ASEN 6519 Project Proposal

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1 Application and Context

Landmark-based navigation techniques have been used reliably in recent space missions to inform the positioning of a spacecraft relative to a body of interest during proximity navigation operations. The landmark information supplements star-tracker, DSN, and other forms of localization data, and enables the spacecraft to reference it's position relative to the body. The OSIRIS-REx mission recently demonstrated a significantly long period of landmark-based navigation implemented beginning in it's Orbit A mission phase and extending until the Touch-And-Go sample gathering maneuver [1]. The Orbit Determination team was able to utilize 200 landmark locations to calculate the nominal trajectory of the spacecraft, supplemented with star observations which could be compared to a catalog [2]. We would like to approach a similar problem for small body exploration. While this mission demonstrated the the benefit of landmark-based navigation, there is additional work to address the issue of navigating around the dark side of the target. If the navigation solution is focused on processing landmark-only data in order to solve for the spacecraft orbit, then it must be robust enough during periods of the orbit where landmarks are not visible or not present. This procedure is significant to investigate in order to learn the limits of the small-body navigation problem, and to identify if certain filtering solutions can overcome periods of drift. The primary motivation for proximity navigation is to enable scientific goals of the mission. A part of these goals are to estimate the gravity of the target body. Estimating this has the additional benefit of refining the dynamics propagation and therefore improve the overall navigation solution.

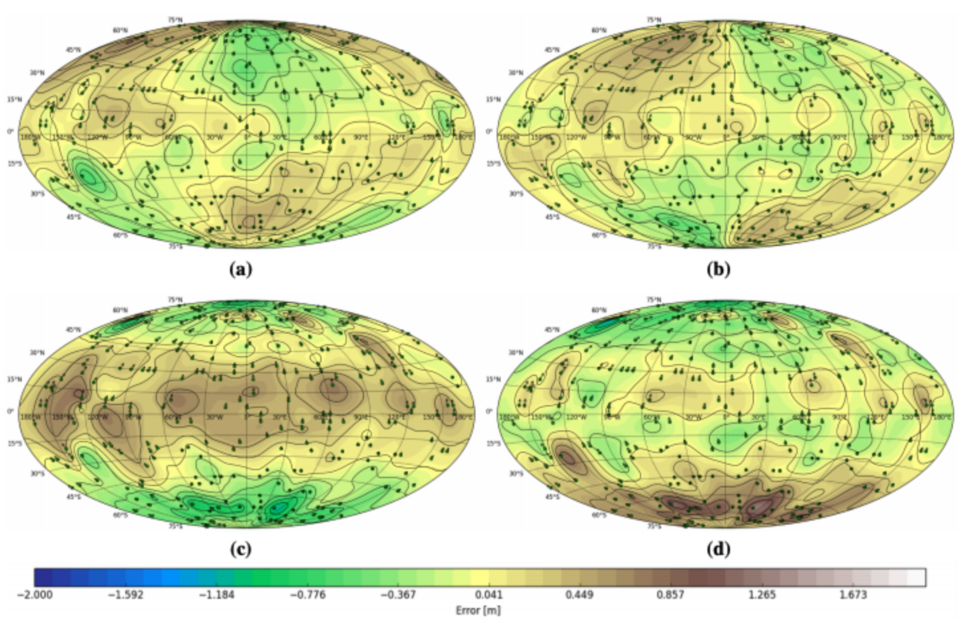

Figure 1: Landmarks Identified by OSIRIS-REx Orbit Determination Team on Bennu during Orbit A

This work aims to perform orbit determination and gravity estimation with infrequent bursts of measurements coupled with long periods of measurement gaps as the spacecraft is eclipsed by the target body. This procedure should be processed autonomously as if done onboard for the spacecraft navigation suite. The input data will be modeled as landmark positions identified from hypothetical optical images. There will be a priori knowledge of the landmarks, and we can assume perfect association between identified landmarks and their coordinated landmark database entry.

We expect the gaps in measurements to cause the significant errors in due to the IMU errors. We expect that the Extended Kalman Filter approach may fail due to the non-linearity of the orbit dynamics, as well as the uncertainty propagation through the measurement gaps. Implementation of more advanced filtering methods may bridge the gap between the assumptions of the EKF and the actual dynamics of the problem, as well as being able to retain robustness over gaps in data input. Uncertainty will be introduced through error in measurements, general process noise, and uncertainty in the gravity of the celestial body. There will also be an investigation into different orders of the gravity field, in which higher orders may be ignored or included during the estimation procedure. This approach to pose and parameter state estimation will address a current problem in modern-day space exploration as well as investigate the limits of specific filtering methods when faced with periods of data loss.

2 Initial Problem Formulation

2.1 Problem Statement

Using precise landmark position information identified from the surface of an asteroid and IMU data taken onboard, estimate the spacecraft position, velocity, and attitude in the body-fixed frame, as well as the gravitational mass parameter of the planetary body despite error in measurement data, IMU uncertainty, and process noise.

The sources of noise in this problem setup are going to be from the measurement errors, IMU error, and additional process noise implemented within the filters. We will be assuming perfectly known camera projection models. A major assumption being made for this approach is that we have access to predetermined landmark database locations which would have been obtained prior to the orbiting stage of the mission. These landmark locations will be known down to a certain degree of precision, and we will implement measurement noise appropriate for the accuracy expected for the range at which our observations will be made.

2.2 Key Variables

Here is the expected formulation of the filter state. It will consist of the spacecraft position, velocity & attitude (represented as a quaternion), estimated IMU errors, and target body gravity parameters (μ, J_2 etc). Here is a sample filter state we expect to be used in this project:

$$\hat{\mathbf{x}}_{S/C} = [\hat{x}, \hat{y}, \hat{z}, \dot{\hat{x}}, \dot{\hat{y}}, \dot{\hat{z}}, a_b, a_{sf}, g_b, g_{sf}, \hat{q}_i^b, \mu, J_2]^T$$

2.3 Sensor and Dynamics Models

We expect to have an IMU and an optical camera in this project.

- **IMU Model:** Will have an accelerometer and gyroscope. The model will simulate accelerometer and gyro bias and drift that the filter will have to estimate.
- **Camera Model:** We will model the camera to have a specific field-of-view (FOV) such that only a subset of the available landmarks are visible. The discrete time measurement model is the line of sight vectors to each identifiable landmark, l_i, in an image taken at time t_k. The number of landmarks varies in each image based on observability.

$$y(t_k) = LOS(l_1, l_2, \cdots, l_i) = \begin{bmatrix} x_{S/C}(1:3) - \vec{l}_1 \\ x_{S/C}(1:3) - \vec{l}_2 \\ \vdots \\ x_{S/C}(1:3) - \vec{l}_i \end{bmatrix}_{BF}$$

where the landmark vector is given also in body-frame coordinates,

$$\vec{l}_i = [x, y, z]_{BF}$$

- **Dynamics Model:** The dynamics will be modeled as two-body orbit problem with the higher order gravity terms modeled as perturbing accelerations. Here is the differential equation for this system

$$\ddot{\mathbf{r}} = \frac{\mu}{r^3}\mathbf{r} + \frac{\partial U}{\partial \mathbf{r}}$$

where U is the higher order gravitational potential function and $\mathbf{r}$ is the spacecraft position.

3 Objectives

- **Level 1**:
  - Characterize the orbit determination problem with the appropriate dynamics, measurement, and noise models
  - Implement an Unscented Kalman Filter over multiple orbits of simulated data which includes lit/unlit transition gaps
  - Implement a Rao-Blackwellized Particle Filter with covariances below that of unrestricted IMU drift
- **Level 2**:
  - Improve the RB Particle Filter solution with IMU Drift as an error comparison
  - Investigate sensor fusion with the integration of StarTracker information and compare results using the particle filter
  - Implement a Gaussian Mixture Model approach to compare to the UKF and RBPF, using one metric of split and one metric for compression
- **Level 3**: Investigate and compare Gaussian Mixture Model approaches with varying levels of split and compression in order to improve upon model uncertainty

4 Task and Milestone Roadmap

4.1 Key Tasks

- Develop the dynamics and measurement models (Level 1)
- Implement an Unscented Kalman Filter (Level 1)
- Implement a Rao-Blackwellized Particle Filter (Level 1)
- Perform comparison of the UKF and RBPF (Level 1)
- Improve upon the initial Particle Filter implementation (Level 2)
- Implement the Gaussian Mixture Model with one approach of assuming Gaussian process noise and measurement noise, using the mixture model on the prior distribution (Level 2)
- Implement the Gaussian Mixture Model approach with multiple options for the split and compression (Level 3)

4.2 Milestones

1. Have the dynamics and measurement models completed
2. Working implementation of the Unscented Kalman Filter approach
3. Implementation of Particle Filter that provides better estimates than IMU Drift
4. Improved particle filter performance
5. Working implementation of the Gaussian Mixture Model/Gaussian Sum Filter
6. Improved/Tuned Gaussian Mixture Model

4.3 Metrics for Success

This work will be considered successful if the proposed filtering approaches at the Level 2 priority are able to perform orbit determination and gravity estimation after gaps in the measurement data. This success will be characterized by an Unscented Kalman Filter which may diverge in the gap of measurements, but a Rao-Blackwellized Particle Filter which can be robust to the time gap and a Gaussian Mixture Model which can also begin to re-converge on an orbit solution after a period of model divergence during the measurement gap. All filters will be compared to the navigation solution resulting from pure IMU drift. A decent navigation solution will constrain spacecraft position and velocity, attitude, and gravity uncertainty below a pre-defined threshold.

4.4 Work Distribution

The distribution of effort in the proposed project is defined as follows:

- Ken Kuppa - responsible for the dynamics model, IMU model, Unscented Kalman Filter implementation and results, and a shared role in the Gaussian Mixture Model including a unique approach to the split and compression factors
- Dahlia Baker - responsible for the measurement model, camera model, Rao-Blackwellized Particle Filter implementation and results, and a shared role in the Gaussian Mixture Model including a unique approach to the split and compression factors

References

[1] Coralie D. Adam et al. "Transition From Centroid-Based To Landmark-Based Optical Navigation During Osiris-Rex Navigation Campaign At Asteroid Bennu". In: *2nd RPI Space Imaging Workshop* (2019), pp. 1–2.

[2] Jason M. Leonard et al. "Osiris-rex orbit determination performance during the navigation campaign". In: *Advances in the Astronautical Sciences* 171 (2020), pp. 3031–3050. ISSN: 00653438.