

DEEP-LEARNING OPTIMIZATION OF A TIME-CRITICAL MULTISPACECRAFT SWARM NEO DEFLECTION APPROACH





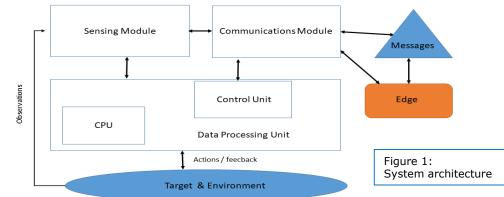
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The operations involve i) tracking the object to be deflected, ii) cooperative guidance for the multispacecraft swarm and iii) a multiple impact deflection on the target.

Each spacecraft is composed of the following modules: Sensing module, Data Processing Unit and Communications module (Figure 1):



In all possible NEO diameter sizes variations and distance to target hitting, optimal solutions are found for low-complexity processing units and a swarm in the order of 10¹ spacecraft units. Lower or higher number of spacecraft units or processing power result in a rapid descent of the system performance figure of merit as described below.

In order to further reduce delays it is proposed not to delegate anti-collision messaging operations to cloud and external nodes.

Based on the simulation results, a metric is proposed as a measure of the swarm proficiency. The figure of merit is the percentage of times the target is detected through time and for different numbers of spacecraft, based on the learning performance in terms of detection rate as proposed by Guerra and Guidi¹.

CONCLUSIONS:

As a conclusion, a hybrid approach in terms of sensing and fast communication capabilities, depending on the particular characteristics of the target, offers the best solution for optimizing the capabilities of this original deflection system. Employment of a large number of coordinated spacecraft accelerates the learning procedure, which is critical when exploring huge environments. Nevertheless, communication delays, in particular with the edge, is a downside that needs to be taken into account when enlarging the size of the spacecraft swarm.

INTRODUCTION:

We hereby present results of the analysis of a multispacecraft swarm NEO deflection simulation using deep learning techniques. Spacecraft could be simpler and operate longer and farther only if their computational capabilities could be transferred to a network. However, in tasks that are time-critical such as the uncommon situation of the deflection of a NEO object, whether this delegation of "intelligence" could be operational in practical terms is still a matter of research..

KEYWORDS:

Deflection, deep learning, swarm, time-critical, multi-agent systems.

SYSTEM ARCHITECTURE:

A multispacecraft swarm of spacecraft should be able to operate and react with a very small latency delay. A multi-agent system has been proposed in a variety of similar applications such as Low-Complexity UAVs¹. In these situations preserving low complexity and low latency for computational data transmission is essential in order for the system to undertake automatic and reliable decisions quickly. Furthermore, a multi-agent system also preserves energy consumption. On the other side, larger swarms may fail to provide reliable full connectivity. An architecture of signal processing techniques is proposed for a swarm multispacecraft network intended to deflect a NEO object.

SIMULATION AND RESULTS:

A real scenario with a NEO object has been simulated afterwards with different swarm architecture configurations. We analyse in particular the localization impact accuracy versus different approach velocities and spacecraft swarm number. Optimization of different parameters has been conducted with a deep learning analysis. Parameters include: approach velocity, distance to target, spacecraft number, NEO diameter, computational capability and spacecraft variability. NEO diameter is varied from 10m. diameter to 700m. diameter. Distance to target may vary from 100km. to close encounter and hitting the target. Spacecraft number ranges from 1 to 500, where computational capability ranges from simple 10^5 Gflops to 10^{12} Gflops although these last ones cannot be considered as low-complexity processing units. Spacecraft variability is defined as maximum communication range from r=0.1 km to r=1 km, up to five hops.

Reference:

¹Guerra A. & Guidi F., "Networks of UAVs of Low complexity for Time-Critical Localization", *IEEE Aerospace and Electronic Systems*, vol. 37, 10, 22-38 (2022).