstrate the effectiveness of the proposed design.

Nevertheless, these approaches are mostly oriented toward classical robust control theory, and their control performance and anti-disturbance ability have been verified by a number of simulation studies and analysis.

3.2. Design and Applications of Stochastic G&C Algorithms

Most of the previously mentioned contributions were designed based on deterministic systems. However, in practical space/aerospace vehicle systems, uncertainties may exist in the system state equations or input sequences, resulting in stochastic systems [65]. In these cases, it is necessary to introduce the concept of stochastic process, which stimulates the development of stochastic guidance and control algorithms.

One typical design of stochastic guidance and control algorithms is to combine stochastic theory with optimal control, thus resulting in stochastic optimal guidance and control algorithms. A number of works have been proposed in the literature to design or apply this kind of technique in a variety of spaceflight missions. For instance, in the work of Kota et al.[66], a stochastic optimal control law was proposed to steer the manoeuvres of a spacecraft considering the probabilistic uncertainties in the system equations. Similarly, Duta et al.[67] applied a stochastic optimal guidance and control scheme to perform spacecraft manoeuvres. In their work, the propagation of uncertainty in the spacecraft system equations was fully considered, and a Monte Carlo simulation framework was established to contribute to the identification of manoeuvre types and the stabilisation of uncertain systems.

Stochastic sliding mode-based guidance and control algorithms are another type of method capable of handling uncertain space or aerospace vehicle systems. This approach combines stochastic theory with SMC and has been successfully applied in space-related missions. For example, the authors in [68] introduced a stochastic SMC-based controller to steer the motion of a space manipulator. In their work, the plant was modelled as a nonlinear stochastic Markovian jump system that considered uncertain time-varying delays. To effectively deal with the uncertain terms, a fuzzy observer was constructed to estimate the uncertain state, thus guaranteeing stochastic stability. In addition, a terminal guidance law was derived in [69] by taking advantage of stochastic NFTSMC theory. In this work, stochastic noise was considered, and the obtained results showed the effectiveness of applying such a hybrid strategy.

Importantly, some research has focused on the development of stochastic adaptive or finite-time guidance and control algorithms [70, 71]. Such approaches combine stochastic theory with adaptive or finite-time control, and their ability to address the uncertainties involved in aerospace vehicle systems has been verified. One example can be found in the work of Chen [71], wherein a stochastic adaptive IGC framework capable of steering hypersonic missiles during exo-atmospheric and atmospheric flights was established. In contrast to existing results, this work investigated stochastic uncertainties in the system equations and derived a novel adaptive law to enforce the stochastic stability of the system.

It is worth noting that most of the aforementioned stochastic guidance and control algorithms were established by exploring the notion of stability. That is, the convergence of the algorithm was established with respect to an equilibrium point or a particular trajectory. In recent years, control techniques using contraction-based incremental stability analysis have received considerable attention [72–74]. Incremental stability can be understood as a requirement that all system trajectories of a dynamical system converge to each other. This concept is of particular importance to observer designs for stochastic systems [74] as well as synchronization problems such as swarms of spacecrafts and satellites [72]. A typical example can be found in the work presented by Chung et al.[72], wherein a phase synchronization controller, derived via the contraction analysis, was proposed for a class of networked systems in the presence of stochastic uncertainties. Then, this controller was applied to reconfigure a large swarm of spacecrafts operating in the low Earth orbit.

In their follow-up research [74], an optimal feedback tracking controller was formed for a class of Itô nonlinear stochastic systems. In this work, the feedback gain, along with other controller parameters, was optimized by constructing a convex optimisation problem where the objective function was to minimize the upper bound of the steady-state tracking error. To verify the performance of this design, an uncertain spacecraft attitude tracking control example was executed. Simulation results confirmed the superiority of the proposed design in comparison to other alternatives.

3.3. Potential Issues and Challenges of Stability Theory-based G&C Algorithms

Based on the introduction of the different methods presented in previous subsections, we can summarise in detail the main advantage of each type of approach. As for robust guidance and control algorithms, the main advantage of some typical techniques is summarised in Table 1.

Although certain advantages can be acquired by applying these stability theory-based methods on the guidance and control of space/aerospace vehicles, some theoretical and practical issues remain open for further consideration. More precisely, these issues are summarized below.

- **TSMC**: The speed of convergence toward the equilibrium point is usually slow. In addition, singularity problems may easily arise when applying TSMC methods.

- **NTSMC**: When the system is far from the equilibrium point, the convergence speed of the system state variables tends to be slow. Additionally, if the unit vector control law is designed in combination with the global arrival condition, some problems may be identified, such as chattering, slow convergence and "stagnation of convergence".

- **NFTSMC**: Similar to NTSMC, although the convergence speed can be enhanced, problems such as chattering and "convergence stagnation" need to be further considered.

- **HOSMC**: In engineering practice, the higher-order derivative information of the system may not be easily obtained. In addition, the HOSMC controller needs to be established using a relatively accurate system model.

- **ISMC**: Under the condition of a large initial error, this method might lead to a large overshoot and a long regulation time, thus degrading the transient performance. This phenomenon becomes more serious when the control input is limited.

Table 1: Main advantages of stability theory-based G&C algorithms

Method	Main advantage
TSMC:	It can stabilise a system with guaranteed finite-time convergence.
NTSMC:	It can alleviate singularity issues.
NFTSMC:	An enhanced convergence speed can be obtained compared with NTSMC.
HOSMC:	Higher-derivative information is fully exploited, thereby effectively alleviating the chattering problem.
ISMC:	It can reduce the steady-state error, alleviate the chattering problem, and enhance stability.
FOC:	It has flexibility in meeting desired performance specifications and tuning the closed-loop response.
NDI	It enables the use of conventional linear control techniques.
INDI	Compared to conventional NDI, INDI provides further improvement regarding system robustness.
BS	The use of the recursive design procedure can increase the flexibility to deal with uncertainties.
H_∞:	It can guarantee control stability while optimising some performance indices.

- **FOC**: The selection of the fractional order is usually key, and it must be properly adjusted. A poor selection of this value can result in the degradation of the system stability as well as its robustness. Moreover, little attention has been paid to the design of the constrained FOC law. Note that in real-world applications, various practical constraints may exist and require proper treatments.

- **NDI**: This type of method usually requires an accurate knowledge of the controlled system in order to acquire an exact dynamic cancellation. This requirement is difficult to meet in real-world applications due to numerical errors, environmental uncertainties, external disturbances, and model simplifications.

- **BS**: According to [75], the control performance of using BS laws tends to be sensitive with respect to the numerical errors. Note that commonly, the guidance and control algorithm has to be performed numerically by an onboard processor for a practical implementation. As a result, this phenomenon is highly undesirable.

Apart from the aforementioned challenges for different finite-time SMC-based methods, a critical drawback is that in practical applications, most of the times the finite time cannot be specified by a user a priori. Hence, even though methods based on finite-time SMC theory have started appearing, their development is still far from mature.

Regarding stochastic guidance and control methods, one advantage is that it has the capability of addressing different types of uncertainties in the system equations. However, some potential challenges are also obvious:

- If the state variables of a practical guidance and control system are unobservable or the feedback control has a time delay, the system uncertainty is difficult to study.

- The design of stochastic guidance and control method may need to introduce a number of assumptions, and because of this, the result tends to be conservative. Although it is acceptable in theoretical analysis, practical stability may easily be lost in real-world applications.

- Although adaptive strategies can be an effective tool to estimate uncertain variables and address their negative impacts, different systems need different analyses. If the estimation process cannot be performed promptly, which is likely to happen in a practical application, the control accuracy may be damaged significantly.

Furthermore, it should be noted that for some space/aerospace engineering applications such as spacecraft swarms and multi-spacecraft formation flying, unique challenges to these problems can be identified by applying the stability theory-based guidance and control algorithms [9, 10, 76]. For example, one challenge is to achieve the desired swarm behaviour governed by both the nonlinear time-varying attitude dynamics and the orbital dynamics, while maintaining an optimal and robust control performance [76]. This problem becomes much more difficult when various actuator, environmental, and communication uncertainties are required to be taken into account [72]. In addition, it might be difficult for a centralized stability theory-based guidance and control algorithm to steer a large swarm of vehicles due to the significant communication and computation requirements [72].

To deal with these open issues, a couple of important works have been reported in the literature [77–80]. For instance, the authors of [78] applied an inhomogeneous Markov chain-based probabilistic swarm guidance algorithm to achieve the desired swarm behaviour for a large scale of space robotic systems. Rigours proofs regarding the robustness as well as the scalability properties of the proposed algorithm were provided.

Also, numerous simulation results were carried out to shown the proposed design has the capability of achieving robust control performance, thereby evidencing the obtained theoretical conclusions.

In [79], the authors developed a decentralized algorithm for multi-spacecraft formation flying. An important advantage of the proposed algorithm is that its computational complexity does not grow as the size of the spacecraft swarm increases. A number of hardware-in-the-loop experiments were executed to verify the effectiveness of the proposed algorithm. This further improves its possibility for future real-world applications.

3.4. Design and Applications of Data-Driven G&C Algorithms

It is worth noting that all the aforementioned algorithms are model-based control methods [81]. That is, the guidance or control law is derived by applying the knowledge and information of the system equations [82]. However, with the development of space and aerospace vehicle systems, the dynamic model tends to become increasingly complex, which introduces additional difficulties in the design of guidance and control methods. Data-driven guidance and control (DDGC) algorithms are therefore proposed to address the problem without using the knowledge of the mathematical model of the vehicle. More precisely, data-driven guidance and control algorithms are developed and applied for the following scenarios:

1. It is difficult to model the uncertainty and external disturbances acting on the vehicle system, or they have significant impacts on the design of the model-based guidance and control algorithms.
2. It is difficult to describe the motion of the space or aerospace vehicle with a unified mathematical model.
3. The mathematical model of the vehicle is too complex to design a reliable guidance and control system.

Recently, data-driven control methods have been developed and applied extensively in the design of guidance and control systems. The basic idea of data-driven control methods is that we only adjust the input and output signals. That is, an approximate input-to-output model is constructed, and this approximate model is updated by using the collected input and output datasets. In this way, no information about the system model is required, and the main problem becomes designing a controller such that the targeted output signals can be tracked. The essence of a data-driven guidance and control algorithm can be viewed as a closed-loop adaptive process. A simplified conceptual diagram of this type of approach can be found in Figure 3.

A number of contributions that have been made to develop this type of method are available in the literature. For example, in [83], the authors addressed the problem of combined spacecraft attitude control with the consideration of noncooperative targets. In their work, a model-free data-driven control scheme was proposed to produce the optimal control commands for the attitude system. The effectiveness as well as the stability of the proposed data-driven control were validated by a series of simulation studies.

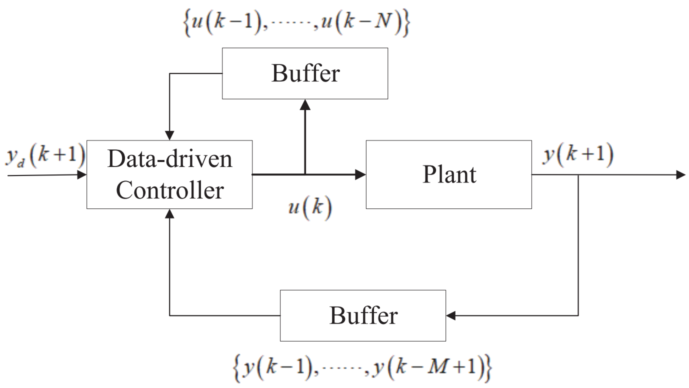

Figure 3: A simplified conceptual diagram of data-driven control

Similarly, a combined spacecraft attitude control problem was solved in [84], wherein the spacecraft model, along with the external disturbances, was assumed to be unknown. To address this uncertain problem, a prediction-based data-driven model-free control scheme was developed. Based on a number of comparative studies, the authors concluded that an enhanced control performance could be achieved by applying their proposal rather than the traditional model-free adaptive control method. In their follow-up work [85], alternatively, the feasibility of combining the data-driven control method with an external state observer to achieve robust tracking control for combined spacecraft was investigated.

For data-driven control approaches, one obvious advantage is that it can complete the controller design task by using the input and output data of the system instead of accessing the model information. However, the main issues are as follows:

- Most DDGC methods are established independently. It is difficult to find a unified theoretical framework associated with this type of approach.
- The theoretical analysis of the robustness issue for DDGC methods is not well established. Moreover, its practical stability may be greatly affected by data noise and data dropout.

4. Review of Optimisation-based G&C Methods

In addition to stability theory-oriented methods, there has been a growing trend of designing optimisation theory-based controllers for space/aerospace vehicles in recent years to meet the growing demand for better system performance. Relevant studies have shown that these newly developed optimisation theory-based strategies can bring a number of benefits from both the theoretical and application points of view. However, certain challenges still exist in terms of designing a promising optimisation theory-based control approach and making this type of method available for the onboard decision-making process. This stimulates further research on this topic.

4.1. Design and Applications of Dynamic Programming-based G&C Methods

One typical example of optimisation theory-based control is to utilise dynamic programming- and approximate dynamic programming-based methods. Dynamic programming (DP) is a classical feedback form of control capable of finding the optimal solution to various control problems based on the Bellman's principle of optimality [86]. However, traditional DP faces two issues: 1) it is difficult to adapt the controller once its structure is determined; and 2) the operation of DP requires a great deal of computational time, which is usually unaffordable in real-time applications. Therefore, researchers have investigated enhanced versions of DP that can be applied as computational guidance and control algorithms.

The literature has reported some attempts to explore the feasibility of applying differential dynamic programming (DDP) in computing the local optimal control actions [87]. DDP can be viewed as a second-order approximation of standard DP. Specifically, consider a discrete dynamic system in the form of $x_{k+1} = f(x_k, u_k), k = 1, ..., N$ with the cost function J given by

$$J(\{u_k\}) = \Phi_{N+1}(x_{N+1}) + \sum_{k=1}^{N} L_k(x_k, u_k) \tag{1}$$

Here, (x_k, u_k) denotes the state and control pair at time t_k. $\Phi_{N+1}(\cdot)$ and $L_k(\cdot, \cdot)$ are the terminal and process cost, respectively. In DP, a cost-to-go function is introduced:

$$V_k(x_k, \{u_k, u_{k+1}, ..., u_N\}) = \Phi_{N+1}(x_{N+1}) + \sum_{i=k}^{N} L_i(x_i, u_i) \tag{2}$$

The aim of DP is to find an optimal control sequence $\{u_k^*, u_{k+1}^*, ..., u_N^*\}$ such that V_k is minimized. If we denote the optimal cost-to-go function as $V_k^*(x_k)$ and substitute Eq.(1) into it, one can obtain

$$V_k^*(x_k) = \min_{u_k}[V_{k+1}^*(x_{k+1}) + L_k(x_{k,u_k})] \tag{3}$$

Then, DDP performs a second-order approximation of Eq.(4) around the reference $(\{\bar{x}_k\}, \{\bar{u}_k\})$ and nullifies the expanded $V_k^*(x_k)$ function with respect to δu_k. Here $\delta u_k = u_k - \bar{u}_k$. This process results in an optimal feedback law:

$$\delta u_k^* = \alpha_k + \beta_k \delta x_k \tag{4}$$

in which α_k and β_k are functions of $V_{k+1}^*(x_{k+1})$ and its first and second order derivatives. Their values can be computed in backward sweep. Subsequently, DDP operates by iteratively carrying out reverse actions on the nominal state trajectory to plan a new control moment. Then, a forward action is carried out to update or evaluate the new state trajectory.

One important feature associated with DDP is that it can achieve a quadratic convergence speed. However, it requires the computation of a Hessian matrix (e.g., due to second-order approximation), thus adding additional difficulties to the real-time implementation. A potential recovery strategy is to apply the finite difference technique. However, this may lead to convergence issues.

Another recently introduced method capable of acting as an optimal controller for a variety of control systems is approximate dynamic programming [88]. This method is also referred to as adaptive dynamic programming (ADP) or heuristic dynamic programming (HDP) in some literature [89, 90]. Unlike the traditional DP and DDP methods, the key idea of this scheme is to approximate the optimal control actions by performing an offline iteration process or online learning update process. A commonly used structure of ADP is shown in Figure 4.

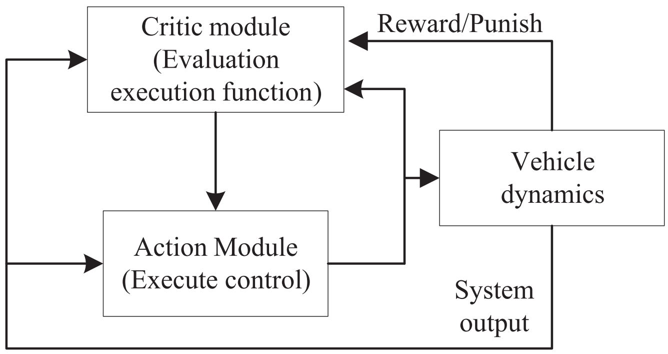

Figure 4: A commonly used structure of ADP

As shown in Figure 4, the controller module produces control actions to steer the system states by interacting with the environment. An evaluation module is embedded to adjust the control by analysing the performance of the system through an evaluation function.

A large number of DP-oriented control methods have been introduced in the literature. Here, we aim to summarise the main advantages of some typical approaches that have been reported in recent years. These methods (summarised in Table 2) have been implemented or have the potential to be implemented in space/aerospace vehicle guidance and control problems.

The key features and advantages of the methods in Table 2 are briefly noted below:

- **ADP**: The ADP method and its variants are mainly established according to policy-iteration or value-iteration strategies. These methods are generally suitable for linear or nonlinear problems and continuous or discrete system variables, respectively.

- **IADP**: This approach combines the merits of incremental nonlinear control techniques and linear approximate DP, which enhances its ability to handle unknown, nonlinear systems as well as time-varying references.

- **INDP**: This approach is a data-driven optimal control algorithm and is established based on the framework of IADP. This approach is capable of dealing with inaccurate and unmodelled systems.

Table 2: Popular DP-oriented methods reported in recent years

DP-oriented G&C methods
Adaptive dynamic programming (ADP)[91]
Incremental approximate dynamic programming (IADP)[92]
Iterative neural dynamic programming (INDP)[93]
Stochastic differential dynamic programming (SDDP)[94]
Action-dependent heuristic dynamic programming (ADHDP)[95]
Sparse Gauss-Hermite quadrature differential dynamic programming (SGHQDDP)[96]

- **SDDP**: The SDDP method is established on the framework of DDP. It modifies the original algorithm structure by incorporating linear feedback control policies and the unscented transform method. It has been verified that more robust solutions and fewer penalties can be achieved by using this approach for low-thrust orbital transfer problems.

- **ADHDP**: Similar to ADP, the ADHDP method is generally suitable for linear or nonlinear problems. In addition, benefiting from its interaction process, the learning and control performance can be significantly improved.

- **SGHQDDP**: This is a compound computational guidance algorithm, which is constructed by combining the merits of DDP and the Gauss-Hermite quadrature rule. By applying this approach, enhanced guidance performance and reduced computational time are likely to be achieved.

4.2. *Design and Applications of Model Predictive Control-based G&C Methods*

Algorithm 1 The online operation of the MPC-based tracking guidance algorithm

At each time point $k := 0, 1, ..., $ do:

(1). Compute $x(k)$ for the plant.

(2). Construct the following optimal control formulation:

$$\begin{aligned}
\text{minimise} \quad & J = \sum_{j=1}^{N} x^T(k+j|k)Qx(k+j|k) \\
& \quad + \sum_{j=0}^{N-1} u^T(k+j|k)Ru(k+j|k) \\
\text{subject to} \quad & \forall j \in [1, 2, ..., N] \\
& x(k+j+1|k) = f(x(k+j|k), u(k+j|k)) \\
& x(k|k) = x_k \\
& x_{min} \leq x(k+j+1|k) \leq x_{max} \\
& u_{min} \leq u(k+j+1|k) \leq u_{max} \\
& h(x(k+j+1|k), u(k+j+1|k)) \leq 0
\end{aligned} \tag{5}$$

where x_{min}, x_{max}, u_{min}, and u_{max} represent the lower and upper bounds of the state and control variables, respectively. x_k is the current state, and $h(\cdot,\cdot) \leq 0$ stands for the mission-dependent path constraints. N is the prediction horizon.

(3). Solve the problem (5) to obtain:

$$u^*(k) = [u^*(k|k), u^*(k+1|k), ..., u^*(k+N-1|k)]. \tag{6}$$

(4). Apply $u_k = u^*(k|k)$ to the plant until the next sampling instant.

(5). Assign $k = k + 1$.

(6). Return to (1).

In addition to DP-oriented control algorithms, the design and applications of model predictive control (MPC)- and receding horizon control (RHC)-based guidance and control methods have also attracted significant attention. A recent review of the applications of MPC in different aerospace systems can be found in [97]. The motivation for implementing MPC-oriented methods is primarily their strong capability of handling mission-related constraints. Usually, in an MPC-based approach, a finite-horizon optimal control problem is constructed and solved online to produce an optimal control sequence. Then, a portion of the control actions are taken from the optimal control sequence and applied to the plant.

In [98], an optimal tracking guidance design problem was studied and addressed. The aim of this work was to design an MPC algorithm to produce guidance commands in real time such that an aeroassisted spacecraft can track prespecified trajectories during the atmospheric entry phase. The operation of the proposed MPC tracking guidance algorithm is shown in Figure 5, where the lower dashed part depicts the optimisation process.

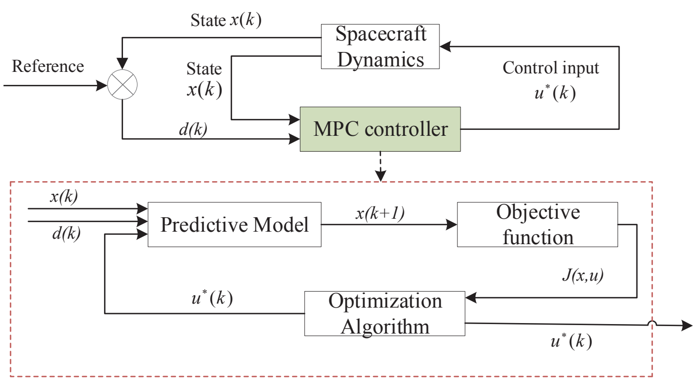

Figure 5: The operation of the MPC tracking guidance algorithm

Some key steps of this MPC-based tracking guidance algorithm are summarised in Algorithm 1. It is worth noting that the effectiveness and efficiency of an MPC-oriented guidance and control algorithm may be greatly affected by the optimisation process, which also stimulates the development of fast optimisation algorithms [99].

New developments regarding MPC technology may follow two paths. The first emphasises the robustness or disturbance-rejection ability of the algorithms, which in turn leads to the development of stochastic MPC (SMPC) and robust MPC (RMPC) [100, 101]. The second path focuses on alleviating the computational burden of the online optimisation process, thus making the algorithm more suitable for practical guidance and control tasks. This leads to the development and application of model predictive static programming (MPSP)[102] and its various enhanced versions [103–105].

Recently, a great number of MPC-oriented guidance and control methods have been introduced in the literature. Here, we aim to summarise the main advantages and features of some typical approaches reported in recent years. Similar to Table 2, some recently published MPC-oriented methods capable of dealing with space or aerospace vehicle guidance and control problems are summarised in Table 3.

The key features and advantages of the methods introduced in Table 3 are briefly noted below:

- **LCMPC**: This approach has been applied to generate guidance commands for the Earth atmospheric re-entry problem. A robust guidance performance can be successfully obtained by performing the linear covariance update process of this method.

- **MPSP**: This approach is similar to traditional MPC except that a prediction-correction process is added to update the control history in a closed form. In addition, the size of the problem can be reduced to a relatively low level.

- **QSMPSP**: This method is established on the basis of the framework of MPSP with smaller optimisation parameters, which significantly increases the computational efficiency.

- **MPCP**: This method is established by employing convex programming techniques to address online optimisation. It has been applied to several vehicle guidance problems, and the results have confirmed that the computational performance can be effectively enhanced.

- **SSMPC**: This method is established on the framework of stochastic MPC (SMPC) [109], modified by adding a computationally friendly offline sampling strategy. It has been implemented to produce control actions for a spacecraft rendezvous and docking mission, and the results on an experimental test bed have confirmed the effectiveness of the algorithm.

- **TRMPC**: The TRMPC is established on the framework of classic MPC except that it uses tube techniques to handle the effects of external disturbances, thereby guaranteeing the robustness of the control process. One important advantage of using a tube over the "min-max" structure is that the computational burden can be decreased effectively. This approach has been successfully applied to steer spacecraft during rendezvous and proximity operations.

- **LPMPC**: This method combines the standard MPC framework with a linear pseudospectral discretisation scheme. The aim is to reduce the number of optimisation variables, thus improving the online computational performance. The results have shown that it has the potential to be applied to a variety of vehicle guidance problems.

4.3. Challenges of Using Optimisation Theory-based G&C Methods in Space/Aerospace Applications

Although certain advantages can be acquired by applying different control optimisation theory-based guidance and control methods, their development is still far from mature, and some theoretical and practical problems remain open for further consideration. More precisely, for DP-oriented guidance and control methods:

- The control performance of most DP-oriented methods may be significantly degraded when a practical guidance and control problem contains multiple mission-related constraints.

- DP-oriented methods commonly require dividing problems into subproblems and storing intermediate results. This will consume a large amount of memory in onboard guidance and control applications.

- Due to the nature of DP-oriented methods, their computational complexity is usually high, and it is relatively difficult to apply this type of method in onboard applications. This issue becomes more serious when a stochastic process is involved in the operation of the algorithm.

In terms of MPC-based guidance and control methods, several challenges can also be identified. One key concern is the rapid increase in online computational complexity as the model nonlinearity, mission objectives, and scale of the system or constraints increase. To effectively decrease the computational burden of the online optimisation process, a large amount of effort has been made by researchers and engineers [110–112]. For example, in [110], the authors aimed to decrease the complexity of the online optimisation process by applying a sequential convex programming (SCP) approach. Specifically, they provided a successful application of SCP to an optimal guidance and reconfiguration problem for swarms of spacecraft. Similarly, a successful application of the SCP-based optimal guidance and control algorithm to a multi-UAV optimal reconfiguration problem was presented in [111]. Experimental results were carried out to further confirm the effectiveness of the proposed design.

Building on and leveraging the aforementioned two important results, in the work of Rebecca et al.[112], the SCP approach was further modified to reduce the processing time while simultaneously improving the algorithmic robustness. Then this approach was applied in real time to produce guidance commands and control actions for rigid spacecraft.

It was shown in these works that the convex-relaxation strategy can effectively overcome the complexity problem caused by nonconvex constraints and nonlinear dynamics and can enhance the computational performance. However, the validity and fidelity of the obtained solution can be questioned. Moreover, these convex-relaxation methods may suffer from

Table 3: Popular MPC-oriented methods reported in recent years

MPC-oriented G&C methods
Linear covariance-based MPC (LCMPC)[106]
Model predictive static programming (MPSP)[102]
Quasi-spectral model predictive static programming (QSMPSP)[104]
Model predictive convex programming (MPCP)[107]
Sampling-based stochastic model predictive control (SSMPC)[101]
Tube-based robust model predictive control (TRMPC)[100]
Linear pseudospectral model predictive control (LPMPC)[108]

poor convergence due to the existence of higher-order linearization errors and artificial infeasibility [113, 114].

Apart from the computational complexity issue, the guidance and control performance obtained using MPC-based approaches can be greatly affected by the consideration of model uncertainties, external disturbances and other uncertain effects. Hence, the robustness concept must be involved in the design of MPC-based guidance and control algorithms. Numerous theoretical results, analyses, and tools aiming to enhance the robustness of algorithms have been reported in the literature. For example, some potential solutions may include robust design based on the constraint tightening [21], min-max structures [115], stochastic tubes [116], and adaptive laws [117]. However, they are still in the early development stage and are less likely to be implemented in practical applications than established methods. In addition, the implementation of additive tools and strategies may have negative impacts on the feasibility of the optimisation process, resulting in poor guidance and control stability.

Furthermore, it should be noted that the applicability of MPC-based approaches to guidance and control problems is of particular importance. However, some existing MPC-oriented designs can lack realistic setups in terms of the problem formulation. For instance, when designing the framework of distributed or hierarchical MPC, researchers commonly assume that the information between neighbouring subsystems can be (partly) accessed [118–120]. However, this assumption might be too strong or unsatisfiable in some space/aerospace engineering applications such as spacecraft formation flying and UAV swarms, due to the existence of communication faults or failures. As a result, alternative strategies are urgently needed so that this assumption can be relaxed or removed.

5. Review of AI-based G&C Strategies

In addition to the great success achieved by applying stability theory-based and optimisation theory-based guidance and control methods, recent research has reported some attempts to explore possible uses of AI-based techniques in connection with the optimal guidance and control of space/aerospace vehicle systems. The key idea of this type of strategy is to establish an optimal guidance and control network by taking advantage of deep learning. Although early works confirmed the feasibility of applying this newly developed strategy, there are still several theoretical and practical issues that need to be further considered in future research.

5.1. Connection Between AI and Guidance and Control Problems

Advances in AI technologies and computational resources allow us to develop machines and methods capable of performing in a more intelligent and efficient way. During the past decade, significant achievements have been made in terms of applying AI techniques to address various engineering problems. Although the application of AI-based techniques in space/aerospace-related practices such as the design of optimal guidance and control systems is still in its early stage, it is undeniable that the interest in applying AI is high, and some connections between AI and optimal guidance and control problems have already been made. Specifically, four potential connections can be identified by reviewing the literature.

5.1.1. AI and Vision-based Pose Estimation for Spacecraft/UAV

In recent years, researchers have investigated the possibility of applying AI and vision-based techniques to act as pose estimators for different spacecraft or aerial robots flight missions. Some representative examples can be found in the existing body of literature [79, 121–125]. Specifically, in [121], the problem of spacecraft proximity operations including formation flying and on-orbit servicing was considered. Different on-board monocular-based approaches were constructed and studied to simultaneously estimate the pose and shape of uncooperative orbiting objects. To achieve the desired robust estimation, the filter-based simultaneous localization and mapping (SLAM) algorithms and architectures were further adjusted. Numerical simulations were provided to evaluate the performance of the proposed vision-based designs.

Similarly, the authors of [122] proposed a novel monocular-based pose estimation algorithm for uncooperative spacecrafts. One unique feature of their work is that by evaluating the performance of existing localization algorithms, a set of robust keypoints can be generated. Then, this set of keypoints was applied to train a convolutional neural network (CNN) such that it can produce specialized descriptors robust to illumination changes. Comparative simulations were executed to appreciate the merit of this particular design.

Besides, aiming at reducing the processing time required to obtain the estimation uncertainty map, a novel estimation approach based on a modified FlowNet2 network was proposed in [124]. A number of simulation studies were carried out on a spacecraft pose estimation problem and the obtained results not only confirmed the effectiveness of the proposed approach but also demonstrated good potentials for practical applications.

5.1.2. *Optimal Trajectory Generation*

Perhaps the most popular connection between AI and optimal control is to apply AI strategies in the design of optimal manoeuvre trajectories for space vehicles [126, 127]. Unlike traditional trajectory optimisation methods [6, 99, 128, 129], applying AI-based methods such as evolutionary algorithms and tree search methods is more likely to locate a global optimal solution for a mission. Moreover, these methods do not require the designer to have strong background knowledge with respect to the problem, and they are relatively easy to implement.

One representative example can be found in [130], where the authors developed a fully automated solution method for the low-thrust interplanetary trajectory planning problem by taking advantage of the genetic algorithm and a monotonic basin-hopping strategy. Apart from evolutionary algorithms, the possibility of using various ML methods in the generation of optimal trajectories has also been explored [25, 131]. An example can be found in [25], in which the authors used a trained AI model to approximate the optimal multi-impulse transfer trajectories as well as the optimal transfer costs of a multi-target mission. This application is important for some mission cases in which fast estimation of optimal trajectories is required or it is computationally expensive to calculate the mission performance index.

5.1.3. *ML/AI-based Nonlinear Control and Estimation Design*

A large number of publications with "neural network control" and "ML/AI-based control" as keywords can be found in the literature [132–135]. For example, a drone landing control problem was considered in [135]. To improve the accuracy of the applied model, a DNN was formed to approximate the high-order effect. Then, a nonlinear feedback linearization controller was established by applying the approximated model. Experimental results verified the effectiveness as well as the stability of this AI-based controller. Note that although this paper is for a drone controller but the proposed technique of using DNN using spectral normalization is straightforwardly applicable to spacecraft control.

However, in these aforementioned works, neural networks are applied as supplemental tools capable of compensating for unmodelled system terms. Subsequently, they are combined with other modern control schemes to steer the motion of the system. Recently, researchers have investigated the possibility of applying AI models to act as online motion controllers and state estimators for different spaceflight missions or UAV swarms. In this context, one representative example is the work presented by Tsukamoto and Chung [136]. In this paper, by addressing a convex optimisation problem, the authors sampled a sequence of data points of the optimal contraction metric offline. Following that, a deep long short-term memory recurrent neural network was trained to approximate the sampled metrics and then served as an online motion controller. The proposed strategy was successfully applied to address the spacecraft optimal motion planning problems in real time.

Similarly, an imitation learning-based strategy was proposed in [137] for multi-vehicle motion control systems. In this work, the authors firstly applied a global planner to produce a number of demonstration trajectories. Subsequently, local observations were extracted and learned via deep imitation learning, thus resulting in a local policy which can be efficiently applied in real time.

In addition, the work of Carlos and Dario [24] is also of particular importance. In their work, deep neural networks were constructed to learn the optimal guidance and control laws. Then, the trained networks were applied as feedback controllers in real time, and the results obtained from a number of pinpoint-landing case studies confirmed the effectiveness of their proposal. In their follow-up research [138], an initial stability study of this DNN-based control method was provided. This further provides credibilities of applying this direct mapping strategy as the main tool to produce the approximated optimal guidance commands for spacecrafts.

Owing to the potential advantages and applications, in this paper, we limit our main focus to designing and applying MI/AI-based technology to achieve online guidance and control.

5.2. *Design and Applications of AI-based G&C Methods*

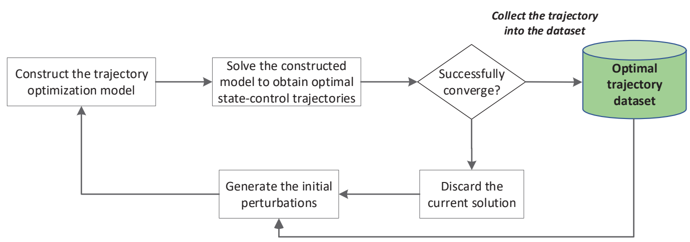

Figure 6: Illustration of trajectory dataset generation

AI-based guidance and control methods combine the merits of well-developed trajectory optimisation methods and deep learning techniques, thereby forming an integrated framework capable of producing optimal guidance and control commands in a relatively short time. Loosely speaking, in an AI-based approach, two steps are involved [24]. The first step is to create a large dataset containing optimal flight trajectories for a specific mission profile. It should be noted that there is usually no open dataset for a specific space-related application. Hence, this step is essential, and simulated results are used as an alternative.

In the second step, (deep) neural networks are constructed and trained on the pre-generated dataset so that they can be applied in later stages to directly represent the optimal relationship between the state and control actions. To better demonstrate how a spacecraft-related mission can benefit from the implementation of AI-based guidance and control methods, the work presented in [139] is recalled. The aim of this work is to design a deep neural network-driven algorithm to produce control actions in real time such that the spacecraft can be steered to reach specified final conditions during the atmospheric entry phase.

The generation of the optimal trajectory dataset is shown in Figure 6, where three main substeps can be extracted: 1) generate the perturbation values for the initial conditions; 2) construct and solve the trajectory optimisation model; and 3) collect the optimal state and control results in the dataset. Once the dataset is generated, deep neural networks are constructed and trained. Then, the trained neural networks can be applied to produce the control actions in real time, and this forms an online feedback structure.

Guidance and control methods developed via various AI models have been reported in the literature. Here, we aim to summarise the main features and advantages of some typical approaches reported in recent years. These methods are summarised below (see Table 4).

Table 4: Popular methods developed via different AI models in recent years

Different AI models
Artificial neural network (ANN)[140]
Deep neural network (DNN)[24, 139, 141]
Support vector machine (SVM)[142, 143]
Reinforcement learning (RL)[144]
Deep reinforcement learning (DRL)[145]

It is worth mentioning that all the methods shown in Table 4 have been implemented in or have the potential to be applied to space/aerospace vehicle guidance and control problems. Key features and advantages associated with them are briefly noted below:

- **ANN**: Benefiting from its simple structure, an ANN-driven guidance and control algorithm is relatively easy to establish and implement.

- **DNN**: Compared to the ANN, the DNN tends to have a more complex network structure (e.g., more hidden layers). However, it has been shown that enhanced control performance is likely to be obtained if a control network has a deeper structure [24, 139]. Moreover, compared to optimisation theory-based guidance and control methods such as MPC and DP, the implementation of DNN-driven control algorithms can save considerable computation time.

- **SVM**: The SVM has the capability of dealing with both linear and nonlinear systems. It applies kernel functions to train the model and is more likely to provide enhanced prediction accuracy. Applications of SVM models to orbital transfer problems have been executed successfully, and the results have confirmed its effectiveness.

- **RL**: One main advantage of using RL is that the learning process can be further enhanced by interacting with the environment. This is usually achieved by designing a reward function, thereby providing feedback to the system. Therefore, an RL-driven model tends to be more adaptive and robust with respect to uncertainties or unexpected situations. Applications of RL to autonomous lunar and martian landing problems have been successfully executed. The results confirmed the possibility of applying RL to design the guidance system.

- **DRL**: This approach is similar to the standard RL and can be loosely understood as a combination of a DNN and RL. The motivation for the use of DRL stems from its enhanced ability to explore functional relationships in high-dimensional state and control spaces.

5.3. *Potential Issues and Challenges of AI-based G&C Methods*

Although certain advantages can be gained by applying different AI-based guidance and control methods, their development is still far from mature, and some problems remain open for further consideration. More precisely, some issues and challenges are listed below:

- **ANN**: Due to its relatively simple network structure, ANN-based guidance and control methods may suffer from an inadequate approximation ability. This problem becomes more serious when a spaceflight or an atmospheric flight mission requires the consideration of nonlinear dynamic systems.

- **DNN**: The performance of a DNN-based method is greatly affected by its network structural parameters, including the size of the dataset and the number of neurons or hidden layers. Setting these parameters so that the network can reach the optimal performance is difficult and may vary from problem to problem. Moreover, when the designer does not have enough knowledge of the problem, it is difficult to determine whether the DNN is undertrained or overtrained. Besides, although reliable simulation results were obtained to confirm the effectiveness of designing a DNN-based real-time optimal control architectures for missions such as planetary landing and orbital transfer, it is undeniable that using this approach in practical missions may result in catastrophic failures if the initial conditions are far from nominal.

- **SVM**: In some orbital transfer test cases, the SVM has shown poor generalisation performance. Hence, treatments should be designed so that the SVM can be well suited for more mission scenarios.

- **RL and DRL**: Due to the implementation of the interaction process, the computational burden tends to be significantly greater than that of the other methods. This raises the threat level of practical applications. That is, the onboard processor may accept a solution which is not fully optimized or even an infeasible one. This is highly undesirable for practical applications and it may result in a failure of the mission.

It is apparent that the development of AI-based guidance and control algorithms is still in its early stage. However, we believe that this type of method will gain in maturity and gradually become one of the mainstream methods for various vehicle guidance and control problems.

6. Conclusions and Future Developments

6.1. Concluding Remarks

Significant effort has been devoted to the progress of exo-atmospheric and atmospheric flight research during the past decade, which in turn has led to the development of various advanced guidance and control algorithms for space/aerospace vehicles. In this investigation, we aimed to review and investigate the newly developed methods capable of offering promising guidance and control performance for various flight missions. More precisely, the reviewed techniques were classified into three major groups: stability theory-based methods, optimisation theory-based methods, and AI-based methods. The key features of different types of algorithms, along with the corresponding issues and challenges, were discussed. Particular focus was given to recent applications of these approaches to further improve the depth and breadth of the literature review. Although most methods reviewed in this paper were designed to fulfil different spaceflight and atmospheric missions, they have the potential to be applied to other similar engineering tasks, such as guidance and control problems for autonomous ground vehicles [146, 147], and unmanned surface vehicles [148, 149].

Based on the work presented in Sections 3 to 5, some concluding remarks are summarised below:

- **Algorithm implementation simplicity**: Stability theory-based methods tend to be more advantageous than both optimisation theory-based and AI-based methods regarding implementation simplicity. This is mainly due to their straightforward method of deriving control laws as well as their ease of operation. However, since it is mainly based on the stability theory, there might be no optimisation possible in general.

- **Algorithm flexibility**: Optimisation-based algorithms may be more advantageous than their counterparts with respect to flexibility. For example, this type of approach can easily be combined with other tools, such as neural network identifiers, adaptive methods, and disturbance observers, to identify uncertain parameters in the system or reject the influence of disturbances. More importantly, some problem-dependent requirements and limitations can be considered in the control process by treating them as additional constraints and incorporating them into the optimisation model.

- **Algorithm efficiency**: Both stability theory-based methods and AI-based methodologies are likely to outperform optimisation theory-based methods in terms of efficiency. This is because in an optimisation theory-based approach, an online re-planning process is usually required, which significantly enlarges the computational burden in real time. This issue becomes more serious for some mission scenarios such as spacecraft swarms and multi-spacecraft formation flying in the presence of environmental and communication uncertainties.

- **Algorithm stability and robustness**: In terms of operational stability and robustness, benefiting from sophisticated theoretical results and various recovery tools, stability theory-based methods and optimisation theory-based methods tend to be more advantageous than AI-based algorithms.

6.2. Continuing Research

Although new applications and progress have been reported in the literature, the development of guidance and control algorithms for space/aerospace vehicles is still far from mature, and future research can be carried out from a wide range of perspectives:

- The implementation of stability theory-based approaches may introduce additional algorithm-related parameters, which may have non-negligible impacts on the control performance. In most applications, these parameters are assigned mainly depending on an expert's knowledge. However, it is desirable to design new optimal parameter-tuning strategies so that the control performance can be optimised.

- For a stability theory-based approach, it is desirable to explore more sophisticated constraint handling techniques to address various practical constraints while simultaneously maintaining the system stability as well as the uncertainty and disturbance attenuation abilities.

- As analysed in Section 3, both model-based and data-driven methods have unique advantages and disadvantages. It would also be worthwhile to develop complementary strategies that have the merits of both techniques.

- To extend the applicability of the optimisation theory-based approach, certain developments should be targeted by researchers to improve its online computational performance. This could be achieved by exploring fast sampling strategies, high-efficiency optimisation algorithms, or simpler optimisation formulations.

- In the design of optimal guidance and control systems, multiple performance indices must usually be taken into account. Therefore, strategies that are able to effectively balance or compromise different user-specified performance indices are urgently needed.

- In an AI-based control algorithm, the pre-generated dataset used to train the algorithm might easily become outdated in practical scenarios. In this case, certain strategies capable of adjusting the mapping relationship are highly desirable.

- One key problem for AI-based control methods is that they lack theoretical guarantees of feasibility and closed-loop stability. Consequently, we believe that the study of the stability of AI-driven control systems will become mainstream in follow-up research.

- For AI-based guidance and control methods, more sophisticated validation tools and strategies should be designed in order to provide space scientists and engineers with a clear view of the credibility of an algorithm.

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