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BLUE SKY

IMU-Based Navigation System for Autonomous Vehicles Using Different Types of Kalman Filters

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- Technion - Israel Institute of Technology
- Collaboration between RAFAEL and CRML

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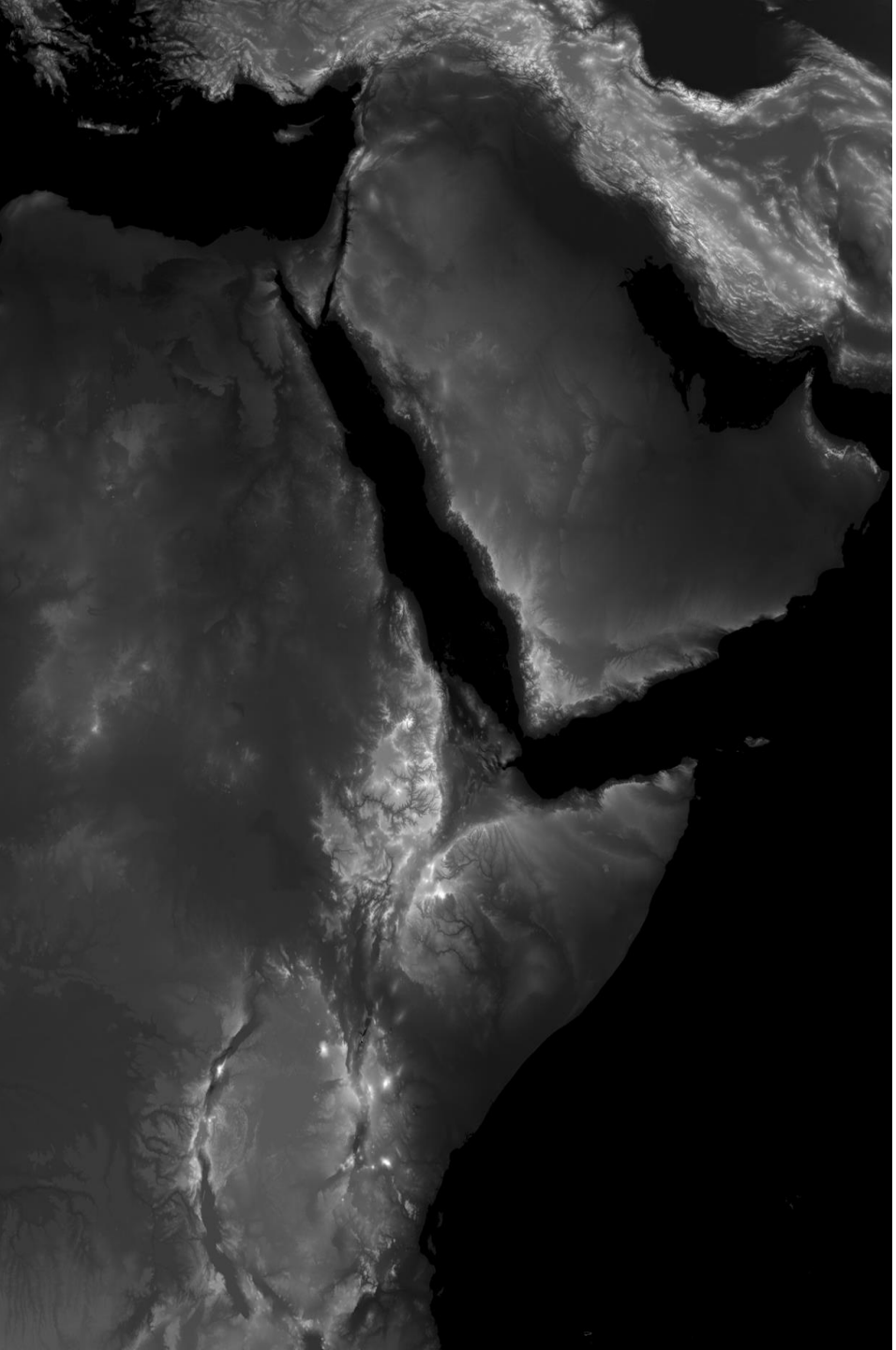

Maps

- The DEM maps were obtained from USGS
- Coverage of the surrounding area
- The maps cover a variety of terrains, including valleys, mountains, and seas
- Map were imitated .dt1 resolution
- Assumption of short-track linearity within each block
- Unit tests were conducted for each method

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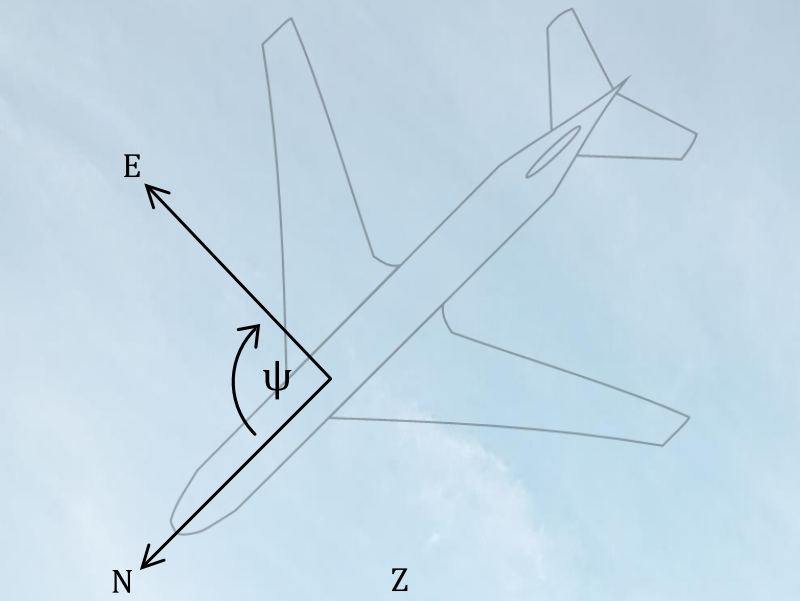

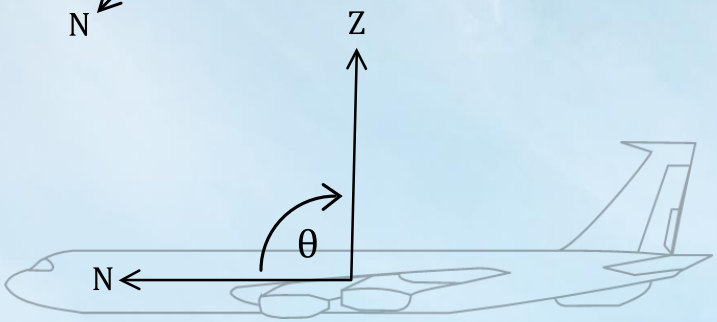

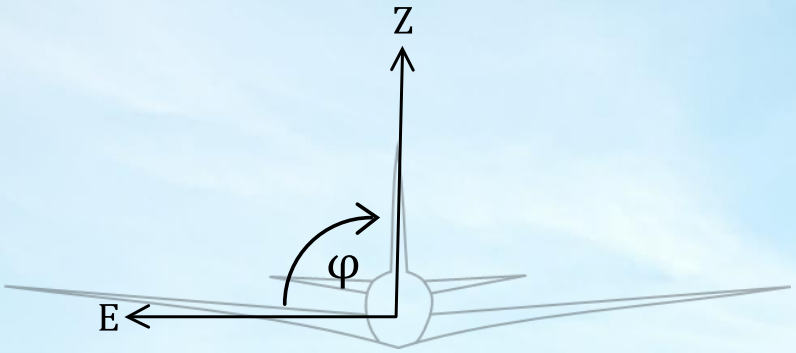

Trajectory Generation

- Could be initialized from a 6DOF or from a generated trajectory.
- Trajectory generation starts by determining the vehicle's orientation using Euler angles based on initial values and angular rates.
- Assumption made about constant acceleration, and constant angular rate, due to IMU rate.

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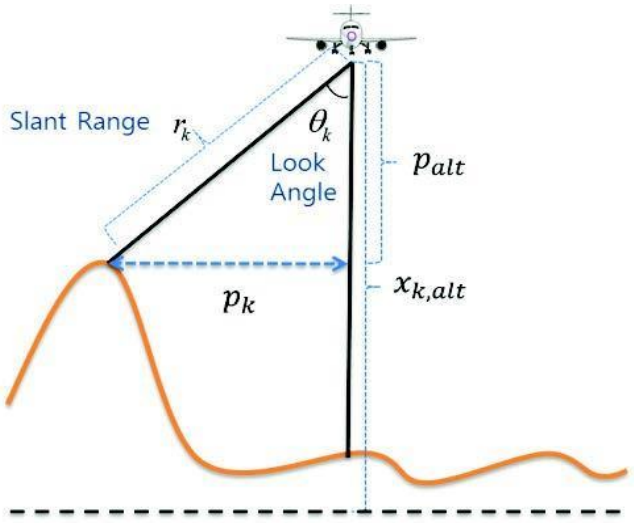

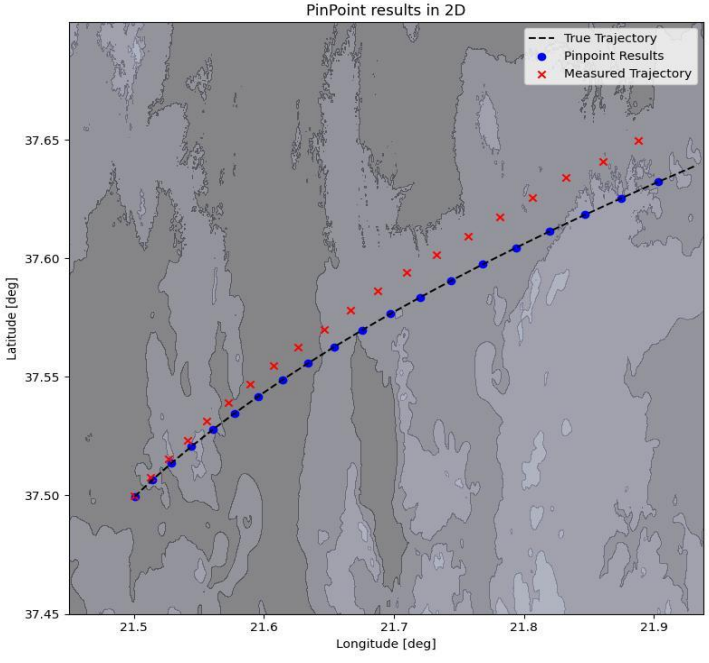

Pinpoint Finding

- Determine the precise location of the vehicle at each trajectory point using the pinpoint finding algorithm.

- **Algorithm Steps:**
  - Measure range using the altimeter.
  - Compute DCM.
  - Convert Δ(north, east) components to (lat, long).
  - Interpolate height differences along the range.
  - Update pinpoint coordinates and ground elevation.

- Algorithm closely follows the true trajectory, providing reliable vehicle positioning.

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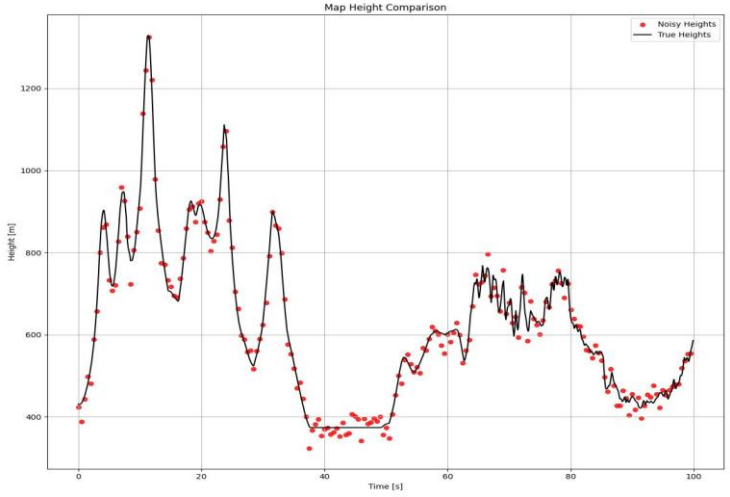

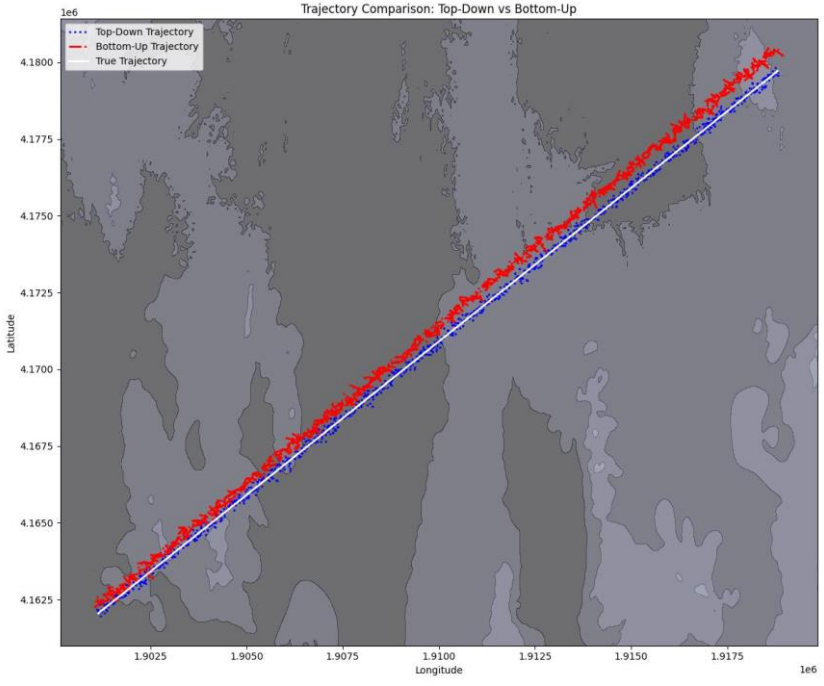

Noising the Trajectory

- Reflecting real-world sensor uncertainties.
- Bottom-up Approach
  - sensor level noise simulation
- Top-Down Approach
  - applies noise to computed trajectory data.
- Noise distributions: normal or uniform.

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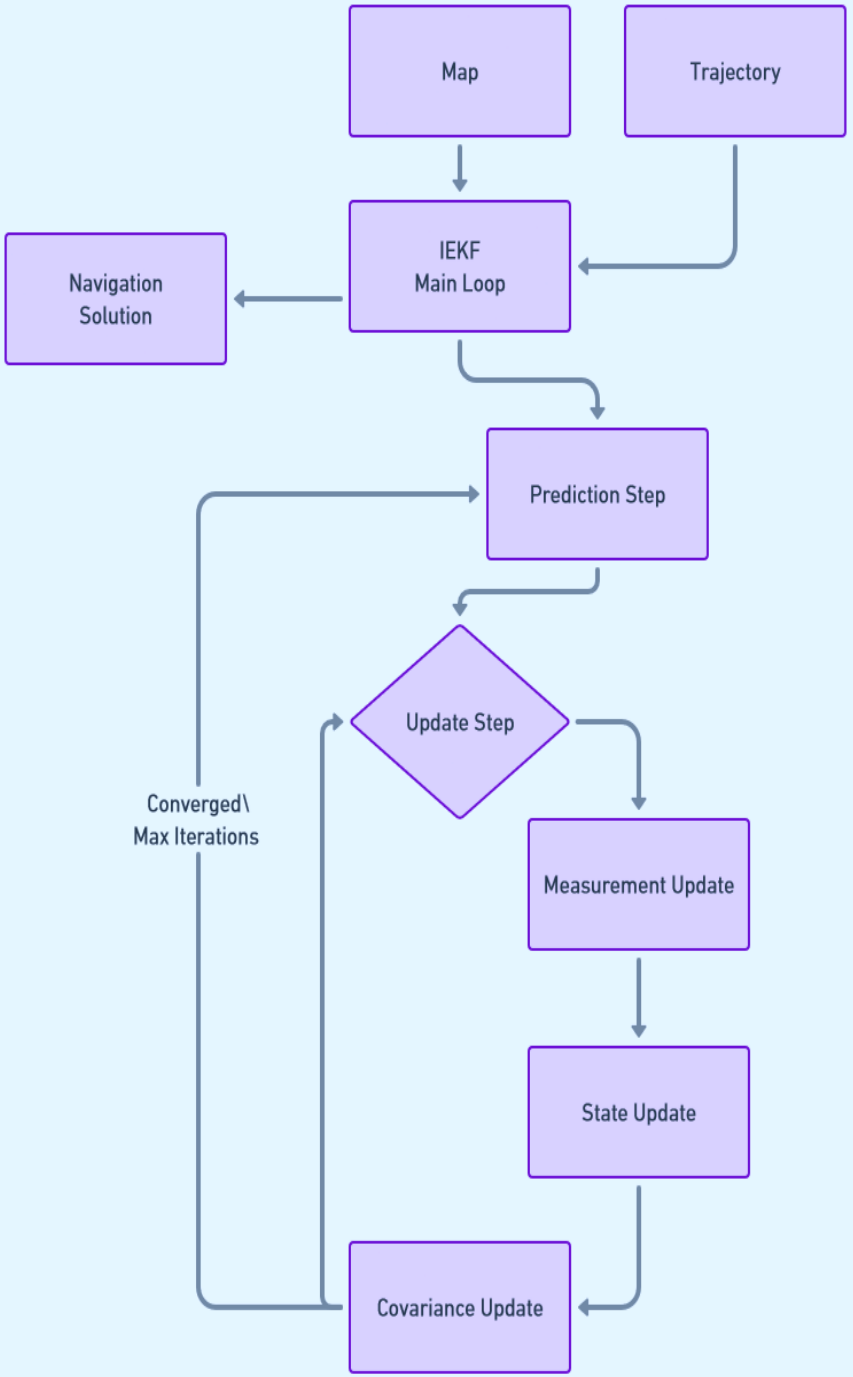

Iterated Extended Kalman Filter

Overview of IEKF:

- Extension of the Extended Kalman Filter to improve accuracy in nonlinear systems.
- Iterative refinement process within the measurement update step.

Algorithm Steps:

- Prediction Step
- Iterative Update Step
- Convergence Criteria

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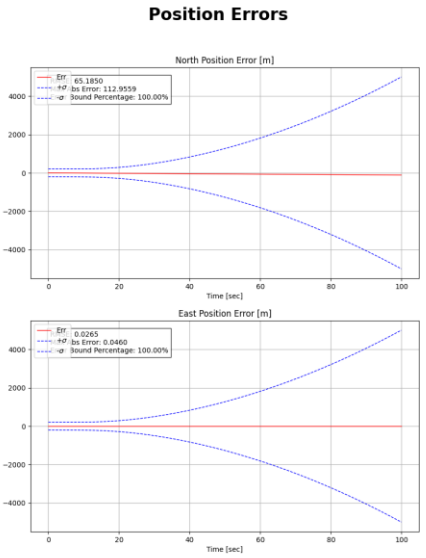
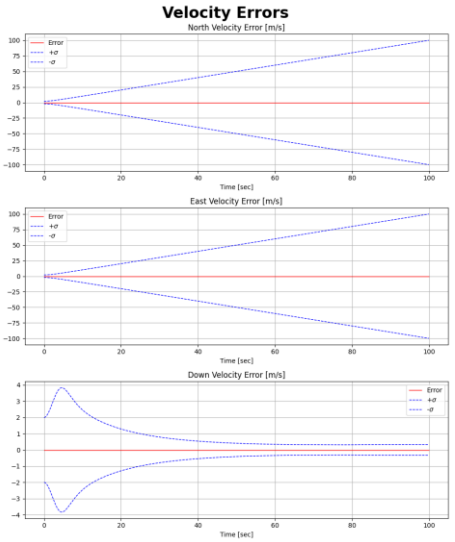
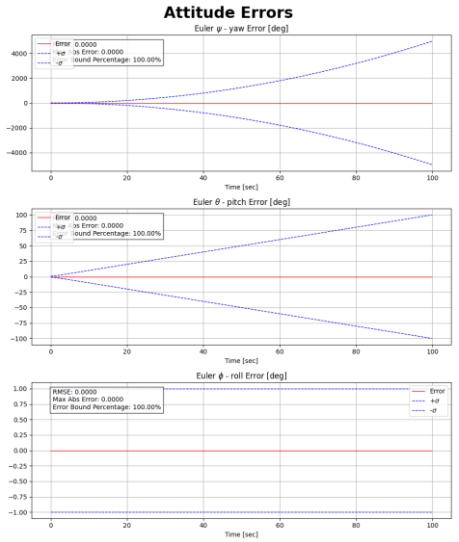
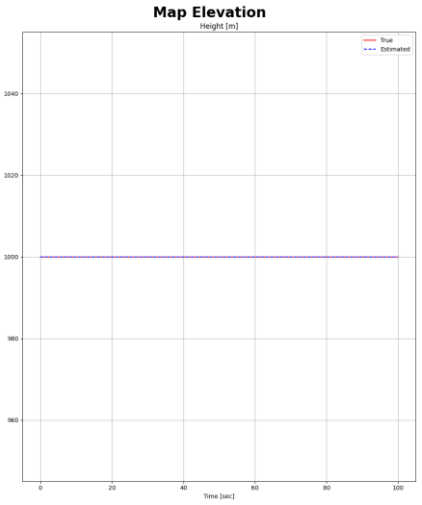
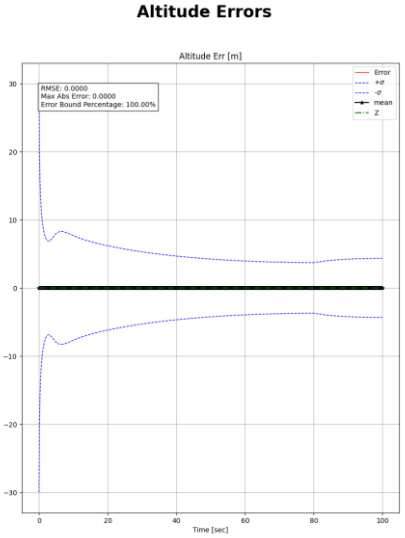
Iterated Extended Kalman Filter – Results on Flat Surface, No Errors

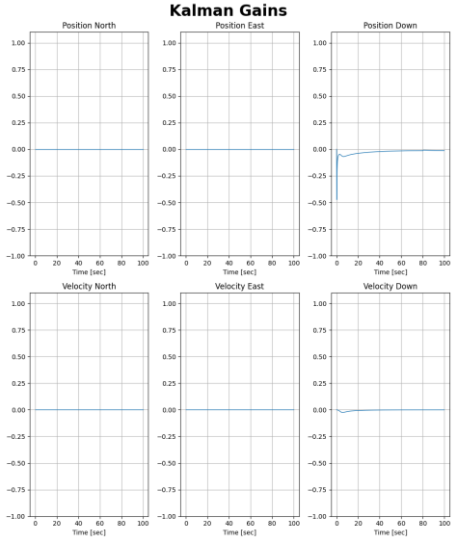












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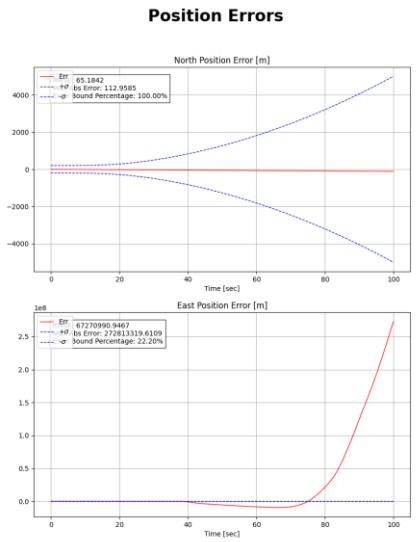
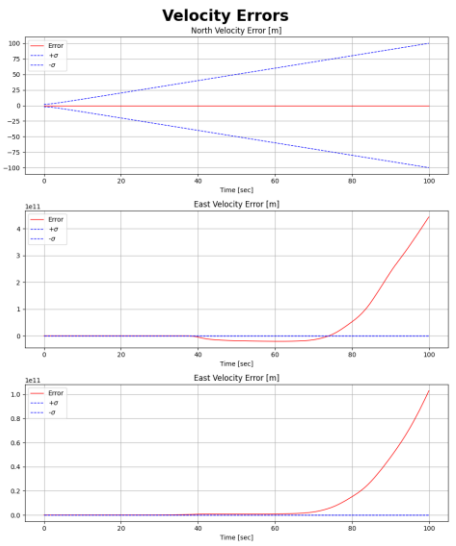
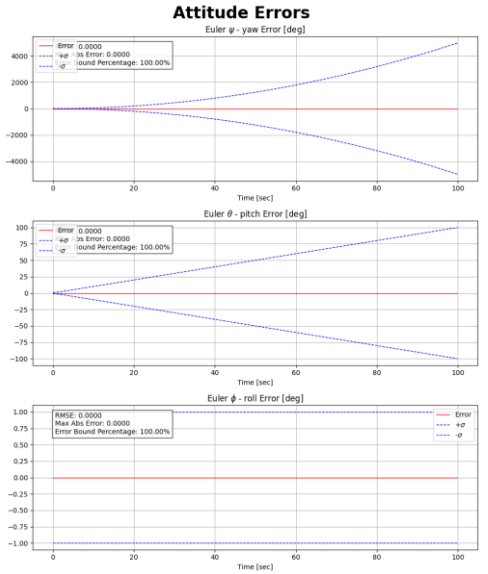
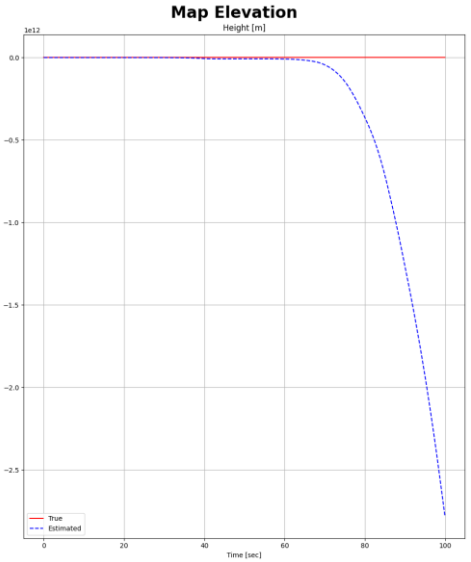
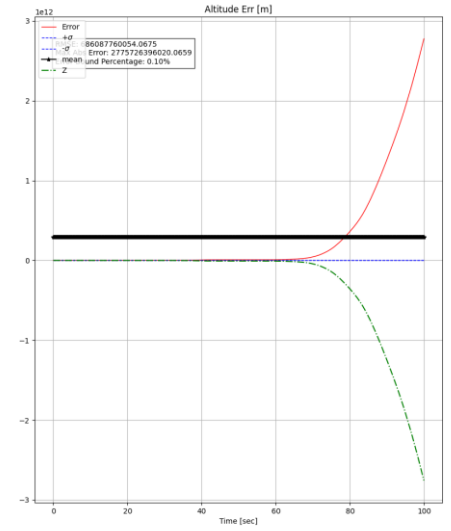
Iterated Extended Kalman Filter – Results on Terrain, No Errors

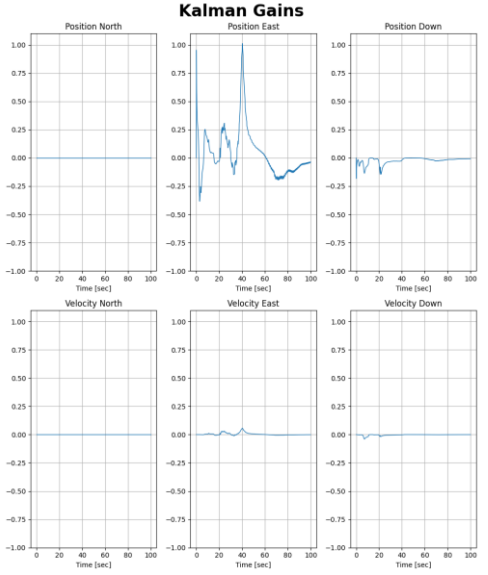












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