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Neural networks for event detection: an interplanetary cubesat asteroid mission case study

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CubeSats are a relatively new category of space systems that is becoming one of the key players for scientific and technological missions in Low Earth Orbit. Lately, interesting concepts for interplanetary nanosatellite missions are also appearing. These missions are affected by several technical limitations, spanning different domains of the mission and system design. Among these, limitations in the data rate and lack of proper ground support are definitely important. This paper focus the attention on event detection capabilities, with the intent of enabling autonomous operations for a nanosatellite interplanetary mission. The paper presents an artificial intelligence algorithm based on the neural network technology, and applies it to a future mission used as case study. The algorithm robustness is also verified.

I. Introduction

CUBESATS are a technology standard for a new category of space systems that was introduced in 1999 by professors Bob Twiggs and Jordi Puig-Suari. The standard specifies several requirements and directions for the design and development of simplified platforms to ease the access to space of universities and new players in the space industry. At the beginning of their history the technology was adopted mainly by US universities, with European and Japanese efforts closely following. Nowadays the CubeSat standard is a promising choice to implement innovative algorithms, or to perform In-Orbit-Testing of a newly developed payload. The result of this is that, to date, more than 450 CubeSats have been launched, both from universities, agencies and private companies. Furthermore, private companies investing and exploiting the standard to provide a service are increasing more and more (e.g. Planetary Resources has launched more than 50 CubeSats in one year) [1].

Thanks to this versatility, they are now being considered for interplanetary missions. The small dimensions are one of the key factor: CubeSats are now potential payload of bigger flagship missions, as the volume they occupy is often comparable to that taken by a complex scientific instrument. In addition, recent advances in propulsion and communication technologies are enabling the feasibility of stand-alone interplanetary CubeSats, that are not brought to the mission site by a bigger spacecraft.

With the consolidation of the technology and the know-how of CubeSat development, several interplanetary mission concepts have been proposed to date, and launches are already scheduled for an interesting number of them (Exploration Mission 1 (EM-1), scheduled to launch in 2018 as a test mission for the new Orion capsule and the new launcher, the Space Launch System, will deploy eleven CubeSat missions that will be placed in a lunar transfer orbit). Moon is not the only destination foreseen, as CubeSats missions have been proposed for Mars (MarCO), Europe (deployed by Europa), and asteroids (COPINS, deployed by AIM) [2,3].

When considering interplanetary missions, and especially low cost ones such as CubeSats missions can be, it is mandatory to include high degrees of autonomy in the architecture of the system. To obtain this, the attention can be surely put on the new frontiers of artificial intelligence algorithms, such as neural networks, fuzzy logics and more. One of the most interesting characteristics of these algorithms is that, if properly designed, they can be used to emulate the expert knowledge and therefore they can be applied in parallel, or even substitute, human workers in certain fields or during specific phases of a space mission, or to perform similar actions when Earth link is not available.

Furthermore, micro- and nano-satellites are one of the most appealing platforms on which to deploy these algorithms, for several reasons: they usually have faster, more flexible development cycles, and are less constrained with respect to larger and expensive traditional spacecraft. In this sense, they can be identified as the ideal test bed to apply new technologies. On the other hand, nano-satellite missions (and especially interplanetary missions) are characterized by a very stringent

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limiting factor: the low data rates available. Therefore, any algorithm that aims at improving the downlinked data would be beneficial to the missions.

This paper presents the use of artificial neural networks to perform event detection for an interplanetary mission to a Near Earth Asteroid carried out by a nanosatellite system. An algorithm to detect when a key mission event happens is presented and tested. The algorithm and the training strategy is designed taking into account the fact that no training can be performed on ground, before launch, since the actual image of the asteroid is not known a-priori.

II. Case study

The reference mission of the paper is the CubeSat Opportunity Payload Intersatellite Network Sensors mission (COPINS), and this mission constitutes one of the secondary payloads of the AIM mission (ESA). AIM is one of the two spacecraft of the joint effort between ESA and NASA to perform an asteroid characterization and redirection experiment. More in details, ESA will provide the monitoring spacecraft, while NASA will launch the impactor that will collide with the secondary body of the system [4].

COPINS mission consists in multiple CubeSats deployed in situ at the Didymos binary system. The small satellites will be carried to the asteroids by the AIM spacecraft, and will be deployed at 10km distance from the secondary body, up to one month before the impact event. The objectives of the CubeSat mission are to provide scientific support to the AIM spacecraft, either by repeating one or more of the main spacecraft's measurements, or by supporting the science goals by performing additional measurements. In addition, the CubeSats can also perform technological demonstration.

Since one of the main scientific objectives of AIM is to assess the impact and determine the change in the physical properties of the asteroid, and since the Earth-CubeSat communications are limited by the fact that the main spacecraft will serve as relay, it is important to carefully design the autonomy functions of the CubeSats, in order to make the operations as independent as possible.

The architecture of this mission is definitely peculiar, as numerous challenging elements will be present: four satellites, inter-satellite links, limited data rates, strict operations scenario and a peculiar environment for the mission, characterized by low intensity and irregular gravity field, that will make the navigation operations difficult.

A. A. The need for autonomy

Several key aspects are fundamental for the success of the described CubeSat mission, and different architecture aspects are among the first attempts of their kind in CubeSat space exploration. Among these we can surely notice:

1) Inter-satellite communication
2) CubeSat navigation and control in low and irregular gravity field
3) Limited data rates and complex scientific objectives
4) Operation control via mothership

One example of intersatellite communication in interplanetary mission involving CubeSats and a mothership is the aforementioned MarCO. Complexity arises from the communication architecture design, as there is the possibility of more than 1 CubeSat communicating at the same time with the mothership. Satellite navigation and control in irregular and low gravity field certainly poses difficulties even for bigger spacecraft [5], therefore CubeSat operations in a similar environment can be supposed complex.

COPINS scientific objectives (irrespective of which will be the final design selected) are likely to involve photography (optical, thermal), spectroscopy and video recording. All of these measurements usually generate a great quantitative of data. In the case of AIDA mission, there is a specified data allowance that can get transmitted by the CubeSats, through the AIM mothership, to Earth, and this is limited to 1 kbit/s (instantaneous) and 1 Gbit (over the mission lifetime) [6]. Similar to what specified for the downlink (CubeSats to Earth) operations, additional constraints exist, as the CubeSat operation control will happen via the mothership. Even in this case, the operation requirements for the mothership could hinder CubeSat control during specified time windows. For all these reasons, it appears evident the need to implement high degrees of autonomy in the Command and Data Handling (C&DH) Subsystem of the CubeSats.

The paper focuses on the autonomy of the payload management algorithms, in particular the research proposes a method to enable automatic payload activation and video/image selection by means of a neural network.

III. Neural networks

This paper proposes an algorithm to perform detection of unpredictable events in situ at a comet-like or asteroid-like body. The underlying technology for this algorithm is based on artificial neural networks (ANN), a type of artificial intelligence algorithms.

The neural networks have been developed in the attempt to model the information processing capabilities of biological nervous systems. In this sense, the science of artificial neural networks is based on the biological neuron, that is modelled on computers in a simplified form. In its basic version, it is modelled by including an input system (that receives the signals), a function entitled to join the signals, and an activation function that produces an output only if a certain threshold is reached. More complex forms include, for example, the possibility to store states in each computing unit (memory) [7]. This computing unit is then joined together with similar units in a complete network, as shown in Figure 2. Since each node in an artificial neural network can be seen as a primitive function capable of transforming its inputs in a precisely defined output, then neural networks as a whole are nothing but networks of primitive functions.

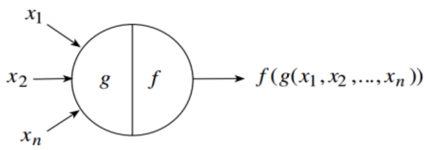

Figure 1. The generic computing unit. *The figure shows a generic model for the neuron used in common neural networks.*

B. A. Architecture

The typical neural network architecture is usually defined by characteristics parameters, such as the number of hidden layers, the number of neurons per layer, the input and output sizes, the weights of all connections and the connection directions.

Summarizing, the network architectures can be grouped into two main categories: feed-forward and recurrent networks, in which the second type differs by having connections that proceed backwards towards the input direction [8].

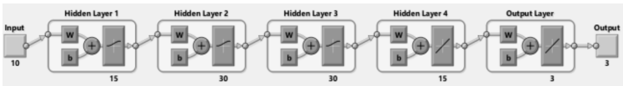

Figure 2. Feed forward neural network example. *In the figure it is possible to distinguish the different layers and the connections between them.*

C. B. Training

Furthermore, the architecture is not the only choice connected to the implementation of neural networks: the training algorithm is also a very important aspect. The problem of neural network learning can be seen as a function optimization problem, where we are trying to determine the best network parameters (weights and biases) in order to minimize network error [9].

Considering the training algorithms, several options and strategies are available, and they can be categorized in three main areas: supervised learning, unsupervised learning and reinforced learning.

1. Supervised learning

In supervised learning, the weights update is done considering datasets that are already categorized and analysed: the provided data already mimics (or is directly taken from) the desired behaviour of the network [8].

2. Unsupervised learning

On the other side, unsupervised learning does not require processed datasets to be provided during the training: instead, the network organizes itself autonomously [10].

3. Reinforced learning

Learning by reinforcement differs from standard supervised learning by two characteristics: input/output pairs are not directly presented to the algorithm, and errors and not-optimal actions are not corrected. In addition, the behaviour of the algorithm is dictated by the evolution of the states guided by a feedback signal, that allows the algorithm to evaluate the actions taken.

IV. Results

The algorithm for impact event detection has been designed keeping in mind the computational cost. The impact event has been simulated and tested from a particular capturing point, from where only the secondary body is shown in the frame. A video of the impact has been realized, with a framerate of 25 frames per second. Frames of the post-impact evolution were selected for the testing of the algorithm.

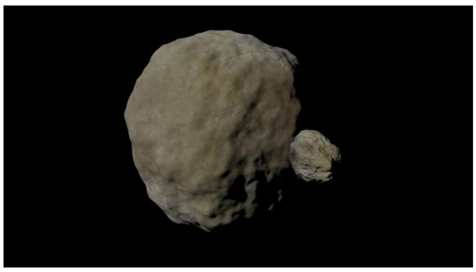

Figure 3. The binary asteroid system Didymos. *The figure shows the binary system as it was modelled in the work.*

D. A. Asteroid and impact modelling

Asteroid modelling and the impact sequence were a fundamental part of the algorithm verification. Didymos binary system was modelled as found on the literature in the Didymos Reference Model [11]. The main body has been modelled as a fairly regular spheroid of roughly 800m in diameter, while the secondary body (of which no radar images were available to date) was modelled as a bumpier, rubble-pile like body, elongated in the direction towards the main body of the system. The impact event has been modelled taking into account the results found in the literature. A spacecraft of the size comparable to DART's one has been inserted in the simulation, colliding at the speed of 6.1 km/s [12].

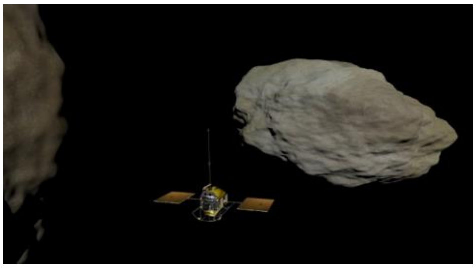

Figure 4. The secondary body of the system, Didymoon. *The actual shape and features of the secondary body are unknown.*

E. B. Network training and impact detection

The network training methodology is the following: use real, in situ taken, images of the asteroid for one class of the pattern recognition algorithm, and use real, in situ taken, images of the asteroid (with an overlay pattern to direct the neuron training) for the second class of the algorithm.

The directed training of the neural network algorithm allows to focus the event detection capabilities only on the area of the image that will experience the most aggressive changes.

The proposed simulation shows the correct identification of the impact event.

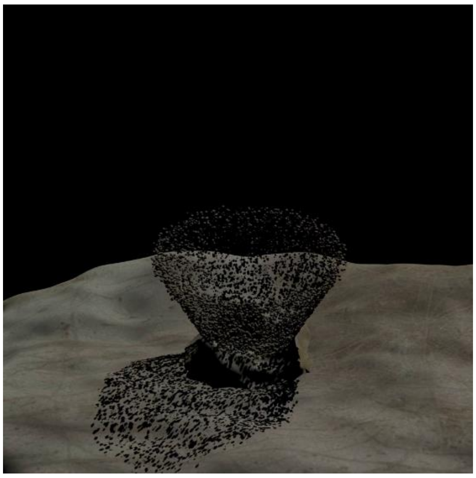

Figure 5. Impact event. *The simulation of the impact event was realized on blender®.*

F. C. Robustness to disturbances

Since the CubeSats can have peculiar orbit control requirements, it is important to test the algorithm to the disturbances due to the positioning errors that may arise. In particular, it must be guaranteed that the algorithm does not trigger false positive results in the event of images with different framing.

The algorithm has been tested using the same impact event and images from the non-impacted asteroid, changing the position of the camera.

To overcome the issue of positioning errors affecting the detection of the impact event, a straightforward solution can be employed: including images with different framing during the training phase. In this case, the network will be trained to compensate for position control imprecisions.

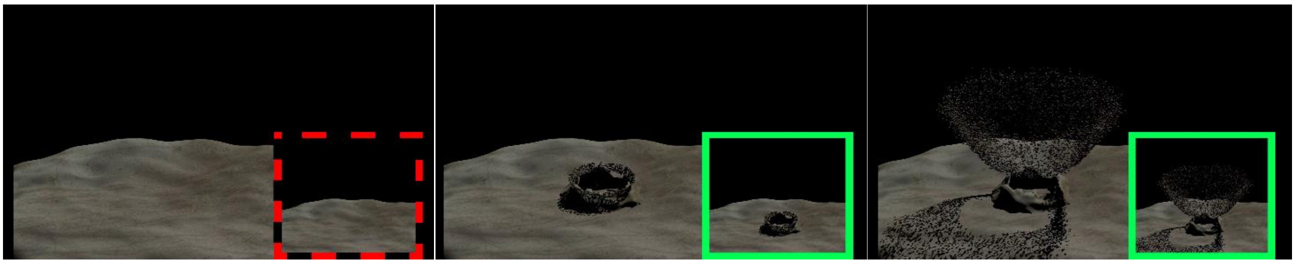

Figure 6. Impact event detection. *Figure shows three frames from the simulated impact sequence. The algorithm is able to identify when a change appears in the frame.*

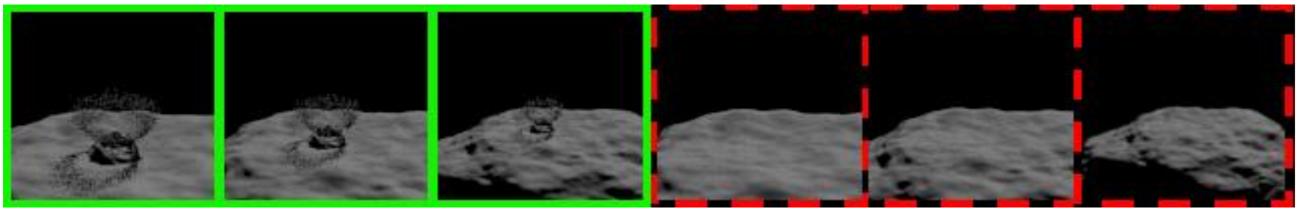

Figure 7. Robustness of the trained algorithm. *The figure shows a sequence of frames in which the asteroid (and the impact itself) are observed from different positions.*

V. Conclusions

CubeSats are set to be the new player even in complex scientific missions, thanks to the interesting mission architectures and operations that are enabled by this type of space systems. One of the major drawbacks of the CubeSats systems is the lack of autonomy, often caused by the simplifying approach used during the design and development of these space systems. Unfortunately, during certain types of missions, a high degree of autonomy is mandatory for the success of the operations.

An application of neural networks for event detection has been proposed, and an interplanetary case study has been used to perform simulations and tests on the algorithm developed. They key achievement of the paper is the use of feed forward neural networks to correctly identify an impact event autonomously. The novelty of the work resides in several aspects: the use of neural networks as mission autonomy enhancers has been scarcely considered in CubeSat systems, and the case study considers an innovative interplanetary mission. Furthermore, the in-situ online training of the network allows to overcome the uncertainties on the dataset that are currently present, since the shape and features of the asteroid are unknown at the moment. The artificial creation of impact images in-situ, with the intent of directing the neuron training, has shown promising results even considering positioning errors.

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