Autonomous Spacecraft Safety: Combining Image Processing and Artificial Intelligence for Real-time Obstacle Avoidance in Space Environments

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1. Introduction: Image Processing and AI in Space

1.1 Current Space Exploration Panorama

As space exploration and travel begin to rise, the need for more advanced, efficient and foolproof software is needed to further make these journeys safe. Therefore, for both manned and unmanned missions, there are already systems such as the DCAS, Debris Collision Avoidance Systems, but currently it has limitations that as of 2024 need to be overcome to aid missions, from simple orbiting satellites to lunar or planetary missions.

Spacecraft require not only robust systems to ensure their safety from various threats, including space debris, but also advanced capabilities to process incoming data autonomously. Combining **image processing** with **artificial intelligence (AI)** for obstacle detection provides a cutting-edge approach to real-time debris avoidance in space. Unlike traditional systems, which are reactive and dependent on Earth-based intervention (e.g., NASA's Deep Space Network), an AI-powered onboard system can process visual data, make predictive decisions, and autonomously adjust its trajectory in a matter of milliseconds.

As of late 2023, there have been an estimate of over 13 000 orbital launches, since the beginning of space age in 1957. Estimate analysis suggest there are around:

- 36 500 pieces of debris larger than 10 cm.
- 1 million pieces of debris between 1 cm and 10 cm.
- 130 million pieces of debris between 1 mm to 1 cm.

These estimates come from data provided by organizations like the European Space Agency (ESA), NASA and other space monitoring systems. The largest debris (greater than 10cm) are actively tracked by space surveillance networks, while smaller debris is estimated based on sampling, modeling, and detection systems like radar and optical telescopes.

The complexity of space navigation lies in the sheer speed at which debris travels, with velocities often exceeding 27,000 km/h. At these speeds, even small objects can cause catastrophic damage. Given the limitations of human intervention—such as communication delays of several minutes when a spacecraft is at interplanetary distances—autonomous systems must take over critical decision-making processes. Image processing techniques, such as **edge detection** and **optical flow**, allow spacecraft to detect debris in real-time, while AI algorithms use this data to predict the trajectory of objects and determine collision probabilities.

Alternatives such as LiDAR (Light Detection and Ranging) can give us reliable data regarding objects, using lasers to emit light pulses and measure the time it takes for the light to return. It also offers high-resolution, three-dimensional data, but its cost and power efficiency make other systems more viable depending on the specific scenario the spacecraft will be put in.

1.2 Proposition

On this document we'll be looking at techniques involving algorithms and image processing with the goal to create an efficient autonomous system that will analyze visual data provided from the spacecraft and use its local hardware to choose the best maneuver to execute.

2. Image Processing and AI for Debris Detection

Incorporating **image processing** and **machine learning** enables spacecraft to effectively identify, track, and predict debris movement. Here's a deeper look at the methods:

2.1 Image Processing Techniques

- **Edge Detection**: Techniques like the **Canny**, **Laplacian of Gaussian** and **Sobel** algorithms are essential for detecting the boundaries of objects in images. This allows the spacecraft to differentiate objects from the background of space. By scanning images taken by onboard cameras, the system identifies potential obstacles and determines their size and location.
- **Object Detection and Classification**: Using a **Convolutional Neural Network (CNN)**, the spacecraft can classify objects based on their shape, size, and velocity. This classification helps determine whether the object is debris, a star, or simply a harmless particle of dust. CNNs have

proven highly effective in real-time object recognition applications and can be trained to adapt to the unique challenges of space.

- **Optical Flow**: This method involves analyzing the movement of pixels across sequential images to track debris motion. Optical flow is particularly useful for predicting the future path of objects. When integrated with an AI model, it enables the spacecraft to determine if a debris object will cross its flight path.

2.2 Artificial Intelligence Approaches

AI adds a critical layer of intelligence to image processing. Once objects have been detected and classified, AI helps in making predictions and decisions:

- **Convolutional Neural Networks (CNNs)**: Trained to recognize space debris, CNNs can classify objects with high accuracy and speed. When paired with **Recurrent Neural Networks (RNNs)**, which specialize in time-series predictions, the system can predict the future position of debris based on its current trajectory.
- **Reinforcement Learning (RL)**: In an RL framework, the spacecraft "learns" optimal avoidance strategies by simulating thousands of possible scenarios. Over time, the system becomes better at selecting the most energy-efficient and safe maneuver. This method allows the spacecraft to continuously improve its decision-making even in new and unforeseen conditions

3. Redundancy and Failure Handling

Redundancy is crucial in any spacecraft system. In the event of thruster or sensor failure, the AI must dynamically adjust its control strategy. One possible solution is using a **fault-tolerant control system**, which adjusts the spacecraft's movements based on which thrusters are operational.

The AI can be trained using simulations where different thrusters or sensors are disabled. The goal is to ensure that, even with partial system failures, the spacecraft can still calculate a safe maneuver. For instance,

supervised learning algorithms could be trained to recognize sensor malfunctions based on anomalies in the data streams.

4. Testing Process

To begin testing and developing, there were X steps needed to be taken:

- Gather sample images valid enough to serve as space obstacle examples;
- Develop codes for each of the digital image processing techniques. Along with the processing itself, we also need to include parameters to set apart their individual performance, storing them in a standalone file for future analysis;
- With the new images now in hand, and a performance log, we developed another code to calculate the average time for each method and plot a graph to visualize their differences;
- After these processes, an object avoidance algorithm was created to infer the maneuver necessary, going through the object's edges and calculating its center;
- With all the previous steps tested, a main code was created to isolate all chosen methods into one file and to output an image for simulation.
- The simulation process involves using the object avoidance algorithm along with real-time images taken from the Gazebo software's camera, of a simulated space with an obstacle, to verify its efficiency and confirm that it can avoid incoming collisions.

5. Comparison of Approaches

Current approaches, such as **Debris Collision Avoidance Systems (DCAS)**, rely on radar and Earth-based monitoring to track large pieces of debris. However, these systems have limitations in responsiveness, especially for smaller debris that aren't actively tracked.

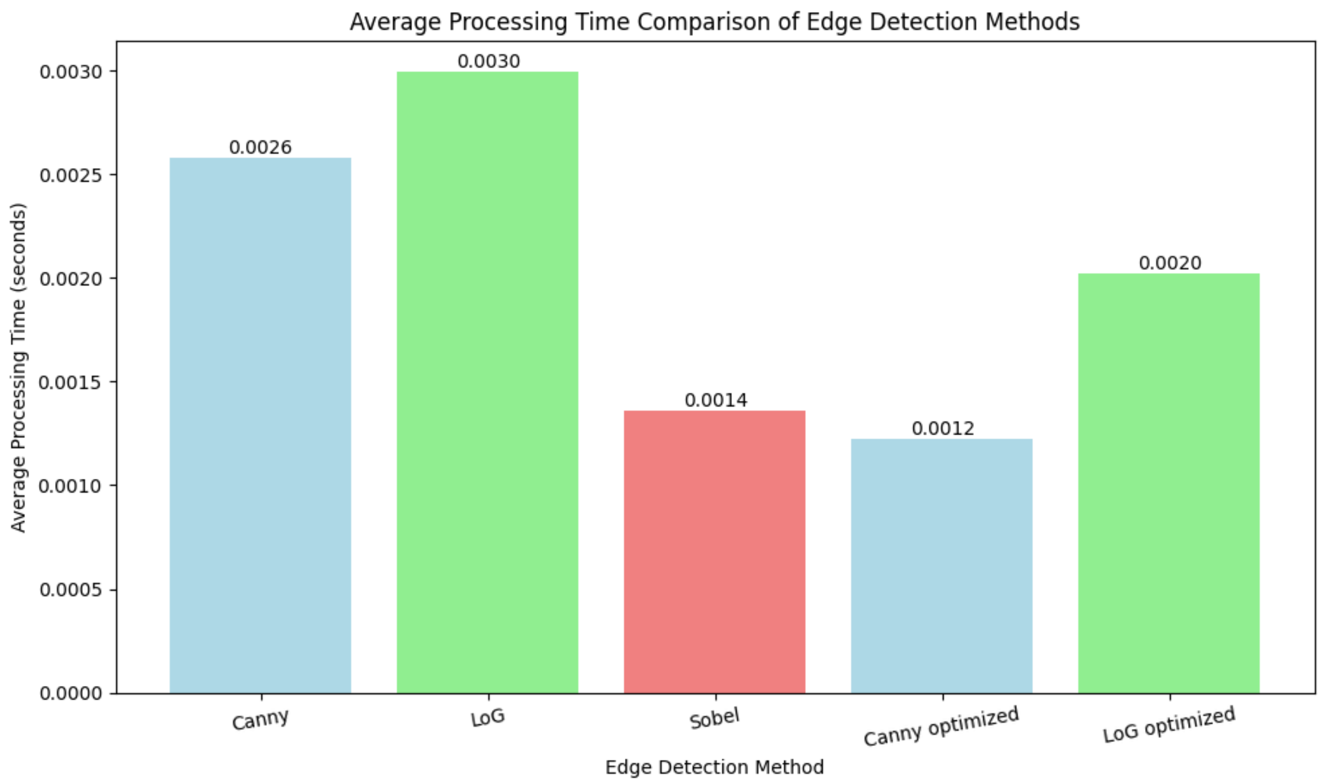
Method	Advantages	Disadvantages
DCAS (Radar-based)	Real-time updates for larger debris	Requires Earth-based intervention
AI + Image Processing	Can operate autonomously and track all sizes	Computationally intensive onboard
Lidar-based	Works in low-light or obscured environments	Expensive and complex

Using AI and image processing onboard solves the issue of communication delays and allows the spacecraft to operate autonomously. While radar-based systems can detect large objects, they rely on external tracking, whereas AI-based systems can handle real-time, small debris detection.

5.1 Image Processing Techniques

Method	Processing Time	Detection Quality	Robustness	Efficiency
Canny	2.6 ms	High	Ignores too much visual data	Low resource use
Laplacian of Gaussian	3 ms	Very high, precise	Moderate to High	Moderate resource use
Sobel Operator	1.4 ms	High, directional	Low, easily becomes noisy	High resource use

Each technique has its advantages and disadvantages. Differences in contrast, brightness, natural light and faraway objects, such as stars, can alter the results drastically, but we can apply some minor changes to their processing to optimize the time, power efficiency, robustness and quality of each one, and overcome these problems.



Apart from the Sobel method, both Canny and Laplacian of Gaussian gained significant advantages to processing time.

With controlled sample images of 256x256 dimensions, the difference in performance after optimizations is virtually irrelevant – from 1.2 ms to 2 ms. Therefore, the technique utilized will be based on its output quality and future performance when integrated with the AI classification and simulation algorithms.

5.2 Image Output Quality

The following images' colors are inverted for better visualization on paper. In them we can see the different results and how they can influence the next steps of the simulation process. All three methods are effective to highlight the objects, though Canny has the most, perhaps, specialized edge detection – whereas the others show a fuller representation of the objects.

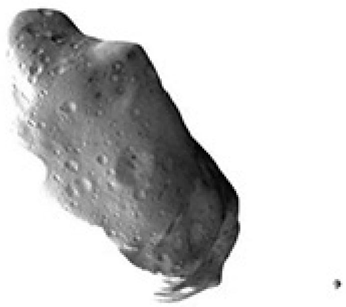


Figure 1 - Sample

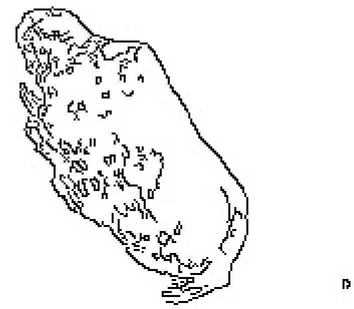


Figure 2 - Canny

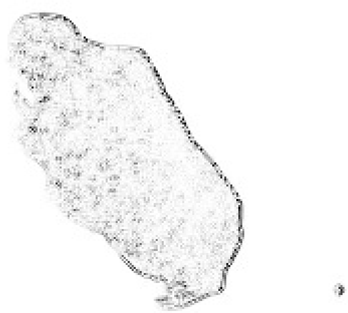


Figure 3 - Laplacian of Gaussian

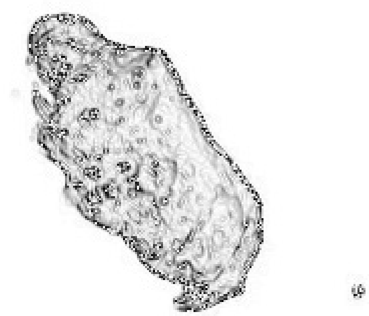


Figure 4 - Sobel Operator

6. Simulation and Testing

To validate the effectiveness of the proposed method, simulations must be conducted. We can use **OpenCV** for real-time image processing and **TensorFlow** for AI modeling. A test environment can be created in **Gazebo** to simulate various debris fields, spacecraft trajectories, and failure modes (e.g., thruster or sensor failure).

In the simulations:

- The spacecraft will be subjected to debris fields with varying densities and velocities.
- The system's response time, energy efficiency, and accuracy in avoiding collisions will be measured.
- Redundancy will be tested by disabling thrusters and sensors in certain simulations to see how the AI adapts.

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