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DEEP LEARNING FOR SPACE DEBRIS REMOVAL

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Abstract. The advances in deep learning have revolutionized the field of artificial intelligence. These advances, as well as new tasks and requirements in space exploration, have led to an increased interest in these deep learning methods among space scientists and practitioners. The problems of controlling the attitude and relative motion of spacecraft are considered for both traditional and new missions, such as contactless space debris removal. Both supervised and reinforcement learning is used to solve such problems based on various architectures of artificial neural networks, including convolutional ones. The possibility of using deep learning together with methods of control theory is analyzed to solve the considered problems more efficiently. The difficulties that limit the application of these methods for space applications are highlighted. The necessary research directions for solving these problems are indicated.

Keywords: deep learning, space debris removal, reinforcement learning, convolutional neural networks.

Introduction. At this time, artificial intelligence methods attract a great interest of researches and practitioners all over the world, which is largely because of the impressive results obtained using deep learning (DL) techniques. DL has rapidly evolved and showed promising results in solving complex tasks, finding non-trivial solutions of existing problems [1].

Different approaches to space debris removal have been introduced recently. Among those approaches, the ion-beam shepherd (IBS) concept can be selected because it assumes the contactless removal of a space debris object (SDO). The main idea of this concept is to use the momentum from an ion thruster plume to transmit the deorbiting momentum to the SDO. To implement the IBS concept, it is necessary to have an efficient technique to determine the force that transmits the ion thruster (IT) to the SDO because these values are required for mission planning and relative control tasks [2]. The conventional approach for this task results in computationally complex algorithms since they are based on integration of the elementary forces over the SDO surface.

This work demonstrates that these tasks can be addressed using supervised [3] and reinforcement learning (RL) [4, 5] techniques.

Determination of the ion beam impact on a space debris object using convolutional neural networks. Using the IBS concept, we consider the deorbiting of an SDO from a low Earth orbit. According to this concept, a shepherd satellite (SS) is equipped with an impulse transfer thruster (ITT) and an impulse compensation thruster (ICT). The ion plume from the ITT is pointed towards the SDO and used for transferring the deorbiting momentum. The nozzle of the ICT is pointed in the opposite direction to compensate for the reaction force created by the ITT.

For efficient contactless de-orbiting, the SS has to fly at a sufficiently small distance in front of the SDO of the order of a few SDO diameters.

The study aims to develop a neural net model, which can map an SDO image to the force transmitted by an IT plume to this object, and estimate the accuracy of such models.

We propose to use a CNN to determine the force transmitted by the IT plume to an SDO using visual images as the input. The input for the CNN is an SDO's image. The force projections in the IRF are the outputs of the network. The hidden layers include two convolution layers with ReLU activation and two max-pool layers to reduce the dimensions of the features. Four consecutive fully-connected layers with ReLU activations follow the last max-pool layer. The output layer consists of three neurons corresponding to three force projections.

The mean squared error between the predicted and ground truth force values is used as the loss function to train the CNN.

In order to calculate the ground truth values of the ion beam force, we use a model of the ion beam interaction with SDO. The upper stage of the Cyclone-3 launch vehicle is considered as the SDO, which is approximated by a cylinder with a height of 2.6 m and a base diameter of 2.2 m.

The datasets contain the images of the SDO as the input and the corresponding force vector as the output. The inputs for this function are generated randomly using a continuous uniform distribution and variation ranges specifically for each input parameter. Then, we use these input parameters to generate the SDO's synthetic images. The images are rendered using Blender open-source software. A camera focal length of 25 and black background are used for rendering grayscale images with a size of 200×200. We did not use any preprocessing techniques for input data, but we normalized outputs to have the ground-truth values in a range of [−1.0, 1.0].

Three different approaches for the end-to-end training of the CNN were investigated. The first model, called CNN1, uses a single CNN, which is trained on the dataset consisting of 10000 SDO images. In this case, the relative position inputs vary in ranges of [−1.0, 1.0] m and [5.0, 9.0] m for *x*, *y* and *z* coordinates, respectively. The input orientation angles ψ, φ, θ vary in a range of [1.57, 1.57] rad. The second model, called CNN2, is an ensemble network. It consists of four sub-models Q1 - Q4. The last model, called CNN3, is very similar to the CNN1. However, it is trained on the extended dataset consisting of all images used to train the CNN2 model. Thus, the CNN3 is trained on the dataset containing 40000 images.

Each trained CNN model can determine the ion beam force significantly faster than the traditional method. Although there is little difference in time performance between the CNN models, they are all at least twice as fast as the conventional method. These results demonstrate that the CNN model is an alternative technique for determining the ion beam force, providing admissible accuracy and a shorter computation time than the conventional approach.

Spacecraft attitude and relative control via reinforcement learning. It is assumed that at the control system design stage an approximate (nominal) model of the spacecraft dynamics is known. This model differs from the real one both by its parameters and unmodeled dynamics. This nominal model is used to synthesize a basic control algorithm sufficient for the SC to perform some initial simple tasks. Next, the SC begins operating in orbit using this control algorithm. Then, the intelligent control system sequentially performs the following actions:

1. Collect data about peculiarities of the SC dynamics;
2. Learn model of SC dynamics using the obtained data;
3. Improve of the SC control algorithm using the updated model.

These actions are repeated until a required control performance is achieved. In the end, the control algorithm should be obtained that is as close as possible in terms of performance to the optimal control synthesized using an accurate mathematical model of the plant.

Neural networks have great potential for describing various processes based on experimental data. Unfortunately, this approach requires a very large amount of data to provide high-quality results, which makes it difficult to use them in the SC cases. Considering this issue, we use a statistical model based on the concept of Gaussian processes. This approach allows us to obtain the posterior distribution of the function based on the available data using non-parametric Bayesian regression. Using this model and the actor critic architecture an efficient RL-based algorithm has been developed.

Simulation results demonstrate that this RL-based algorithm can outperform conventional control laws in terms of accuracy, propellant consumption, thruster firings.

Conclusions. This work demonstrates how supervised and RL techniques can be used for space applications. CNNs are utilized to determine the force impact of the IT plume on the SDO. The CNN models can determine the force impact without prior information about the SDO's relative position and orientation using only the SDO's images as the input. Moreover, CNNs make it possible to obtain the results significantly faster in comparison with the methods used before. Although the CNN models turn out less accurate than the traditional method, their errors are insignificant for practical applications. All these features allow us to state that the CNN model is a promising technique for both spacecraft onboard algorithms and the simulation of contactless space debris removal missions.

Spacecraft control performance can be improved the during its operation using RL. To increase the effectiveness of training, a model-based concept with Gaussian processes was used. The use of the apparatus of Lyapunov functions allows us to guarantee the stability of controlled motion when using such models. The proposed approach makes it possible to develop control systems that can improve their performance as data accumulate during the operation of a specific object. The methodology makes it possible to reduce requirements for control system's elements (sensors, actuators), avoid using special bench equipment, and reduce development time and cost.

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