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Editorial

Guidance, Navigation, and Control for the Moon, Mars, and Beyond

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1. Introduction

The interdisciplinary field known as Guidance, Navigation, and Control (GNC) has been one of the key contributors to the tremendous advancements in space exploration since the inception of the Mercury and Apollo programs. These advancements have revolutionized science, communications, and, ultimately, the lives of billions of people. With the increasing complexity and frequency of missions—at the time of writing, only a few hours have passed since SpaceX successfully captured its Starship's *Super Heavy* reusable booster using the *Mechazilla's chopsticks* system) [1]—the pursuit of more efficient, sustainable solutions, and even more ambitious programs, continues to shape the future of space exploration.

As we look ahead, innovative GNC solutions will play a critical role in shaping the course for the next phase of space *exploration and exploitation*; see, for instance, recent examples of proposed solutions for reusable systems [2–8], for the study of maneuvering in cis-lunar space [9,10], as well as for deep-space missions [11,12]. Efforts are also ongoing in the improvement of advanced simulation environments [13,14] as well as in the use of state-of-the-art machine-learning-based solutions [15–17]. In the same spirit, this editorial highlights contributions in Guidance, Control, and Navigation across various mission types, including those to the Moon, Mars, and even deep space. One particular contribution focuses on reusable rocket applications, with the implicit assumption that the knowledge gained in this area can be applied to other celestial bodies as well.

In the following section, a more detailed description of the individual contributions to this Special Issue is provided, followed by a comprehensive list of the papers included in this Issue. Finally, the editorial concludes with some brief remarks.

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2. An Overview of the Contributions to this Special Issue

Stefano Farì et al. [18] delved into the complexity of GNC validation and verification techniques, based on the use of a dedicated multi-body Modelica-based library. They focused on the application of these advanced multi-body techniques to the validation of the behavior of GNC systems for reusable systems and, more precisely, in the context of the CALLISTO rocket demonstrator [19]. Using numerical results, they demonstrated how to apply the techniques to complex subsystems such as Thrust-Vector Control and Leg unfolding mechanisms.

D'Ambrosio's and Furfaro's [20] work focuses on the use of a particular class of Physics-Informed Neural Networks, that is, *Pontryagin Neural Networks* (or PONNs) in Spacecraft Guidance. Specifically, the contribution shows the capability of the proposed machine learning technique not only to provide feasible solutions to two challenging problems, namely, an Earth–Mars transfer problem and a Mars Landing scenario, but to learn the optimal policy, by leveraging the Extreme Theory of Functional Connections [21].

Ref. [22], by Critchley-Marrows et al., explores the interoperability of Earth-independent navigation architectures for Moon missions, to enhance reliability and develop safer and more resilient missions. In particular, authors focus their attention on the use of elliptical frozen orbits around the Moon, with performance in terms of position accuracy that can reach the order of 100 m in the cases assessed in the study.

The work by Sabatini and Palmerini [23] investigates the problem of concurrently estimating both the absolute position expressed in a lunar inertial reference frame and the relative position between two systems, for instance, an orbiter and a lander, or two spacecraft in formation, by using a single-stage Kalman filter, and performed an assessment of such a solution with respect to more traditional cascaded Kalman filter implementations.

Machine learning is once more leveraged in [24] by Bacu et al. to classify asteroids by using Deep Convolutional Neural Networks, in the context of space awareness activities, which, to date, do not yet fully exploit the benefits of artificial intelligence-based solutions. The work relies on state-of-the-art image classifiers and exploits the capability of learning transfer among networks.

In [25], by Li et al., a trajectory planning strategy for rovers is developed. The solution treats non-convex obstacles by decomposing them in convex substructures to come up with a safe convex corridor construction method. A corresponding nonlinear programming problem formulation then computes the corresponding solutions, which are compared with more traditional approaches.

Malgarini et al. [26] propose to exploit pulsar signals to obtain navigation solutions for deep-space missions performed by CubeSats. The techniques to detect, process, and exploit the corresponding pulsar signals onboard are simulated, showing the feasibility of the idea for deep-space autonomous navigation in the context of miniaturized systems with limited computational capabilities.

Finally, Ref. [27], by Santoro et al., studies the problem of inserting a spacecraft into a repeating-ground-track highly elliptical Martian orbit. This is done at the end of the interplanetary transfer by using low-thrust nonlinear feedback control, with the stability of the approach proven by leveraging Lyapounov stability theory. The strategy proves efficient and, since no reference trajectory information must be provided a priori, also shows a high degree of autonomy.

3. Concluding Remarks

The contributions to this Special Issue of *Aerospace* address various aspects and challenges in developing GNC solutions for missions to the Moon, Mars, and deep space. These studies present potential pathways for transforming new concepts and technologies into operational capabilities, helping to shape the future of space exploration. Many of the insights offered by these contributions suggest promising directions for further research, which will play a critical role in advancing the field in the coming decade, and we hope that readers will find the ideas, methodologies, and results presented in these contributions both helpful and inspiring, encouraging them to join the journey to the Moon, Mars, and beyond.

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Conflicts of Interest: The author declares no conflicts of interest.

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