Improving Autonomous Guidance using Machine Learning Technologies

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Summary

Active debris removal missions pose demanding requirements on the visual guidance system. We investigate the potential applications of machine learning technologies to solve some of the remaining challenges for these missions. A novel method of attitude determination of an unknown and uncooperative debris satellite is presented, which adopts machine learning technologies to detect and track inherently useful image landmarks. We then apply image segmentation and object detection approaches to this domain and demonstrate their advantages. The performance of the algorithms are analysed via numerical simulation and compared with conventional approaches. In order to facilitate further research into the applications of machine learning for visual guidance in space, we make available a simulation framework which is capable of generating realistic image data simulating the relative motion between co-orbiting satellites.

Keywords: *active debris removal, spacecraft attitude determination, machine learning, image processing*

1 Introduction

In the past 60 years, the amount of debris in the Low Earth Orbit (LEO) has been increasing steadily [1, 2], thus posing a threat to current space infrastructures and future missions. Consequently, recent years have seen an concentration of efforts aimed at reducing the risks of space debris, including novel Active Debris Removal (ADR) concepts [3, 4, 5]. However, most of these novel technologies remain mostly unproven and at a relatively low technology readiness level (TRL), as many key challenges remain to be met before a mission can be flown. In particular, an ADR mission would pose very demanding Guidance, Navigation and Control (GNC) requirements in order to guarantee the safety of close proximity operations near the debris, which may include docking or berthing with it [6].

In this study, we demonstrate how machine learning technologies can be used to improve the TRL of in-orbit visual guidance systems. We present a novel approach for tracking the attitude of an unknown and uncooperative co-orbiting target object using data from different visual sensors. Image segmentation approaches are employed to predict suitable locations on the debris target for grappling, grasping or impaling to enable contact-based removal. We also show that object detection can be applied to locate the target, in the presence of different background details and various lighting conditions. These approaches all have the advantage of using GPUs for processing, which are becoming more attractive for on-board computation due to their improved performance and energy efficiency for a lower cost when compared with CPUs. Finally, we make available the simulation framework which we have constructed to generate the training data, in order to facilitate further research in this area.

2 Attitude determination

A key difficulty of GNC for co-orbiting satellites lies in accurately determining the attitude and rotational state of the target. This is of critical importance for many active debris removal methods, where the relative angular rate between the two satellites must be minimised. We propose a machine learning based approach which is capable of estimating the rotational state of a target satellite in real time during a monitoring phase and, using knowledge of the chaser's attitude from on-board sensors, reconstruct its local attitude over time, enabling the use of different debris removal solutions.

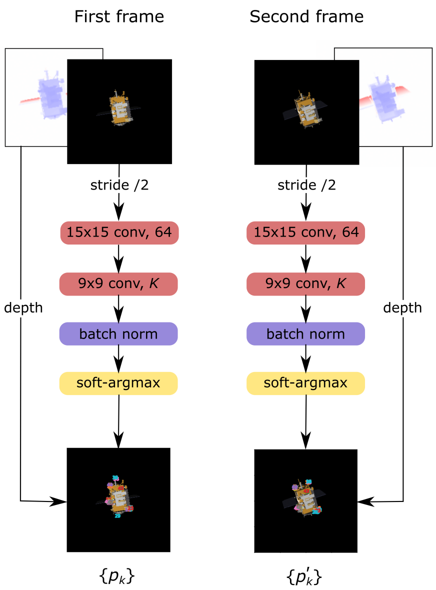


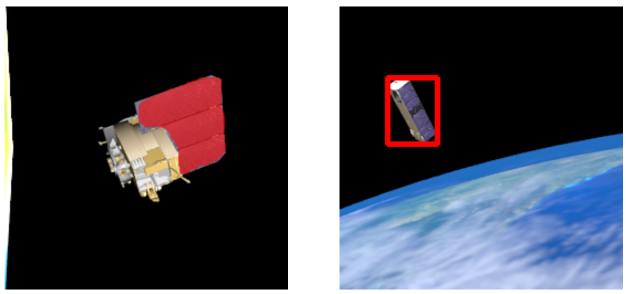
Figure 1: Landmark detection network architecture

Whereas most previous work in this domain assumes a-priori knowledge of the target's geometry [7, 8, 9], we present a solution to the fully general case where the target is completely unknown. By reducing the problem to a series of instantaneous rotations between short time steps, we can predict the relative rotational state at each step using a feature matching approach based on convolutional neural networks, as shown in Figure 1. This novel approach removes the requirement for complex feature matching algorithms, since the properties of neural networks dictate that the features can be matched simply by their position in the output vector. In addition, the use of machine learning techniques ensures that the extracted image features are inherently useful for the specific problem.

However, using only the information from one time step to predict the rotational state is not efficient, particularly in space where the motion parameters will not change overmuch. Where conventionally a Kalman filter might be used to process the measurements of the rotational state over time, we propose a different method based on machine learning technologies, which uses knowledge of past measurements to improve the current estimate, and fits within the end-to-end trainable framework. This method does not require accurate estimates of the process and measurement noise to be provided initially, which is a key difficulty with Kalman filtering implementations.

3 Segmentation and Detection

Convolutional neural networks have lead to significant advances in image processing techniques in recent years [10]. We demonstrate how these techniques can be easily adapted to this domain and can be used to locate the target as well as to determine which surfaces on the object will be good targets for contact-based removal methods and which should be avoided. Again, we assume in both cases that the target is completely unknown beforehand.



(a) (b)

Figure 2: Using neural networks to find fragile surfaces such as solar panels (a), or detect the target satellite in the camera's view (b)

3.1 Satellite Surface Segmentation

Neural network models have been shown to perform well in image segmentation problems. We demonstrate that pre-trained models, such as Mask R-CNN [11], after finetuning on our training datasets, can be used to identify different surfaces on a target satellite. For example, in Figure 2a we see that this technique can determine which surfaces are more fragile, such as solar panels, that should be avoided. This is of particular use for contact-based active debris removal missions, where it is imperative that there is no risk of further break-ups as a result of making contact with the target. Other potential uses of surface segmentation include identifying suitable grappling locations; finding tough, flat surfaces at which to aim a harpoon; and identifying the locations of specific expected features, such as an engine.

3.2 Detecting Satellites in Images

Similarly, object detection is another area which has seen significant advances in recent years due to machine learning. We show that this, too, can be adapted to our problem. As shown in Figure 2b, we can use neural networks to determine the exact position of the target in the view of the on-board cameras. This can aid with relative navigation as well as enabling the images to be cropped around the area of interest for further processing.

4 Simulation of Co-Orbiting Satellites

Machine learning systems have the advantages of being fast and robust to non-linearities, such as the varying lighting conditions in space. On the contrary, the drawback of these methods is the requirement for vast amounts of labelled image data, required for training the network. Such a dataset does not exist for this problem, which is a hindrance to further investigation into the applications of machine learning in space-based guidance systems. In order to overcome this, we use synthetic image data generated by simulating the relative motion between two satellites, from the point of view of a chaser satellite. We also publicly release our datasets and the simulation framework used to construct them.

The synthetic datasets simulate the relative motion of co-orbiting satellites, capturing the lighting conditions of space and visualising a selection of realistic small satellite targets. The data is labelled with the 6D pose of both target and chaser satellites, the bounding box around the target and surface labels. The simulation framework allows control over all simulation parameters, enabling its application to various machine learning techniques and allowing for robust testing and analysis.

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