Demonstration And Analysis of The Guiding Control System for Aerospace Crafts

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Abstract. The development of space vehicle guidance and control systems gradually becomes a focus in recent research as a key to space vehicles' information processing and control in the space environment. In general, among the popular methods in G&C systems, artificial intelligence-based algorithms contain a wide prospect. This study offers descriptions of the current methods in AI-based algorithms, proposed challenges involved in this field, and described the recent achievements in solving these issues. To be specific, the basic descriptions of the controlling systems as well as the various state-of-art machine learning approaches that are suitable for the G&C system are demonstrated and analyzed including ANN, DNN, RL, SVM, DRL, etc. According to the analysis, the challenges as well as the drawbacks of the advanced scenarios are estimated as well as propose the future prospects to improve the performance of landing. Overall, these results shed light on guiding further exploration of aerospace vehicles.

Keywords: Space vehicles; guidance and control system; artificial intelligence.

1. Introduction

The human trajectory of universe discovery largely depends on the development of space vehicles. As the transportation tool in space, space vehicles associate with activities including planetary exploration aiming moon and Mars [1], space debris collection [2], and surveillance of satellites [3]. The G&C system ensures the efficiency of instruction outputs and operation executions in space vehicles [4]. Since the functioning of the G&C system involves inputs, processing, and outputs of information about velocity, position, altitude, and rotation rates, and so on, the stability and flexibility of algorithms adopted in the system are required. Currently, the three main G&C methods are stability theory-based, optimization theory-based, and artificial intelligence-based [5]. The stability theory-based guidance and control system is designed to cope with the effect of environmental disturbances. Currently, it is the mainstream of the newly developed G&C systems for space vehicles. At the beginning of the century, fast progress in robust control, adaptive control, stochastic system, and data-driven control provides a solid theoretical backup to this subject.

The applications of stability theory-based G&C system requires means to reject negative effects, and scientists achieved several successes in this field. In Ref. [6], it presents an example of robust control. The new applicable tracking law of ADRC holds a strong robust feature towards parameter variations, noises, and environmental disturbances. As shown in Fig. 1, TD is used to generate the transient profile of reference drag accelerator. Total disturbance can be estimated and rejected by ESO. Along with nonlinear feedback combination, the ADRC method is used to steer the bank angle to track the reference drag acceleration profile so as to track the reference trajectory. After performing the simulations using data mainly from the MSL lander's data, the ADRC methods proved to show a better performance on landing compared with previous tracking laws.

After solving the primary issue, recently the study of robust theory-based G&C systems developed techniques. When it comes to situations where uncertainties appear in the system state equations, the concept of a stochastic system shall be applied. One typical work in this field would be Ref. [7], where the stochastic system is combined with numerical simulations without the assumption of linear dynamics. The optimization theory-based guidance and control system comes out due to the merging of the theory of optimization. This is becoming more and more accepted in recent years. Its main advantages lie in the fact that the system gains optimal performance when the dynamics outside of

the system are transformed into an optimization task and its availability to combine with other algorithms such as ANNs and DNNs, which is known as the AI-based G&C system [8].

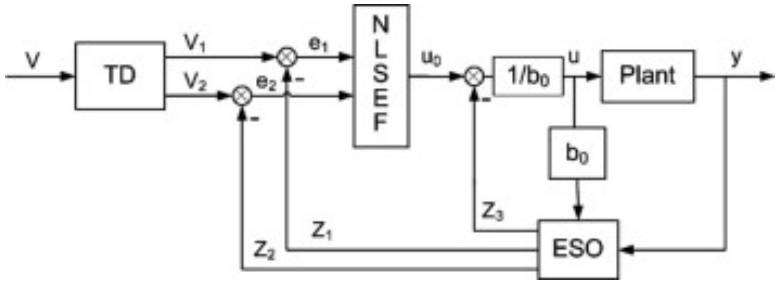


Fig. 1. ADRC topology [6].

This paper aims to demonstrate the application of AI-based techniques in guidance and control systems, and potential AI algorithms that may improve its efficiency and stability. The rest part of the paper is organized as follows. In section 2, a description of the mechanism of AI-based guidance and control systems is provided. Section 3 points out the difficulties faced to improve the defects of this strategy. Recent potential AI-based strategies attempting to overcome these difficulties and technical defects are reviewed in section 4. Finally, a conclusion and possible future topics are provided in section 5.

2. Description of AI-based G&C System

The AI-based G&C system originates thanks to the booming field of machine learning, artificial intelligence, and deep learning. It aims to build an optimal system based on the results of deep learning. By applying ANNs or DNNs, the modeling of robotic perception and action proved to be qualified to drive the entire onboard decision-making system. According to Ref. [9], the AI-based G&C system is capable of landings by generating an optimal response according to a large set of data about the original states. Different recent popular AI models would be discussed detailly in this section.

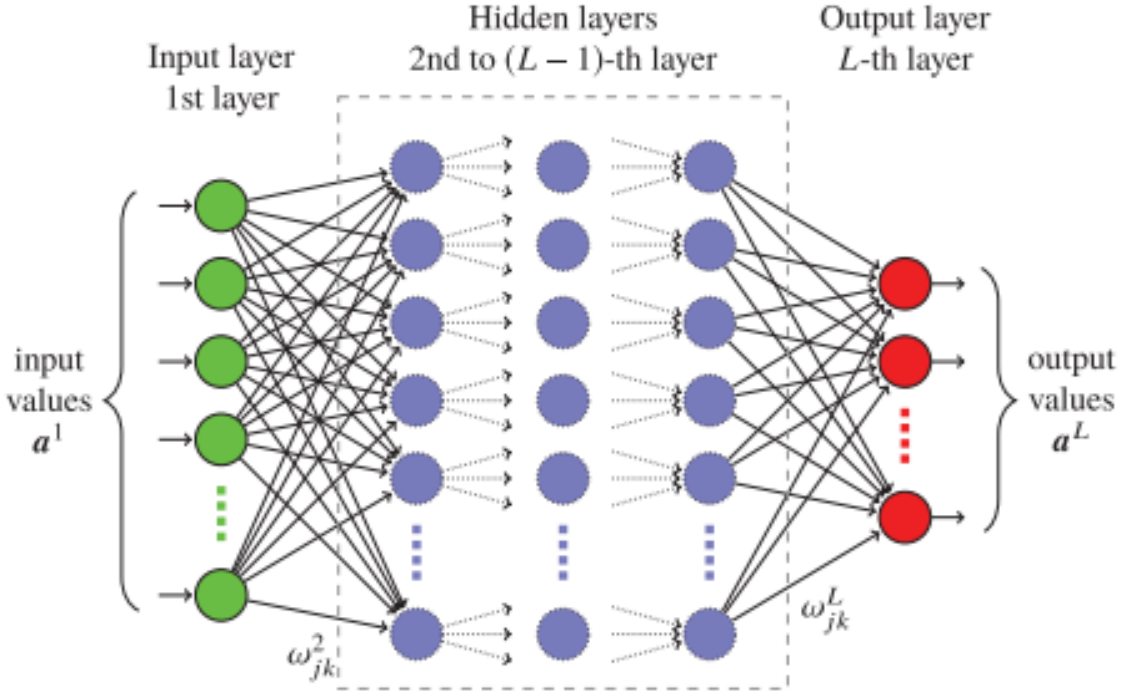


Fig. 2. A sketch of ANN.

2.1. ANN

The ANN is the processing of data by considering it as neurons and applying weighted summation and nonlinear mapping as the neurons pass through different layers. As shown in Fig. 2, hidden layers help process the data with restraints and perform orders to get the intended result. Inspired by the machine learning approach, this type of algorithm is investigated for the accuracy of space vehicles' orbit prediction [10]. In the simulation supported by data from a resident space object (RSO), ANNs showed good performances in various environments. This type of structure is simple, making it easy to be established. However, due to its simplicity, the approximation efficiency is in doubt in complex situations, especially in nonlinear dynamic systems.

2.2. DNN

As shown in Fig. 3, the DNN has a more complex structure than the artificial neural network with more hidden layers. A DNN-based control system is applied in the 6-DOF HV reentry flight [11]. The DNN shows an advantage in the real-time design of trajectory optimization. However, because of the complexity compared to ANN, the DNN-based system requires more strength in the design of optimal control architectures and heavily relies on the data given. Once the initial condition is different from the nominal condition, the capability of this algorithm would need to be retested.

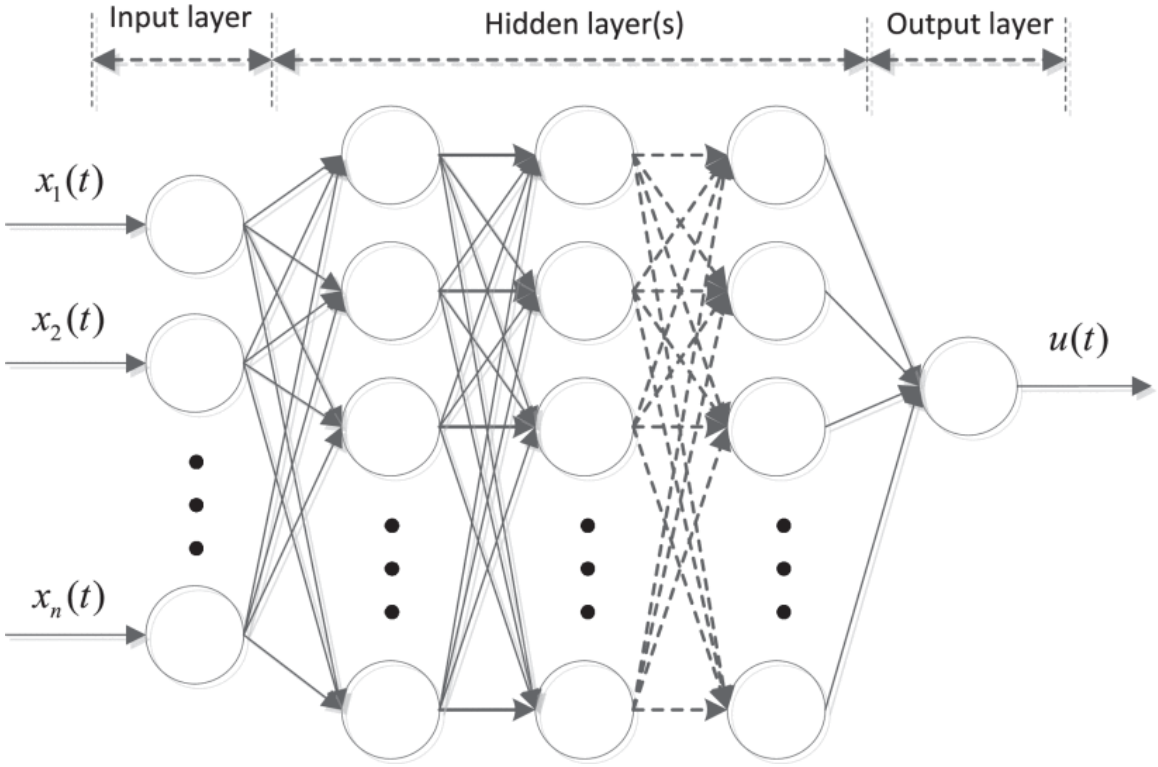


Fig. 3. DNN illustration.

This technique is also used to approximate the irregular gravitational field for asteroids based on the samples provided by polyhedral methods [12]. In Fig. 4, a normalization module is used for network inputs and an anti-normalization module is used for network predictions while training the data, thus the DNNs can directly predict the optimal control actions according to the flight state and no longer needs to solve the original OCPs onboard.

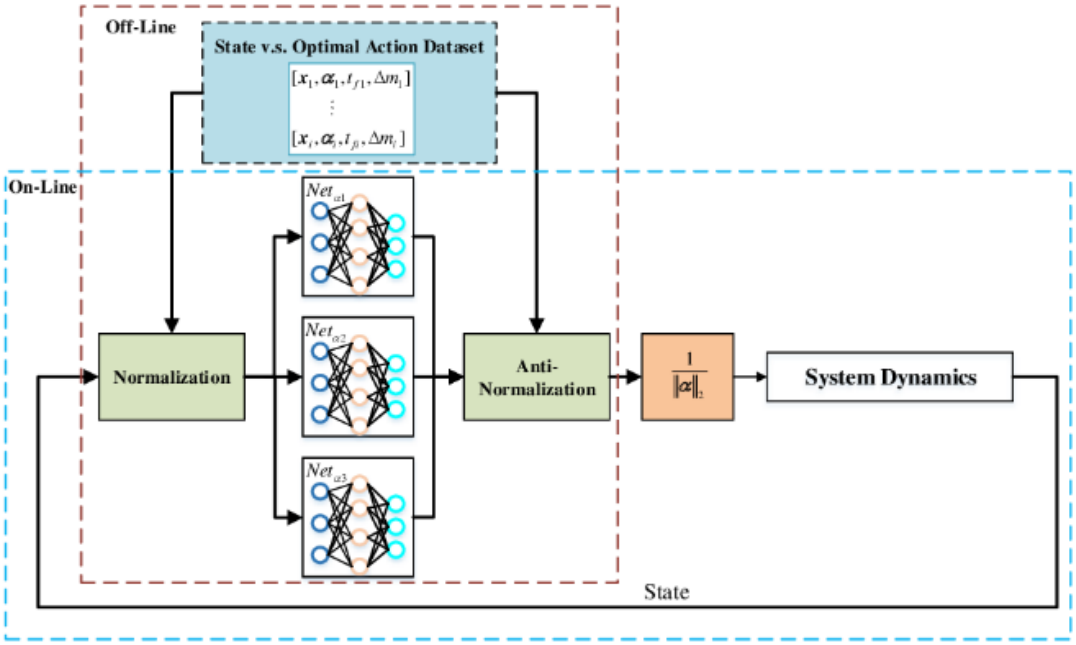


Fig. 4. DNN-based real-time optimal controller.

2.3. SVM

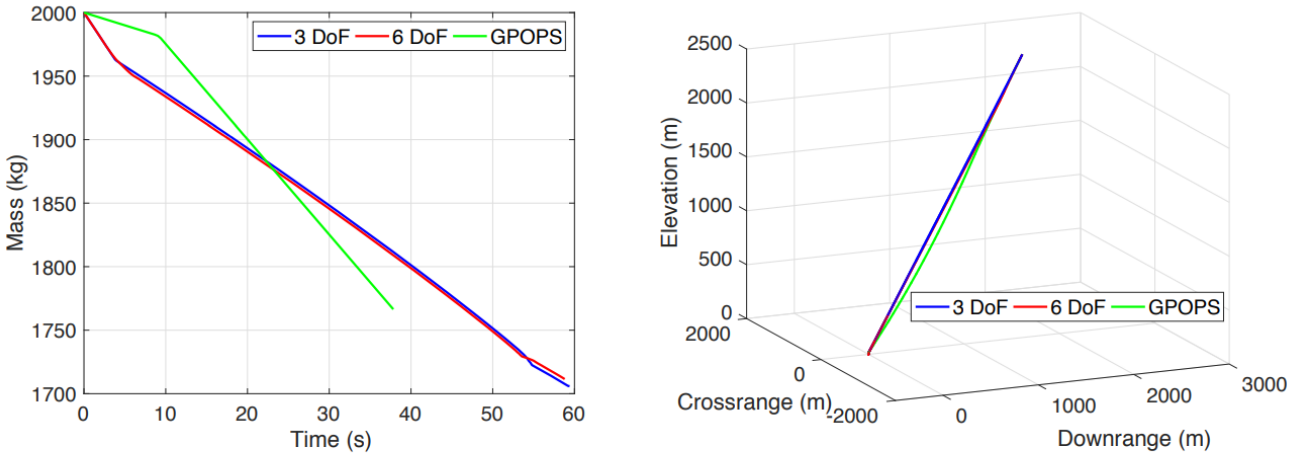
Associated with machine learning, the support vector machine applies linear classification and regression analysis to analyze data. What makes it applicable to the G&C systems is that it can deal with non-linear classifications using the Kernel method. Currently, it has proven to be successful in the prediction of satellite orbit problems to increase accuracy. One successful example would be Ref. [13], SVM effectively reduced the errors of orbit prediction with high average standards and individual performances through the training of data. This helps make up the defects in the physics-based model prediction in the avoidance of collisions in the orbit. It proves the accessibility of this technology in G&C systems. Another example would be the success in classifying the trajectories [14].

2.4. Reinforcement Learning

Reinforcement learning enables the enhancement of learning by interacting with the environment. With a reward function set, the system would receive feedback and become more adaptive and stable in an environment with uncertainties. According to previous study, the RL agent outperformed with high variations such as landing on Mars and asteriods [15].

2.5. Deep Reinforcement Learning

Similar to the reinforcement learning method, the deep reinforcement learning combines DNN with RL to achieve a more promising processing ability in high-dimensional state and control spaces. By adopting proximal policy optimization, a policy resulting in trajectories with high accuracy and fuel efficiency can be designed for space vehicles in a 6-DOF environment [16]. As compared with current systems such as Gauss Pseudospectral Optimization Software (GPOPS) in Fig. 5, this G&C system achieves a significant prescision.



(a) 3-DOF Trajectories (b) 6-DOF Trajectories

Fig. 5. Comparison of 3-DOF and 6-DOF [16].

3. Challenges

Similar most Artificial intelligence-based algorithms, the AI-based G&C system does face the challenge of its explain ability, robustness, and over-reliance on data collecting. The training through received data must assume a perfect condition where there's no mistake with the initial data set. And even a slight change in the provided data would cause unexpected variations in the concussions made and models built. The way of the training models and robotic perceptions and actions solely through data makes it hard to explain the theory behind the mechanism. Disturbances from the environment would cause variations from time to time, thus the method of AI-based G&C system cannot enter a state of maturity until it develops a robust and lower data-reliance system.

4. Potential AI Strategies

In the past few years efforts have been made to improve the robustness of the AI-based G&C system. The relatively simple structures of ANNs and DNNs cause a lack of robustness. One improvement of the algorithms for ANNs and DNNs is to reformalize the setting of the system to increase the efficiency and rigor of system design, benefitting the later study in neural network areas. Regulations and verifications are made in aspects of semantic classification and trace-theoretic classification [17]. Semantic classifications include the system-level specification, input-output robustness, input-output relations, semantic invariance, monotonicity, fairness, input / distributional assumptions, coverage criteria, temporal specifications, specifications on learning algorithms, and bridging system-level specifications with component-level specifications dealt with the possible confusions caused by different adopted notations and standards for input and output level specifications. And trace-theoretic classification including trace properties and hyperproperties defined the two main categories mentioned in the properties of the ANN and DNN methods. Other scholars follows up the previous one of the reformalization of neural networks by proposing a general formal definition of the robustness of neural networks and a general method in this field of study [18]. In addition, to increase the explainability of the DNN methods, scholars propose the way of introducing physics models to the training of algorithm. By combining physics model's constraints, the result from DNN would be more explainable compared to solely data-based algorithms.

5. Conclusions

In summary, this paper introduced the two main popular types of space vehicle G&C systems and gave a detailed description of the artificial intelligence-based guidance and control systems, a specific type of optimization theory-based G&C systems with a broad prospect due to the rapid development of artificial intelligence, with different methods involved. Later, this study proposed the current challenges faced by the AI-based and some recent improvements in its robustness. In the future, more advanced models can be proposed and implemented to enhance the stability and performance. Overall, these results offer a guideline for G&C systems deveopments based on the state-of-art approaches and algorithms.

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