RECENT TRENDS IN COMPUTATIONAL GUIDANCE AND CONTROL FOR SPACE APPLICATIONS

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ABSTRACT

This paper presents an overview of recent developments in the field of computational guidance and control. Both model-based and data-based techniques are presented, with a focus on model predictive control, convex optimisation, artificial intelligence, path planning and artificial potential field methods. The considered applications incude attitude manoeuvres, orbital transfers, powered descent landing and proximity operations. In the conclusions, challenges and potential future developments are identified for the presented techniques.

1 INTRODUCTION

In recent years, the space sector has changed significantly, shifting towards solutions requiring increased performance and autonomy. This change has also been accelerated by the technical and economic needs of the new space approach. However, traditional Guidance and Control (G&C) techniques cannot always meet the increasing requirements of autonomy and performance. For this reason, Computational Guidance and Control (CG&C) [45] has become of increasing interest to the aerospace sector. In contrast to traditional G&C, CG&C generates commands in real time by using on-board numerical computation. It represents, therefore, a fundamental step on the way to system autonomy and autonomous operations, with the potential to increase system capabilities and reduce operational costs. On-board computation introduces, however, a series of challenges, including the need to develop algorithms which are computationally efficient, reliable and robust.
CG&C techniques can be divided into two categories: model-based and data-based. The model-based category encompasses all techniques in which the G&C laws are explicitly related to the system dynamic and kinematic models. On the contrary, data-based techniques infer G&C laws from a set of data, derived from the models, but do not explicitly use such models in the algorithm itself. Model-based CG&C includes Model Predictive Control (MPC), Convex Optimisation (CO), Path Planning (PP) and Artificial Potential Field (APF). Data-based CG&C includes Artificial Intelligence (AI).
The aim of this paper is to provide a summary of recent developments in the field of CG&C, and to serve as a reference starting point for further developments of autonomous solutions in the G&C

sector. The discussed applications include attitude maneuvers, Powered Descent Landing (PDL), orbital transfers, Proximity Operations (PO) and Rendezvous and Docking (RVD).
The paper is structured as follows: Sections 2 to 6 present MPC, CO, PP, APF and AI separately. Section 7 provides an overall discussion of CG&C and the conclusions.

2 MODEL PREDICTIVE CONTROL

Overview The general concept behind MPC is to solve a constrained Optimal Control Problem (OCP) repeatedly, for example every time new measurements for the state of the system are available. The solution of the OCP is represented by a sequence of controls that minimise a cost function and satisfy the constraints, and is based on the predicted evolution of the system over a predefined time window, called prediction horizon. The MPC implements only the first element of the OCP solution. The process is then repeated at the next time step, using the current state as initial conditions. When the prediction model, cost function and constraints are nonlinear, Nonlinear MPC (NMPC) is considered.
The OCP of the MPC framework can be solved in an implicit, explicit, or combined way [44]. Implicit MPC solves the OCP online and for the specific values of the state encountered at the considered time step. Explicit MPC solves the OCP offline and regionwise, for a set of states of interest. Spacecraft (SC) with limited on-board computational capability might benefit from explicit MPC, which implements the control law on-board as a fitted function or look-up table [7], [37]. However, explicit MPC is generally feasible only for low-dimensional problems, due to the exponential growth of the number of regions in the partition of the state space with the length of the control [20]. On the other hand, a major disadvantage of implicit MPC is the need to solve the OCP online repeatedly. This introduces challenges due to the computational time and the HW requirements [33]. When MPC is based on linear models or models that can be linearised, the OCP becomes either a constrained Linear Programming (LP), a Quadratic Programming (QP), or a Second Order Cone Programming (SOCP) problem. The OCP reduces in these cases to CO, which can generally be solved on-board with the available processing power, and for which guarantee of finding a global optimum exists. On the contrary, for NMPC, there are no a priori guarantees that the solver will converge to a solution, even if continuation and warm starting strategies can mitigate this risk [37]. Additional challenges of MPC are connected to its reliability and verifiability [44].
One of the main advantages of the MPC as control technique is its ability to handle system constraints. Other advantages are its applicability to both linear and nonlinear models, architectural heterogeneity [44], and reconfigurability, since MPC can be used as part of an adaptive control system (the cost function, constraints and prediction model can be updated online [25]).
Attitude Manoeuvres and Control For attitude manoeuvres applications, the fast dynamic requires a short MPC sampling time. In addition, in order to ensure closed-loop stability of MPC, the predictive period should be long enough [9]. As a consequence, the large prediction horizon combined with a small sampling time results in increased length of the OCP control [23]. To solve this issue, the use of variable sampling time has been proposed [9]: when the SC is far away from the reference position, large actuation is required, and a small sampling time is adopted. When the SC is closer to the desired position, a reduced magnitude of the actuating force is expected. In this case, stability is more important, and a larger horizon is required. Therefore, to keep the problem tractable, an increased sampling time is used when the SC is closer to the desired state.
Another defining aspect of MPC is the choice of the prediction model. For attitude control applications, when the dynamic is described in SO(3), the use of numerical integration methods does not preserve the quantities of motion, such as momentum and energy, and this can lead to large differences between true and predicted values [18]. Lie group variational integrators have been developed

to preserve the conserved quantities of motion: they update the rotation matrix by multiplying two matrices in SO(3), ensuring that the rotation matrix evolves on SO(3) and the quantities of motion are preserved. Lie group variational integrators are used as MPC prediction model in [18] and [24].
Among the references that propose the use of NMPC solutions for attitude control applications are [18], [35], [37], [83]. Implicit MPC solutions are presented in [22], [23] and explicit MPC in [4].
An additional point of interest is the type of actuators. In [18], [24], [27] the control torque is a generic external torque. These works were extended in [35] to the case of a SC with a Reaction Wheel Assembly (RWA): by extending the problem to a RWA, the OCP needs to consider also RW speed and angular momentum, and the problem dimension increases. RW are still used in [37], but in this case for an underactuated SC with two RW. References [8] and [9] propose instead MPC attitude control using magneto-torquers, while [26] presents NMPC for control moment gyros control.
In terms of use case, most of the references discussed so far focus on constrained reorientation manoeuvres. Attitude control is coupled to station keeping and momentum managements in [39]. Momentum management and station keeping is presented also in [31] and [32]. In [83], MPC is used for the combined attitude and antenna spin control of a SC equipped with a large rotating flexible reflector. MPC is used to control the SC during a spin-up manoeuvres and during the science phase.
Rendezvous and Proximity Operations MPC has been tested in space by PRISMA [5], [11], a mission whose aim was to demonstrate GNC for formation flying and RDV.
The study ORCSAT (On-Line Reconfiguration Control System and Avionics Architecture) has addressed the application of MPC RDV to the Mars sample return mission [13], [17]. In the MPC scheme proposed in ORCSAT, MPC provides both guidance and control functionalities.
The use of linear-quadratic (LQ) MPC applied to multi-constrained RVD has been presented in [36], [47] and [56], where experimental results on physical test bed are also presented. In [36] both LQ-MPC and NMPC are tested while [47] presents NMPC for the RDV with a rotating platform. The same test bed is used to validate also robust and stochastic MPC for RDV ([46] and [53]).
Explicit MPC for proximity operations applications is proposed in [20], where the parametrisation of the low-thrust profile is performed with a set of Laguerre functions, to allow for the description of a long control horizon without using a large number of decision variables.
Landing In [29] MPC has been proposed for the CG&C of the Mars powered descent of a Reusable Launch Vehicles (RLV). The test of the MPC on embedded processors shows that the computational times are lower than the time step of the control loop, even if spikes could happen due to the distribution of computational resourcs among the running processes.
In [35], one of the main points of interest is the representation of position and orientation as unit dual-quaternions: rotational and translational dynamic are described with a single equation. This also facilitates convex representation of nonconvex constraints, so that the OCP can be formulated as CO. CO is used also in [63], where at each MPC update, two algorithms are executed. The purpose of the parallel execution is to guarantee feasibility of the MPC updates and to improve performance and robustness. The proposed architecture is particularly suitable for multicore processors.
More recently, in [95], the 6-dof PDL problem is solved using two different MPC architectures: in the first one, MPC is used only for guidance and the controller is a PID. The second architecture is a more classical MPC approach in which the OCP is solved with higher frequency and the solution is used to directly feed the controller.
Reference [100] proposes MPC with a time-dependent decreasing horizon for the PDL of a RLV. The prediction horizon is adapted as a function of a time-scaling factor and of the time elapsed since the last MPC iteration. The solution is suboptimal but less demanding in terms of computational effort w.r.t. [95], where an optimal time of the horizon was searched at each iteration.
Orbital Transfers MPC/NMPC applications to low-thrust orbital transfer fall mainly into the online NMPC category: rigorous mathematical models for the dynamic behaviour of SC under low-thrust

are nonlinear, and local linearisation can fail when the control horizon is extended [3]. In addition, low-thrust transfers last long times, and provide additional time allowance for potentially solving an OCP on-board. Use of MPC for low-thrust transfers is proposed in [3], [6], [10], [14], where in [6] and [10] NMPC is used to track a precomputed reference trajectory.
In [99] NMPC is proposed for high-thrust manoeuvres. The case study is an autonomous non-coplanar LEO-GEO transfer. The control system is divided into two NMPC loops, one for altitude and eccentricity, and one for orbit orientation. The cost function of the NMPC is defined to promote a thrust behaviour that favours thrusting at favourable points along the orbit, and results show that the system is able to split the velocity change into multiple ΔVs applied at the apses.

3 CONVEX OPTIMISATION

Overview CO has recently been applied to nonconvex problems through Lossless Convexification (LC) and Sequential Convex Programming (SCP). SCP consists in solving the original non-convex problem through a sequence of convex sub-problems. These are obtained from convex approximations of the original problem, each one computed around a reference trajectory obtained from the previous iteration. Convergence proofs exist just for a limited number of cases. This method works heuristically well, since it exploits the high computational speed provided by convex solvers. The steps to follow for the formulation of an SCP algorithm consists in convexification and discretisation. The convexification is done writing the dynamic constraint as a linear approximation around a reference guidance trajectory [105]. In the linearisation, a virtual control term is added, in order to deal with the artificial infeasibility caused by the linearisation residual. A key concept of linearisation is the thrust region, a region of the state space where a solution can be found that satisifes the original non-linear dynamics of the system. Usually, the discretisation step is done with Zero Order Hold (ZOH), First Order Hold (FOH), higher order hold discretisation or Pseudospectral (PS) methods [48], [80]. PS discretised problems have the feature of being often more sparse compared to ZOH or FOH interpolations, with equal accuracy. The resulting transcribed sub problem is usually augmented with slack variables (such as the virtual control norm) and with convex-analytical constraints (such as thrust region deviation). SCP algorithms are applied in literature mainly to PDL and Low Thrust (LT) interplanetary trajectories. Other applications, not discussed in this paper, are autonomous attitude re-orientation manoeuvres [90], [103].
Landing In PDL, the real time and computationally lightweight solution requirements are at odds with the non-convexity of the problem, which is driven by the system dynamics and the specific constraints. In [48], the author proposes a trade off between methods based on the hybridisation of different PS CO, characterised by high run time performance. The author proposes the Mars PDL of the NASA Mars Science Laboratory as a test case, considering glideslope, maximum thrust, initial and final state constraints and using the final mass as cost function. This approach is expanded in [62], where the authors present the concept of Hp PS methods, discretising the original problem in a number p of nodes collocating the equations of motion in an H number of nodes for each p segment. In this way, the accuracy of the dynamic description is increased with an equal number of nodes. Hp PS method is applied in [89] to an aerodynamically controlled descent and powered landing phase of RLV. Simulation are provided for a CALLISTO-class rocket, proving how well this approach can handle the complex air dynamics. Reference [105] proposes a convex-concave decomposition for convex but nonlinear equality constraints, to decrease the linearisation error. As a consequence, the authors are able to directly enforce the quaternion norm constraint in the optimisation problem of a 6-dof minimum-time and minimum-fuel free-time PDL of a RLV. Different lines of research have been conducted by different authors. The problem formulation of [57] takes into account the accuracy requirements of a vision sensor, linearising the covariance matrix elements of an Extended Kalman

Filter. The result is a trajectory that aims at being as close as possible to the ground, while still being dynamically feasible. This work is expanded in [68], with the addition of a 3D hazard area. In [71] an implementation of an SCP algorithm is proposed for a PDL initialised with a straight line (linear interpolation between the initial and final state) and results are provided for the case of a planar PDL problem showing high computational performances. Two different algorithms for SCP are proposed in [76], applied to an hypersonic re-entry vehicle based on line-search and thrust region. Two approaches are proposed, that give different convergence and computational performance. The first includes the thrust region constraints directly in the cost function; the second adds a constraint, bounding its minimum deviation. In [86] is formulated a 6-dof PDL problem for a vehicle actuated by a single gimbaled variable thruster and single ignition thruster. Aerodynamic forces are not considered and the kinematic is represented with Modified Rodrigues Parameters (MRP). A combined Machine Learning (ML) SCP based approach is presented in [101], for a 6-dof PDL, where the initial guess of the SCP is provided by a deep neural network, trained on ground with an SCP initialised with a straight line. In [87], is proposed a minimumum fuel SCP PDL for Titan landing, using a parafoil as actuator. Dual quaternion representation is used in [102] for the lunar landing problem. Attention is paid to the problem scaling and the initial guess trajectory is the straight line solution. The proposed algorithm is tested with a hardware in the loop Monte Carlo campaign. In [12] the authors propose a LC approach for Lunar PDL, considering maximum tilt rate and acceleration, maximum thrust ramp rate, and a terminal vertical descent phase. Results are provided for an Apollo-like mission. Finally, in [104] is presented an SCP algorithm for hypersonic re-entry trajectory optimisation with a high level modelling of the air drag. Constraints of no flight zones and control authority are imposed with the cost function being the flight time minimisation.

Orbital Transfer In [81], the authors propose a robust and computationally light minimum fuel LT guidance. The problem is convexified and discretised using an adaptive flipped Radau PS method. The modelled dynamics consists in the two-body problem with the Sun as primary and no other perturbation, taking into account the estimated actuator switching on and off times. This work is expanded in [79], where a mesh refinement method is used to increase the accuracy with respect to the nonlinear dynamics at each iteration, which results in convergence improvements. A similar problem is presented in [80], with the introduction of third-body perturbation, solar radiation pressure and thruster models to enhance the dynamic model complexity. The SCP algorithm is initialised with a simple cubic interpolation. The author shows that SCP outperforms NLP in terms of computational time also with complex dynamical models. A trade off is presented in [97] between different discretisation and trust-region methods for the fuel-optimal LT trajectory optimisation. The discretisation is executed with adaptive PS Legendre–Gauss–Radau, an arbitrary-order Legendre–Gauss–Lobatto and a FOH. Moreover, the trust region deviation is imposed first as a constraint (hard trust-region) and then inserted in the cost function (soft trust-region). The SCP is initialised with an interpolation of the tangential thrust trajectory. This work concludes that FOH with a hard trust-region is the most suitable method for onboard LT fuel-optimal trajectory in deep space. The dynamics is further enhanced in [96], with the introduction of an n-body problem and engine shutdown constraints. The authors use a FOH discretisation and hard thrust region policy. This work shows that increasing the complexity of the dynamical model at each iteration can increase convergence. Another publication that deepens the topic is [84], where it is considered the problem of trajectory design in the three-body problem near the Lagrange points, with the scenario being a Halo orbit in the Earth-Moon system. The problem is linearised and discretised with a ZOH. Results are provided against NLP (matlab fmincon). Finally, in [88], is proposed an homotopic approach considering the two body dynamics. The problem is discretised with an arbitrary-order Gauss–Lobatto scheme and the convex problem is solved introducing an adaptive second-order trust-region mechanism developed to increase the convergence rate. The homotopic approach consists in solving a sequence of simpler problems, increasing the dynamic modelling complexity at each iteration: the solutions of each problem serves as initial guesses for the next subproblem. Results are provided comparing the minimum fuel, minimum energy and homotopic minimum-fuel approach.

4 PATH PLANNING

Overview In the references discussed in this paper, PP methods provide the guidance for constrained attitude reorientation manoeuvres. Most of the PP algorithms work in three steps. First, the problem domain is chosen. The most popular attitude representation in literature are quaternions, Gibbs vector, Airy–Rodrigues Parameters (ARP) and direction cosine matrix (DCM). Then, the domain is discretised creating a graph whose nodes correspond to attitude configurations compatible with the constraints. The discretisation can be a regular grid *full discretisation*, random, or based on more complex strategies, where the discretisation is combined with the graph search. Finally, the path from the initial to the final node is obtained using techniques from the Graph Search Algorithm (GSA) family, such as the A* algorithm or the Rapidly-exploring Random Tree (RRT and RRT*). The A* provides the sequence of nodes of the graph to go from the start node to the destination node, while minimising a cost function. For the A*, the cost function is the sum of the cost to connect two nodes plus the cost to connect each node to the final node. More complex approaches, such as the ones presented in [34], [93] and [92] allow to use the SC control effort as cost function of the A*.
Attitude Manoeuvres An early approach to PP is presented [16] and [28], where the unit celestial sphere is discretised so that individual points on the sphere correspond to constraint-compliant directions of a selected single body-fixed axis. With this approach, only constraints on a single body-fixed axis can be considered and it is not possible to include keep-in constraints. The complete attitude guidance (e.g. the guidance on all the axes) is then derived analytically, while the angular velocity guidance is not an output of this method. Compared to earlier approaches such as [1], this method is however easier to implement and computationally less expensive, so that it could also be implemented on-board CubeSats. The same authors in [28] follow a different approach. Rather than using a single axis, they use quaternions for the PP domain, so that keep-in/out constraints can be included. The discretisation scheme distributes the nodes evenly, and the eigenangle for a rotation between any two neighbouring nodes is approximately constant. The cost function of the A* is the number of points visited: since the nodes are equidistant, visiting the smallest number of nodes coincides with the lowest cost. In [30] ARP are used in order to avoid the distortion characterising the cubic interpolation of other representations. The search graph considers equidistant nodes. To avoid the sharp edges characterising the search step, a Savitzky–Golay filter is used. The resulting trajectory does not include the original grid points or the target attitude. This is solved by performing a closed-loop tracking of the trajectory, so as to provide a guidance profile that reaches the target attitude. The same author proposes in [38] a modification of his original algorithm, applying it to the case of a nadir pointing axis target attitude. The problem is re-written as a 2D path search, allowing for a modification of the GSA in order to quickly find the shortest path in the presence of three-axis attitude constraints. The final trajectory is smoothed as in [30]. In [75], the authors use SO(3) as domain. The whole domain is sampled using overlapping cells around the sampling points, whose union covers the whole search space. The A* is than used on the graph, using the distance in the SO(3) space as cost function. Once the optimal path is identified, the authors tackle the task of providing setpoints of angular velocities. These are obtained by fixing the time interval between subsequent attitude setpoints, and defining the corresponding control law and all the dynamical components. In [34] the attitude is represented using MRP and sampling is performed using equally spaced nodes. The main point of interest of [34] is that a desired norm of the angular velocity during the manoeuvre is assigned, so that the angular velocity and control vectors can be obtained with a B-Spline interpolation. In this way, both the min-

imum distance and the minimum control effort can be used as cost function of the A*. In addition, the proposed method has the advantage of being able to consider non-rest to non-rest slew. When the minimum control effort is used as cost function of the A*, the algorithm becomes computationally demanding. An evolution of [34] is proposed in [92], focusing on the improvement of the derivation of the dynamical profile. The aim is to solve the problem of the parasitic oscillatory behaviour observed at the interpolation step. The proposed solution is to use Least Squares approximating Non-Uniform Rational B-Spline C^3 curve, for which the condition of precise passage through the waypoints is not strictly enforced. This allows for a smoother final trajectory with respect to [34]. Reference [93] presents a comparison of PP techniques, considering four different planners of increasing complexity, three of which based on A*, and with the last one being the one presented in [34]. Direct comparison is obtained using performance metrics such as total energy consumption, control torque integral, attitude error integral, and total keep-in/out violation time.

5 ARTIFICIAL POTENTIAL FIELD

Overview The APF method is a guidance technique used to synthesise the control commands to drive the SC towards the desired state. The core idea is to define a non-negative, state-dependent scalar potential function $V = V(\mathbf{x})$ typically (but not necessarily) as the sum of an attractive potential and repulsive high-valued potentials. The former has its global minimum coincident with the target state while the repulsive ones are used to shape the interaction of the SC with its surrounding environment. The control commands are in turn computed to steer the SC state to regions of lower potential values, until the target state is achieved. The method hinges on the Lyapunov's second stability theorem: the negative APF gradient information, $-\nabla \mathbf{V}(\mathbf{x})$, is embedded in a general Lyapunov's function candidate $\Phi(\mathbf{x})$ on top of which the controller is synthesised to grant $\frac{d\Phi}{dt}(\mathbf{x}) < 0$ throughout the entire problem space. The control inputs are readily available in analytical form making the APF able to cope with complex domains and to react in real-time to a dynamic environment. These advantages come at the price of a non-optimal solution since no OCP is solved to derive the control input. Moreover, during the potential design, local minima and actuator saturation issues must be properly tackled to grant convergence under all possible circumstances.

Attitude Manoeuvres The classification criterion proposed in this paper is based on the controller synthesis logic and divides the approaches in two major sets: model independent and model dependent controller synthesis. This classification is drawn from [19] and might serve as a high-level reference frame. Control laws in the model independent synthesis category are based on the knowledge of the potential function gradient $\nabla \mathbf{V}(\mathbf{x})$ and of the state error alone. The control synthesis process is carried out via the direct Lyapunov's method. Given the target state, $\mathbf{x}_d$ and a candidate Lyapunov's function $\Phi(\mathbf{x}, \mathbf{x}_d, V, \mathbf{u})$, the controller $\mathbf{u}(\mathbf{x})$ is selected such that $\dot{\Phi}(\mathbf{x}, \mathbf{x}_d, V, \mathbf{u}) < 0$. The latest developments in the field focus on embedding the actuators saturation limits directly inside the potential formulation. An elegant solution is proposed in [69] where the attitude error enters the APF definition via a smoothing function, cutting out undesired high-term values and ensuring that the control remains within feasible bounds. It is demonstrated that this potential function is also able to cope with local minima by proper parameter tuning. The local minima topic is deepened in [58], where an explicit characterisation of the critical points of the potential field is carried out. Moreover, [58] formulates its APF to naturally incorporate an anti-unwinding attitude error function which guarantees that the ordinary equilibrium quaternion and its redundant counterpart are global minimisers. In [19] logarithmic barrier functions are used to define both attitude forbidden and attitude mandatory regions. In [49] instead is noteworthy the control law synthesis based on a strictly convex velocity-free potential function, proved to achieve rest-to-rest three axis attitude reorientation manoeuvres of a flexible SC. To the model dependent synthesis category belong papers where APFs are used at kinematic level to define the reference velocity ω_c which grants the system asymptotic stability around the origin. The angular velocity ω_c serves afterwards as reference trajectory for the tracking controller synthesised at dynamics level. Recently the interest has shifted towards two major controller categories: sliding mode controllers and backstepping controllers. For the first category, [91] and [55] are worth a mention. If in [91] a detailed discussion on local minima is carried out, in [55] the aforementioned problem is neglected, as the attention is steered towards angular rate saturation issues. As anticipated previously, backstepping techniques are also a natural choice in this context, as they turn out to be perfectly suitable to address input saturation issues, and are analysed in [19] and [42]. In [19] a modified integrator backstepping technique with an improved error function is adopted to smooth down high-terms characterising the initial part of the trajectory. Reference [42], on the other hand, relies on a less sophisticated controller but adjoined with a non-linear disturbance observer to enhance the system capability to stochastic disturbance accommodation.

Proximity Operations In the PO field the ability to deal with complex topology in a safe-critical manner is essential. In [52], [60], [85] and [41] the trajectory and control generation for the chaser SC pose, i.e. position and attitude, is addressed by superimposing an attractive potential together with a repulsive potential surface centred around the target station which shapes the docking corridor the chaser has to follow to get to destination. In [85] the dual quaternion parametrisation is used to describe the SC pose, and the model independent controller synthesis is carried out via Lyapunov's second theorem. Conversely, the APF is used to generate the 6-dof reference trajectory used as reference track for the sliding mode controllers in [41], [61] and [52], and for a backstepping controller in [60]. References [43] and [40] are worth mentioning due to their focus on spatial trajectory generation. In [40] an adaptive potential field is designed depending on the error between the current SC state and the reference trajectory, the latter chosen to be the bang-bang solution of a obstacle-free optimal control problem. In [43] instead, a standard sliding mode controller is synthesised on the surface designed according to a quadratic attractive potential and Gaussian repulsive ones.

6 ARTIFICIAL INTELLIGENCE

Overview Of the whole spectrum of AI methods that have been created along the years, the one that has found the most uses for space applications has been Machine Learning (ML), more specifically Supervised Learning (SL) and Reinforcement Learning (RL).

SL can be used either to label the input into a certain category (classification) or to yield the relationship between a dependent and independent variable (regression). The SL model typically takes the form of a Neural Network (NN): a NN connects the system inputs to the required outputs by arranging them as nodes in a layer. Learning the decision logic flowing from the input nodes to the output nodes is for what the dataset is used. When the NN has three or more layers (including input and output) the architecture is called Deep Neural Network (DNN). Other NN architectures are Convolutional NN (CNN), mainly used for recognition of images, and Recurrent NN (RNN). RNN can learn from previous data inputs and their use has given rise to the concept of meta-learning [67], [73].

RL is used to train an agent to learn a policy of actions that works best in a given environment in order to accomplish a given objective (normally, the maximisation of a reward). The learner is not told which actions to take, as in most forms of ML, but instead must discover which actions yield the most reward by trying them. Also for RL the most common architecture used is NN; when using DNN the learning method is known as Deep RL (DRL).

It is important to bear in mind that optimality and feasibility of the solution provided by ML techniques, even after extensive training, is not guaranteed [72], [66], [106]. Reference [106] states that a possible way of obtaining suitable solutions from ML techniques is to feed the output provided by the data-based approach as initial guess point to a conventional solver.

Table 1 provides an overview of the different methods and architectures used in the reviewed papers.

Table 1: Summary of ML techniques applications.

	DNN	RNN	CNN
SL	[59], [78], [2]	[51]	[51]
RL	[66], [101], [72], [74], [70], [82], [98]	[73], [94], [77]	[73]

Landing Reference [51] proposes a strategy for autonomous lunar PDL based on a combination of deep learning and optimal control. By processing a sequence of optical images taken by on-board cameras, the objective of the architecture is to train a set of NN to land the SC on the Moon. This is achieved by employing CNN for image processing and RNN for generation of the most appropriate thrust commands, which has been trained to find fuel-optimal guidance profiles.
Reference [66] uses RL to integrate both the guidance and control architectures into a single system. The policy learned by such system is given by the defined potential landing sites and the deployment ellipse, and it is trained through simulated interaction between such environment and different random initial conditions that covers the deployment ellipse. In practice it is possible to get close to the optimal performance, but there is no guarantee that the profile provided by the system is the optimal for the given landing scenario. The author concludes by promising to investigate further into more robust systems able to adapt in real time to disturbances and changing dynamics, so that the same architecture can be used in other applications like hypersonic reentry or close proximity operations.
An additional approach making use also of RL is introduced in [73]. The authors propose to integrate guidance and navigation functions by means of meta-RL methods, designing a simulation environment able to gather the system dynamics and to simulate image acquisition from SC cameras. The images are then processed by means of CNN and RNN, and the optimal policy is computed with proximal policy optimisation. By using RNN and the meta-learning concept, the agent can adapt to uncertain environments (for instance, one with uncertainties in the SC mass or the gravitational field, or one in which one actuator fails), based on the outcomes of previous actions. The results of the paper show how such adaptation and learning abilities make the agent keep progressing towards a more accurate policy just by training with more episodes.
Orbital Transfers Reference [59] presents the use of ML algorithms in the design of interplanetary transfers, making use of the intermediate solutions computed and assessed during the optimisation task as the dataset needed to train the AI. For instance, SL can be employed to build a model that provides a more accurate initial guess to the optimisation algorithm, or a ML model can be trained to directly provide the target trajectory. Offline trained DNN on a data set consisting of thousands of OCP solutions can be employed to learn the optimal control structure that the problem requires, and then be used on-board to compute the optimal feedback.
In [78], the authors make use of a guidance system based on NN aiming to increase the autonomy of the SC and its robustness to failures and uncertainties. The learning process reduces to a SL task: the goal is to generalise the expert behavior (normally a numerical solver). The author explores the use of RL and the concept of meta-learning for such application in [94]. Reference [72] also uses RL to design trajectories resilient to missed thrust events (MTE), exemplified in a low-thrust long-duration transfer from Mars to Earth. An MTE occurs when the SC encounters an event (whose onset and duration is stochastic), triggering a safe mode while thrusting. Safe mode deactivates all non-essential components, including the propulsion subsystem, with the objective of protecting the SC and communicating with Earth. Therefore, if the SC is thrusting and the safe mode is activated, it will miss thrust that is actually required by the guidance profile, which can greatly impact the mission since 60% of SC enter safe mode at least once every 200 days.
DRL is used in [74] to design the control of a LT SC approaching a periodic orbit in a system modelled via circular restricted three body problem and for closed-loop manoeuvre planning in [98].

Proximity Operations Deep-space formation flying is addressed in [2]. In this work, NN is employed to compute an adaptive signal that compensates for the effect of the model inversion errors caused by the nonlinear control methodology. This methodology uses an approximate dynamic model which is inverted together with a linear compensation of the ideal feedback linearised model.
Reference [67] focuses on asteroid close PO, and considers an adaptive GNC system able to interact with the asteroid's environment dynamics. The system is optimised with meta-RL. The fact that the asteroid environment does not have to be characterised as accurately as possible allows for enhanced mission flexibility. This, in turn, permits envisaging a wider mission objective, such as visiting multiple asteroids. The authors ensure adaptability of the system by introducing partially observable Markov decision processes to treat sensor noise, different environmental dynamics, actuator failure, and unkowns in the SC's center of mass and inertia tensor.
RL is also used in [70] to deal with close-proximity and docking maneuvers of a 6-dof system. The policy followed by the agent aims to be valid for different initial conditions, avoiding collisions and minimising control and error costs, and is implemented as a feedback control law. Reference [82] employs DRL to teach an agent the guidance strategy only for pose tracking and docking, using control theory to design the controller. The authors call this approach deep guidance, and implement it experimentally, obtaining results comparable to the simulation even though the simulated environment did not incorporate all effects present in the real experiment. DRL is also used in developing proximal policy optimisation in [77].

7 DISCUSSION & CONCLUSION

This paper has presented a summary of recent developments in the field of CG&C. The previous sections have shown that technical advancements are already taking places in many fields of applications. In addition, CG&C is already being applied, with the notable example of CO for rocket landing and MPC for proximity operations.
However, challenges can be identified that needs to be addressed in order to allow for a wider use of CG&C techniques. For MPC and CO, these challenges include: (i) computational speed of numerical solvers; (ii) reliability of solvers for non-convex optimisation problems; (iii) capability of obtaining global optimal solutions for non-convex MPC; (iv) computational and memory resources of on-board computers; (v) verification and validation methods (e.g. use of reachability and controllability set analyses for MPC) (vi) security measures for aerospace system with autonomous capabilities [44].
Even more advanced techniques, like AI, can have interesting repercussions in the field of CG&C. The versatility and flexibility of AI techniques allow for their use in a wide range of relevant space applications. Once the burdensome, time- and resource-consuming learning phase has been overcome, a trained system is able to obtain G&C commands in extremely small times, or assist a more classical G&C scheme in achieving similar performances. In the papers studied, the authors commonly express their enthusiasm for the potential of ML systems use for the future of the space industry. Similarly, they agree on the embryonic stage of the technology as main drawback of these methods, and on the need for further study and analysis before successfull implementation at industrial level.
Promising future developments of MPC in the space sector could make use of learning techniques and include the following aspects: (i) *Adaptive MPC*, that is, the combination of MPC with learning-based algorithms, so as to estimate the parameters of the dynamic model online. Example of learning-based MPC are provided, among others, in [15] and [21]. In [15] it is proposed to use a learning-focused adaptive controller to guarantee stability while the uncertain system parameters are being learnt, so as to avoid the initial transients often observed during online learning. The system switches automatically to MPC when sufficient confidence in the estimated parameters has been obtained. In [21] the dynamic model is complemented by a learned disturbance model using Gaussian

process. (ii) *Approximation of the MPC optimal control law*, using function approximation through SL. While in adaptive MPC learning methods are used to learn and describe the dynamic model, in this case learning methods are used to approximate directly the optimal control law. For example, in [64] the control law is learned through SL. During the online phase the quality of the approximated MPC law is checked: if the check fails, a backup controller is used. Other examples of MPC control law learned through NNs are presented in [54] and [65]. (iii) *Reconfigurable MPC*, that is, the online reformulation of MPC (e.g. reformulation of cost and constraints) in response to system failures [44].
In addition to the combination of AI and MPC, the combination of other CG&C methods could be of interest for future developments. For example, AI and PP can be used to provide an initial guess to SCP. Using the NN output as initial guess for SCP, as done in [101], would allow to refine the NN solution to guarantee convergence. On the other hand, using PP to generate an initial guess for SCP would mean providing an already dynamic and kinematic compliant trajectory. Both approaches could boost the SCP computational performances.
With regards to PP alone, in recent years this method has been evolving toward approaches that provide not only the kinematic but also the dynamic guidance profile; in this respect, the challenge is to maintain good numerical performance.
A combination of PP and APF is proposed in [50], where the RRT* algorithm is modified to account for a preferable search direction in its branch development. Such preferred direction is given as the potential gradient directions, thus generating optimal smooth trajectories while reducing the computational effort required by the RRT* algorithm.
Overall, the techniques and references presented in this paper show major advancements in the field of CG&C. It is believed that CG&C has the potential to evolve even further, satisfying the increasing autonomy and performances requirements.

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