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

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Extended Abstract—

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.

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 UAVs[1]. 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 (Figure 1). 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.

Design of the communication protocol and the physical distribution of the multispacecraft swarm are closely interconnected. If a unit is unable to process the computational load on-board in real time, it should delegate the processing to an external entity (the cloud or an edge) so that a communication protocol is required. The protocol should be able to push and pull packets with information from the sensors. On the contrary, if the processor power is enough to process the information completely on-board, then the most feasible protocol are D2D (device-to-device) communications.

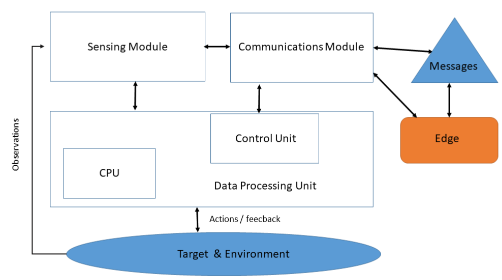

Figure 1: System Architecture.

The network of multispacecraft comprises the following modules:

- Sensing module. Allowing sensors to observe environment and target.
- Core module. It refers to the capability of each spacecraft to process data, acquire critical information about the environment and take decisions to interact or delegate some tasks to other multispacecraft entities.
- Communication module. It makes possible to exchange messages with other entities in the network through radio transmitters.

The interactions between each spacecraft and the others and the environment is specified as follows:

- Measurements: sensors inform about the environment and target.

- Acting: An agent can enable movements to navigate and optimize performance of the network.
- Metrics: They are a combination of quantitative indicators that are related to the accuracy of hitting the target.
- Messaging: They can be spacecraft to spacecraft or edge messages. They allow cooperation between different spacecraft or with the edge.

It is worth discussing here that D2D communications delays and infrastructure-based communication schemes on the spacecraft swarm may have a role in the overall performance of the system. Our choice requires a higher degree in terms of flexibility of communication modes. Each spacecraft is considered as a low-complexity agent dynamically acquiring new knowledge from the environment and also from the final target via observations collected permanently.

A real scenario with a NEO object has been simulated 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.

The deep learning optimization process was performed using Stochastic Gradient Descent (SGD) Algorithm with momentum, with Python code and Numpy.

NEO diameter ranges from 10 m. diameter to 700 m. Distance to target may vary from 100 km. 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 in terms of maximum communication range from r=0.1 km. to r=1 km. and up to five hops. In all possible NEO diameter sizes variations and distance to target hitting, optimal solutions arefound for low-complexity processing units and a swarm in the order of 10^1 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.

When the spacecraft network runs fully on a D2D configuration, not delegated to the edge or external entities, the processing task is performed locally, exchanging data with other spacecraft. Then each spacecraft from the swarm runs with a limited amount of data which has been recently collected by its sensors and D2D messaging with sensed or processed information about swarm location information.

On the other side, when low-processing power spacecraft are due to process a large amount of information in order to perform complex movements, and at the same time, some spacecraft are isolated, a sudden decrease of performance may appear. On the contrary, when the swarm is fully interconnected, it makes possible to perform fast decisions as the spacecraft does not need to interact with external units. This latter situation further increases the reliability of the system against temporary glitches or malfunctions which can suddenly appear during a deflection mission.

As the swarm is not supervised, the spacecraft can make up clusters simply adding to the shortest distance among them (in multiple hops) or relying in a configuration that allows the different spacecraft to rely on one another. In order to preserve low latency, some packets carrying messages can then be dropped and therefore, lost. Then, the availability of information may impact the accuracy of real-time decision-making.

Regarding the spacecraft agent intelligence, it is proposed a double-module intelligence processing unit:

i) A fast AI engine module that integrates the available information and estimates the location and velocity of the target, and

ii) A Control Module allowing for dynamic learning and updating rules and policy strategy.

A computational complexity analysis has been performed as well. We have evidenced in the simulations that the edge can be of benefit in reducing the overall time needed for identifying the optimal swarm formation that leads to better approaching the target. 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 Guidi[1].

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.

Reference:

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