Designing A Federated Learning Satellite System to Incentivize Space Situational Awareness and Mitigate Space Debris

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***Abstract*—This paper proposes a solution to address the challenges posed by the increasing number of satellites in space, leading to a lack of Space Situational Awareness (SSA) and cooperation in space debris mitigation. The proposed solution involves a commercially incentivized federated system of sensors applied to a federated learning model. This approach aims to provide an accurate, up-to-date, and open-source data model to prevent collisions in space. The solution focuses on two main aspects: Federated Satellite Systems and Federated Learning. By combining these technologies, we can improve SSA, enhance space debris mitigation efforts, and promote cooperation among space-faring nations**

***Keywords*— Space Situational Awareness, SSA, Federated Satellite Systems, Federated Learning, Space Debris Mitigation.**

I. Introduction

The increasing number of satellites being launched into space has led to a crowded and complex orbital environment, resulting in a lack of knowledge regarding the location and trajectory of objects in space. This poses a significant challenge to Space Situational Awareness (SSA). Additionally, there is a lack of cooperation among space-faring nations to mitigate and avoid space debris, further complicating the situation. To address these challenges, this paper proposes the use of a commercially incentivized federated system of sensors applied to a federated learning model.

II. Federated Satellite Systems

Federated Satellite Systems (FSS) are a network of satellites that work together to achieve a common goal. By sharing data and resources, FSS can improve SSA by providing a more comprehensive view of the orbital environment. Additionally, FSS can enhance space debris mitigation efforts by detecting and tracking debris in space. To incentivize the use of FSS, commercial entities can be given access to the data collected by the system, which can be used for various purposes such as satellite navigation, weather forecasting, and telecommunications.

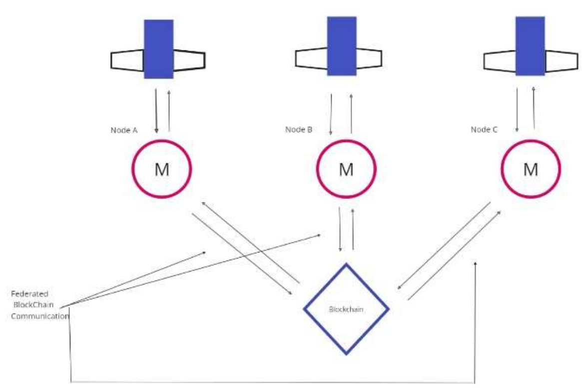

Figure 1: Federated System Representation

III. Implementation in Satellite Systems

The implementation of the proposed solution in satellite systems involves the use of advanced sensors such as Lidar and other technologies for detection purposes. Lidar (Light Detection and Ranging) sensors can be used to accurately measure distances to objects in space by illuminating them with laser light and measuring the reflected light. These sensors can provide detailed information about the position and trajectory of objects in space,

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which is crucial for SSA and space debris mitigation efforts. Other technologies, such as radar and optical sensors, can also be used in conjunction with Lidar to improve detection capabilities. By integrating these sensors into satellite systems and applying Federated Learning techniques, we can create a powerful tool for improving SSA and enhancing space debris mitigation efforts.

A. Sensors for Tracking Under-Catalogued Space Debris:

1. LiDAR (Light Detection and Ranging): LiDAR systems emit pulsed lasers and measure the reflected light's time-of-flight to determine the distance and size of objects. Their high-resolution 3D data allows for effective detection and characterization of debris in this size range.

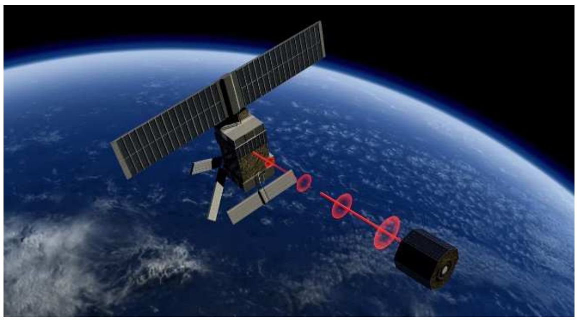

Figure 2: LiDAR Integrated on a Satellite.

2. Millimetre-wave Radar: Operates at higher frequencies than conventional radars, offering superior resolution. This enables the detection of smaller objects (1-10 cm) due to the shorter wavelengths used, providing a clearer picture of the debris' presence and movement.
3. Optical Sensors with Image Processing: High-speed cameras capture rapid sequences of images. Advanced algorithms analyze these images to identify debris objects based on their size, shape, and movement patterns relative to the background. This offers the potential to track debris even in low-light conditions.

B. STAR TRACKERS

Using the multi-star tracker joint positioning method, the angle measurement data of the star tracker is converted into the spatial coordinates of the target. Most satellites already have one or more star trackers for attitude determination, which, if properly utilized, can constitute a zero-cost space surveillance system. In this way, unlike most space-based missions designed specifically for space situational awareness, no specific attitude maneuver is required.

Detection of Space Debris

- Detecting space debris is essential for SSA and space debris mitigation efforts. Advanced sensors such as LiDAR detection technologies, such as radar and optical sensors, can be used to detect space debris and track its trajectories. By integrating these sensors into satellite systems and using federated learning techniques, we can create a comprehensive system for detecting and tracking space debris, helping to prevent collisions and improve space situational awareness.

i. Conditions needed to improve the detection capability the system:

- High atmospheric transmission- achieved from high altitude and low target zenith angle
- Low Sky Background Radiance (SBR)- achieved from a small target zenith angle and low solar altitude

ii. Methods to improve the detection capability:

- Increasing the receiving aperture of the telescope.
- Improving the quantum efficiency of the detector.
- Increasing the emitting power and frequency of the laser.

While this approach deals with the lack of data, another key issue is a lack of cooperation in sharing data among all involved parties. This is where using a federated learning model can facilitate collaboration and reduce resistance to sharing data. The federated learning model uses blockchain technology to allow secure and accurate sharing of information about orbital data to train a machine learning model. This model will be trained to compute and predict conjunction events among satellites in space and inform the affected operator to perform necessary maneuvers.

Consider a scenario where multiple countries are collaborating to track satellites in orbit to avoid collisions. Each country possesses its satellite tracking data, which is sensitive and confidential. Traditionally, sharing this data directly could pose security risks as it could be intercepted or tampered with by malicious actors.

IV. Federated Learning

Federated Learning is a machine learning approach that enables multiple parties to collaborate on a machine learning model without sharing their data. This is achieved by training the model locally on each party's data and then aggregating the model updates to create a global model. Federated Learning can be applied to SSA by using data from various sources, such as ground-based sensors, telescopes, and satellites, to train a model that can predict the location and trajectory of objects in space. By using Federated Learning, we can create an accurate and up-to-date data model for SSA, which can help prevent collisions in space.

A. FEDERATED LEARNING WITH BLOCKCHAIN CAN PROVIDE A SECURE SOLUTION IN THIS SCENARIO

1. Every nation uses its own satellite monitoring data to build a local model. Instead of storing the raw data, the model learns to recognize patterns and forecast the motion of satellites.
2. Uploaded to a blockchain are the model updates as opposed to the raw data. Since changes on blockchain are visible and safe, they cannot be removed or changed when they are recorded.
3. The blockchain is available to all participating nations, enabling them to confirm the accuracy of the model changes.
4. The model updates from every nation are combined by a central algorithm to produce a global model that includes all of the data. Predicting satellite trajectories and identifying possible collision risks can be done with this global model

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❖ ***Benefits of using blockchain in this scenario:***

A. Security: The security and integrity of the training data are guaranteed by the tamper-proof nature of blockchain technology. An attacker cannot change the data or insert harmful updates without being discovered, even if they get to access the blockchain.

B. Transparency: By allowing everyone to view the complete history of model revisions, this promotes international cooperation and mutual confidence.

C. Privacy: Sensitive information is protected because no nation is required to disclose its raw satellite monitoring data directly.

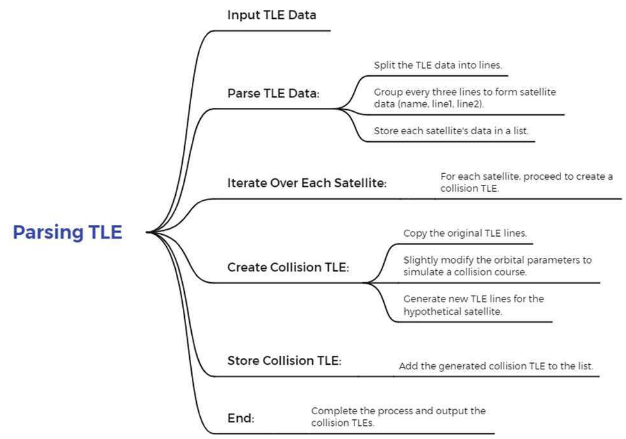
❖ **Challenges of using blockchain in this scenario:**

A. Scalability: Blockchain technology requires access to enormous computational resources, which vary depending on how many countries use it. When dealing with a high number of data, it can become slow and incompetent.

B. Complexity: Setting up and maintaining a federated learning system based on blockchain technology can be difficult, requiring cooperation between the participating nations as well as technical know-how.

C. Security of the underlying platform: The federated learning system as a whole could be compromised by security flaws in the particular blockchain platform that is being used.

B. MODEL OVERVIEW



TLE data is a standard format encoding the orbital elements of satellites, necessary for tracking and prediction. Each satellite's TLE consists of two lines containing numerical values representing its orbital parameters. The parsing process involves splitting the TLE data into individual lines and grouping them to form satellite data sets (name, line1, line2). This parsed data is essential for further calculations and simulations.

To understand the potential for satellite collisions, it's vital to calculate the relative distances and velocities between satellites. Using the SGP4 (Simplified General Perturbations) model, which propagates the orbits of satellites based on their TLE data, we can obtain position and velocity vectors for each satellite. By computing the Euclidean distance between position vectors and the difference between velocity vectors, we determine the relative distance and velocity, which indicates the potential for collision.

To simulate potential collision scenarios, we generate hypothetical TLEs that represent satellites on a collision course with existing satellites. This involves slightly modifying the original orbital parameters (inclination, right ascension, eccentricity, argument of perigee, mean anomaly, and mean motion) to create new TLEs that are close enough to simulate a collision.

The implementation involves parsing TLE data, calculating relative distances and velocities, and generating hypothetical collision TLEs. The code utilizes libraries such as `sgp4` for orbit propagation and custom functions to handle data parsing and modification.

We are considering and looking into Logistics Regression and Random Forest for the mentioned applications as we get a scope of scalability without compromising the model.

V. Conclusion

In conclusion, the proposed solution offers a novel approach to improving SSA and enhancing space debris mitigation efforts. By using a commercially incentivized federated system of sensors applied to a federated learning model, we can create an accurate, up-to-date, and open-source data model for SSA, which can help prevent collisions in space and promote cooperation among space-faring nations. The implementation of advanced sensors and detection technologies, such as Lidar, can further enhance the effectiveness of the proposed solution by improving the detection of small debris particles and space debris in general.

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Team SAHA

Spacecraft Automated Harmonisation Algorithms

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