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Control, Navigation and Dynamics of Spacecraft Using Artificial Neural Networks and Deep Learning

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Abstract

Several areas of technology and robotics research are being influenced by an increasing interest in AI. The space community has only recently begun to investigate artificial neural networks and deep learning techniques for space systems. The most important aspects of these topics for controlling, guiding, and navigating spacecraft dynamics will be discussed in this paper. In an effort to draw attention to the benefits and drawbacks of employing the most prevalent architectures of artificial neural networks and the training strategies that go along with them, we examine these components. Quantitative and qualitative metrics are used to compare and review particular system identification, control synthesis, and optical navigation applications of artificial neural networks. The end-to-end deep learning frameworks for spacecraft guidance, navigation, and control are presented in this overview, as are the hybrid approaches that combine neural techniques with conventional algorithms to boost their performance.

Keywords: Artificial neural networks • Spacecraft • GNC • Deep learning • Dynamics • Autonomous • Navigation

Introduction

The advancement of an older idea known as artificial intelligence (AI) has been one of the most significant developments in autonomous systems over the past ten years. This broad term includes several research areas. Additionally, one of its sub-clustering terms is frequently misunderstood because AI is a broad term. The well-known artificial neural networks (ANNs) are nearly as old as artificial intelligence, but rather than a method for implementing AI in autonomous systems, they represent a tool or model. A typical architecture can be used to describe nearly every deep learning algorithm: According to, the idea is to combine a model, a cost function, an optimization method, and a specification dataset. In fact, due to distribution mismatching, using a dataset for guidance, navigation, and control yields subpar results. The aforementioned dataset distribution mismatch, as comprehensively presented in, justifies the requirement to update the dataset using simulated observations and actions during training even when training is carried out in a simulated environment but not during deployment. Overfitting issues are also less likely to arise when incremental observations are used to update the dataset. The theoretical foundation for the fundamental work of is laid out in this survey [1].

The goal of this overview is to provide an overview of the current trends in the application of AI-based techniques to space applications, particularly in relation to hybrid applications of artificial neural networks and traditional algorithms in the areas of control, navigation, and guidance. Despite the fact that these are the only domains covered by the survey, the subject remains extremely broad and various points of view can be found in recent surveys. Applications range from initial spacecraft design to mission operations, with a focus on navigation and guidance and control algorithms; lastly, new research areas include astronomical object classification and perturbed dynamics reconstruction. The authors intend to limit the discussion to spacecraft guidance, navigation, and control (GNC) and the dynamics reconstruction domain due to the large number of applications. However, the most promising AI-based applications are mentioned in the discussion of the most common network architectures in addition to those that fall into the aforementioned categories [2].

Literature Review

An active area of research is the development of an adaptive guidance and control system through the application of reinforcement learning and meta reinforcement learning. Particularly, autonomous guidance and control during proximity operations and landing trajectories have been generated using deep reinforcement learning. For a variety of scopes, autonomous trajectory planning has been generated using reinforcement learning. Pesce and others, Piccinin and team and Chan and co utilized DQN and neural fitted Q as value-based methods to examine the autonomous mapping of asteroids. Federici and co proposed an actor–critic proximal policy optimization framework for real-time optimal spacecraft guidance during terminal rendezvous maneuvers in the presence of both operational constraints and stochastic effects, such as the presence of random in-flight disturbances and inaccurate knowledge of the initial spacecraft state [3].

Brandonisio and others proposed a direction and control regulation to play out the examination of an uncooperative rocket. Advantage actor-critic (A2C) methods and a DQN in this. State-activity esteem capabilities are approximated utilizing fake brain organizations (ANN); in particular, straightforward MLPs are utilized. While the state space is continuous, a discrete action space is maintained. Transfer learning (TL) is also used to make it easier to train for more difficult tests. Pre-training the RL agent on a simpler task prior to training on the main task is one transfer learning technique. In the paper, the different assignments are addressed by expanding intricacies of the prize models. Policy-based methods, according to many researchers, produce better results. Derivatives and proximal policy optimization (PPO) are two of those that are frequently used. A PPO formulation that makes use of recurrent neural networks (RNNs) is frequently utilized in order to enhance the agent's stability and robustness under various scenario conditions [4].

Recurrent layers' capacity to store information from previous states, as predicted in Section 3, may have a significant impact on agent-safe trajectory planning and speeding up progress toward mission objectives. In addition, the research asserts that improving an RNN's environmental conditions sensitivity through training contributes to the agent's robustness regardless of the operational environment. A deep reinforcement learning-based guidance method for spacecraft proximity tracking operations is proposed in this work. The D4PG algorithm, which stands for distributed distributional deep deterministic policy gradient, was utilized. This kind of algorithm has a deterministic output and operates in continuous state and action spaces. The actor–critic algorithm is a subset of the D4PG algorithm [5].

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The domain features that are useful and frequently used in particular space-based applications are the focus of the discussion. Deep learning (DL) and machine learning (ML) research is extremely extensive and complex. The author recommends referring to [1] in order to acquire the proper understanding of the subject. Thusly, just the most important ideas are accounted for to contextualize the work created in the paper. The terms "machine learning" and "deep learning" should be distinguished as the first significant distinction [6].

Unaided learning calculations are taken care of with a dataset containing many highlights. The framework figures out how to extrapolate examples and properties of the design of this dataset. In the context of deep learning, as stated in [1], the objective is to learn the underlying probability distribution of the dataset, either explicitly for tasks like density estimation or implicitly for synthesis and de-noising. Other unsupervised learning algorithms perform other functions, such as clustering, which involves dividing the dataset into distinct sets, or clusters, of experiences and data that are similar. In the spacecraft GNC domain, the unsupervised learning approach has not yet been widely used [7].

The trade-off between exploration and exploitation is one of the difficulties that arises in reinforcement learning, in contrast to other types of learning. In most cases, the agent must investigate the environment in order to acquire an appropriate optimal policy, which identifies the necessary action in a particular perceived state. The agent must simultaneously make use of this information to carry out the task. For practical reasons, the balance in the space domain must shift toward exploitation only for online deployed applications. As shown in Table 3, there should also be a distinction made between model-free and model-based reinforcement learning methods. Model-free methods primarily rely on learning, whereas model-based methods rely on planning as their primary component. Even though these two kinds of methods have a lot in common, they also have a lot in common. Anything that an agent can use to predict how the environment will react to a given action is referred to as an environmental model [8].

Discussion

In the spacecraft guidance, navigation, and control domain, this paper provided an overview of the applications of machine learning, deep learning, and artificial neural networks. In particular, in order to provide the reader with a customized introduction to the novel approaches, a brief outline of the theoretical foundations of the Artificial Intelligence-based methods has been presented. The paper's objective was to draw attention to the emerging ideas of artificial intelligence in the space community as well as the drawbacks and limitations of these approaches in the challenging space environment. The most frequently used neural network architectures have been thoroughly examined, along with their underlying principles. Every artificial neural network's uniqueness has been emphasized and linked to specific research domain applications. The use of sensed data to retrieve temporal structures, approximate disturbances, encapsulate dynamical behavior, and perform parametric system identification is one of the most intriguing applications in the spacecraft dynamics, guidance, navigation, and control domain. Recurrent neural networks typically have better performance at approximating temporal series, but their training complexity is high. Since many different kinds of convolutional neural networks are used to process images from optical sensors, the most promising use for them is in optical navigation, where neural-based methods and image processing techniques are combined [9].

In fact, the most up-to-date CNN-based methods for pose estimation and planetary landing were discussed in two applications. In addition, the paper examined the extensive field of deep reinforcement learning and its applications to autonomous guidance and control in a variety of contexts, including proximity operations and planetary landing. In addition, a number of different approaches, including transfer-learning and meta-reinforcement-learning ones, were examined and described for the purpose of improving the robustness of algorithms. However, applying AI algorithms to GNC systems faces a number of unresolved issues, such as a lack of training data, a theoretical understanding and modeling of any AI system's behavior, the application of learned features to a variety of situations, and validation [10].

Conclusion

Spacecraft control problem-solving strategies based on reinforcement learning (RL) have been the subject of this survey. The focus of the investigation has been on how RL techniques are used in particular application areas, such as guidance, navigation, and control systems for spacecraft landing on celestial bodies, maneuver planning for orbit transfers and interplanetary mission trajectory, spacecraft attitude control systems, guidance and proximity maneuvers in scenarios involving rendezvous and docking, constellations, and so on. We set out to create a helpful review and tutorial for professionals in the space industry who want to adopt deep learning and artificial neural networks or who want to stay up to date on the most current AI concepts for space applications.

Acknowledgement

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Conflict of Interest

None.

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