MAPT: A Near Real-Time Adaptive Multipath Modeling and Clustering Algorithm for GNSS Urban Positioning

National Aeronautics and Space Administration

Julian Gutierrez, Russell Gilabert, J. Tanner Slagel, Evan Dill – NASA Langley Research Center
Pau Closas – Northeastern University

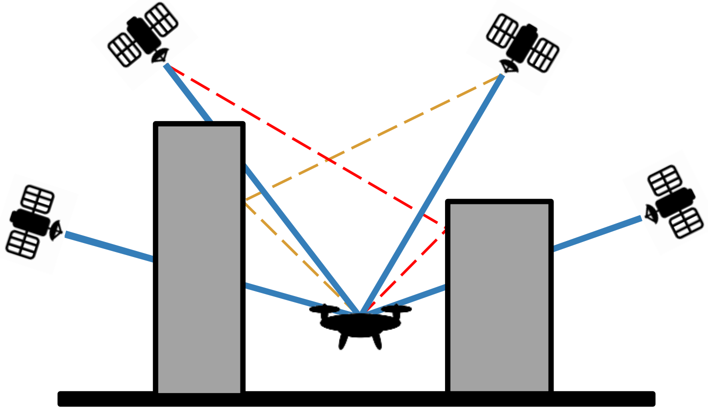
Julian Gutierrez
NASA Langley Research Center

April 2025

Motivation

Urban Environment Challenges

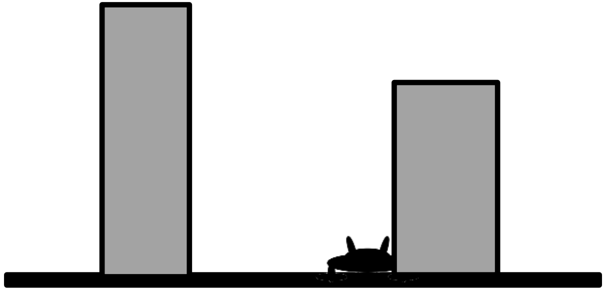
- Reduced Satellite Visibility: Tall buildings can block line-of-sight (LOS) to many satellites, making it difficult for receivers to determine their position
  - This can lead to poor geometry of LOS satellites, resulting in reduced accuracy
- Multipath Interference: Signals from satellites can bounce off buildings, bridges, or other structures, causing multiple signals to arrive at the receiver at different times
  - Leading to large positioning errors
- How can we give the receiver better situational awareness of its environment and reduce or remove these errors?



Motivation

Prior Work*

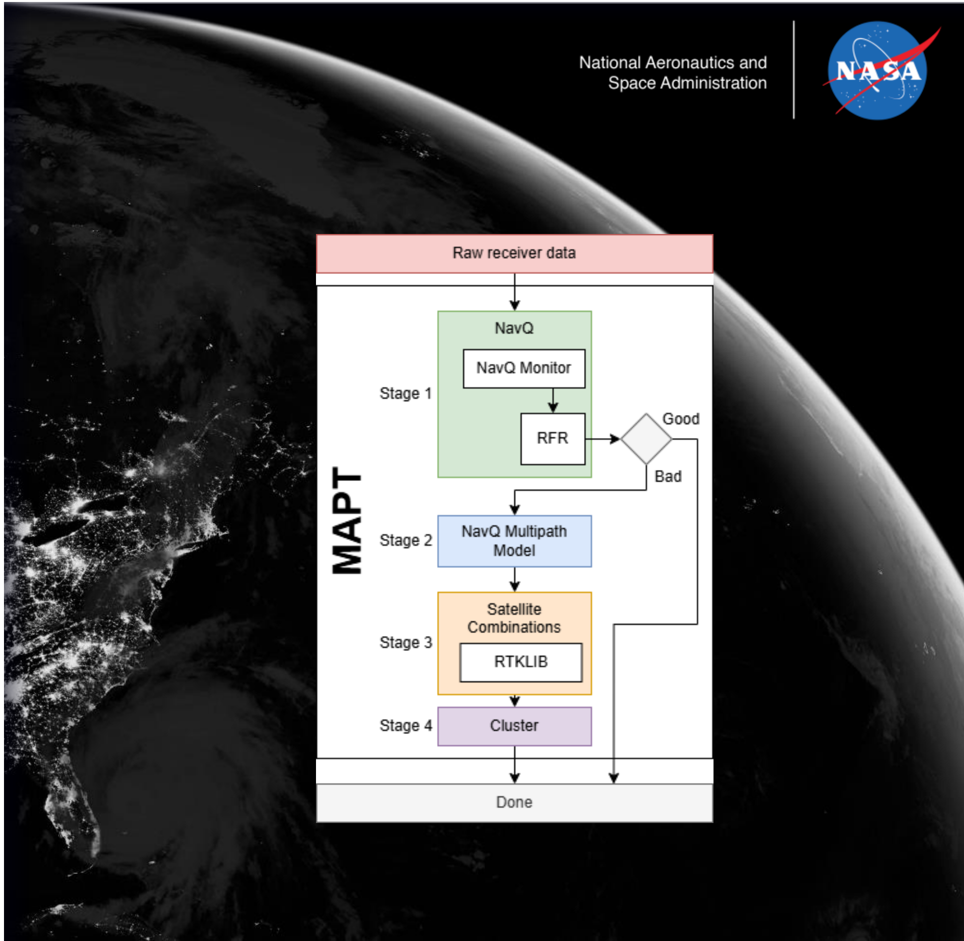
- Focused on the idea of analyzing the position solutions of satellite combinations
  - But we can't analyze ALL satellites, so we made an educated assumption:
    - Let's analyze the lowest elevation LOS satellites
- In this work, we take this research a step further and try to deduce which satellites might have LOS multipath
- Let's see how we tackle this



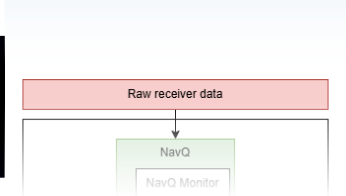
*Published at ION Pacific PNT in 2024

Outline

- Multipath Adaptive Positioning Techniques (MAPT)
- Performance Results
  - Montecarlo
  - Real World
- Conclusions



MAPT

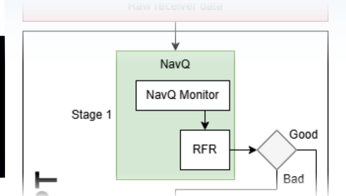


National Aeronautics and Space Administration

Stage 0: Raw Receiver Data

- Receiver collects satellite pseudo-range information
    - Estimated distance between each satellite and the receiver
    - We use the list of satellites (and measurements to each satellite)
- We also use the fused estimated position of the receiver based on the GNSS and IMU data

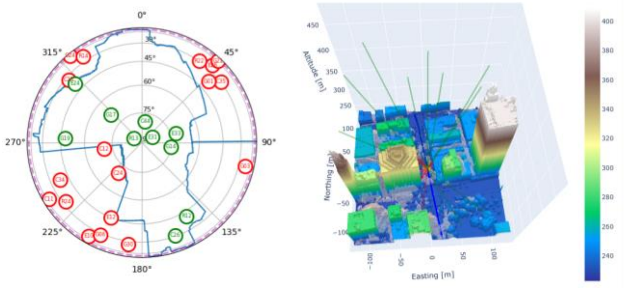
MAPT

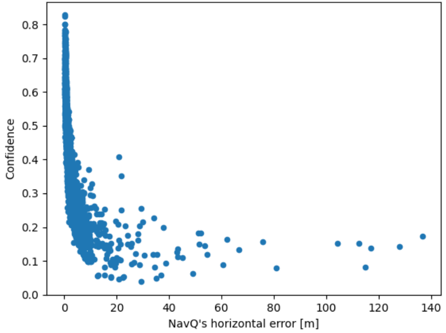


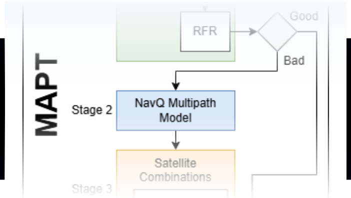
National Aeronautics and Space Administration

Stage 1: NavQ Monitor

- Simulation model to determine satellite visibility using 3D models of cities
  - Categorize satellites into LOS/NLOS
- A random forest tree regressor (RFR) is used to determine the confidence in the output solution from NavQ trained to use:
  - LOS satellite count
  - HDOP
  - Percentage of sky visibility
- We selected a threshold of 0.33 to determine continuation of the algorithm

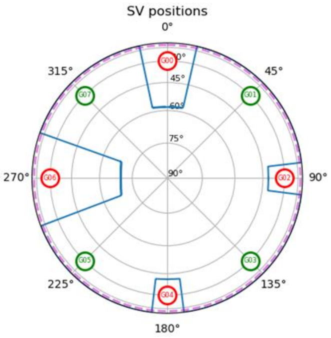


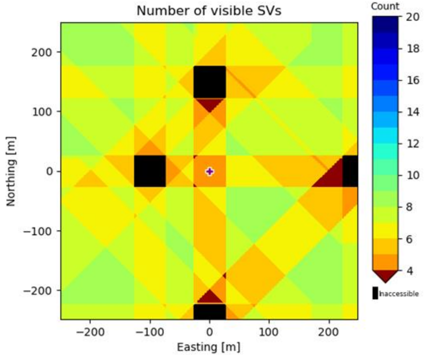


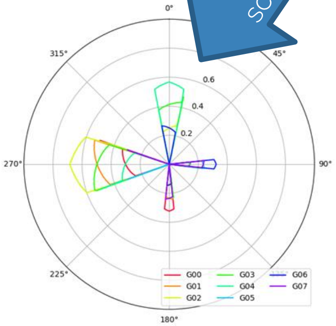


Stage 2: NavQ Multipath Model

- A geometric multipath approximation is used to estimate the probability of multipath for any satellite from any direction considering:
  - SV elevation angle
  - SV azimuth direction
  - Distance to reflection
  - Angle of reflection

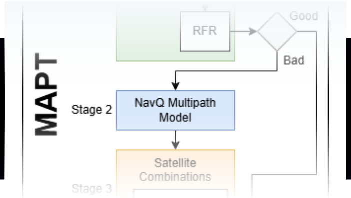






The multipath score is the radius

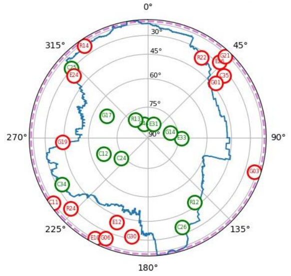
MAPT

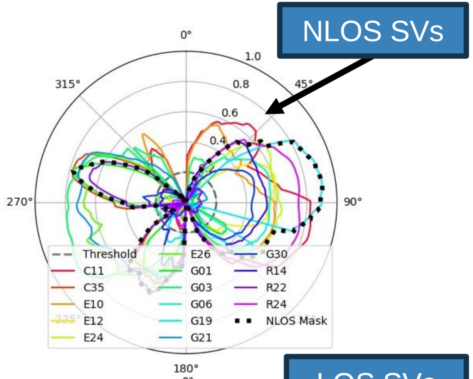


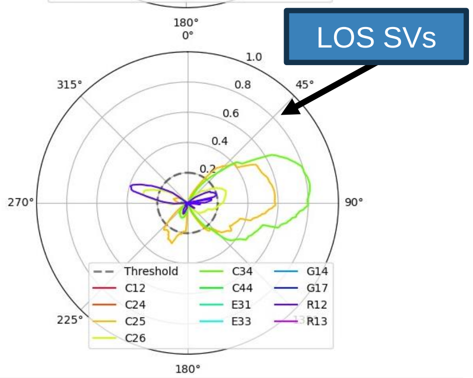
National Aeronautics and Space Administration

Stage 2: NavQ Multipath Model

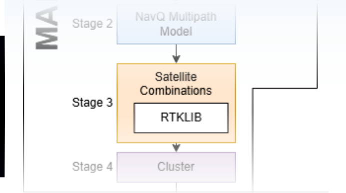
- NLOS Masking
  - When a receiver observes satellites NavQ identifies as NLOS (due to multipath), we can infer LOS multipath could come from the same directions
  - We can use this information to determine which LOS SV might have been affected by a multipath bounce





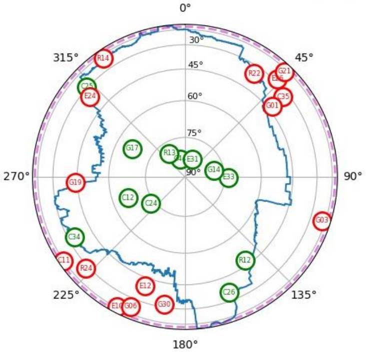


MAPT

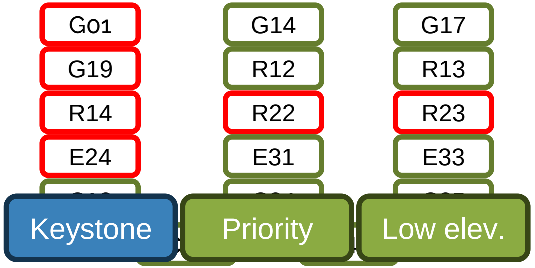


Stage 3: Satellite Combinations

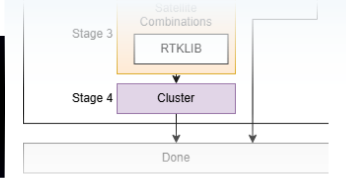
- The goal is to create a list of satellite combinations and compute the position solutions from them
- We select a max number of satellites we want to process
- Satellites are prioritized based on
  1. LOS/NLOS
  2. Multipath model probability
- If there are more than 7 LOS satellites, highest elevation satellites are considered **keystone** satellites (they are used in all combinations)
- Compute the position solutions for each combination of satellites using RTKLIB



Example, receiver observed the following satellites:

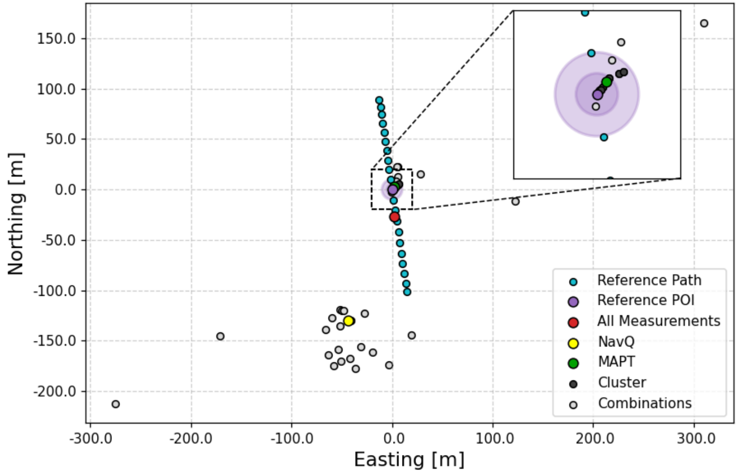


MAPT



Stage 4: Cluster

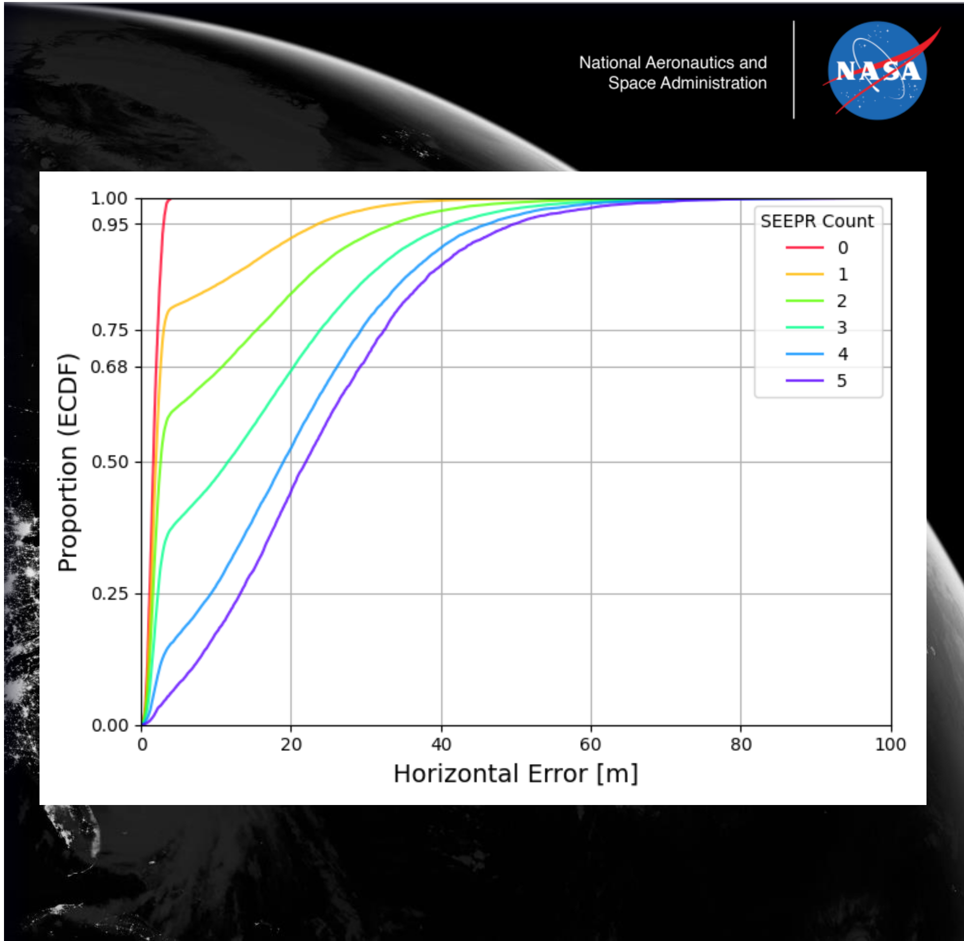
- We analyze the position solutions from all the combinations of satellites
- We use a clustering algorithm and Iterate through the parameters until we find a cluster that meets the minimum position-solution-count we have defined



Results

Montecarlo Simulation

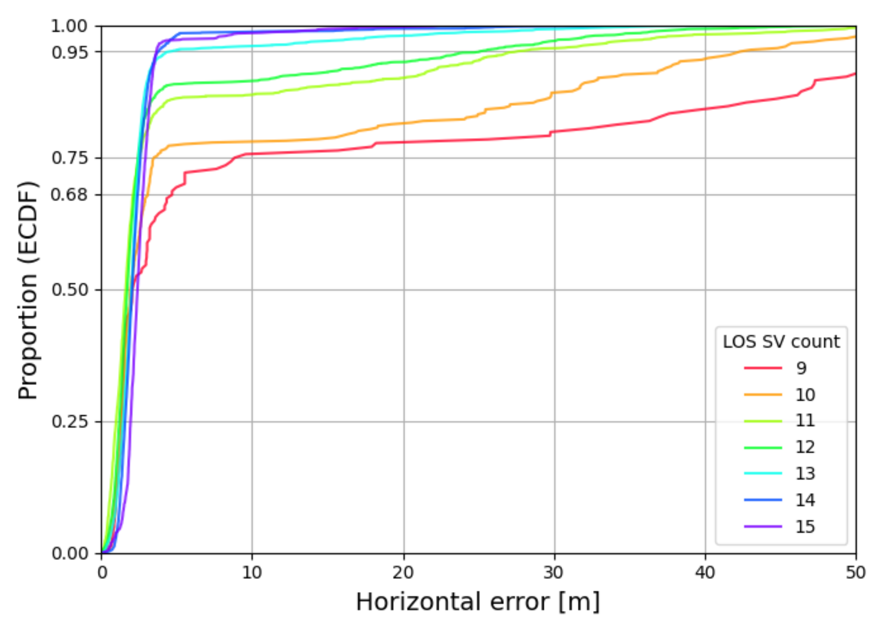
- Injected random pseudo range errors to random satellite measurements measured by a CORS station NYBP (almost fully open sky)
- 288,000 epochs were analyzed
- Satellites with an erroneous estimated pseudo range (SEEPR) count between 0 and 9
- MAPT analyzes 7 satellites each epoch
- **Main problem**: we are injecting errors into keystone satellites (MAPT can't remove those errors)



Results

Montecarlo Simulation

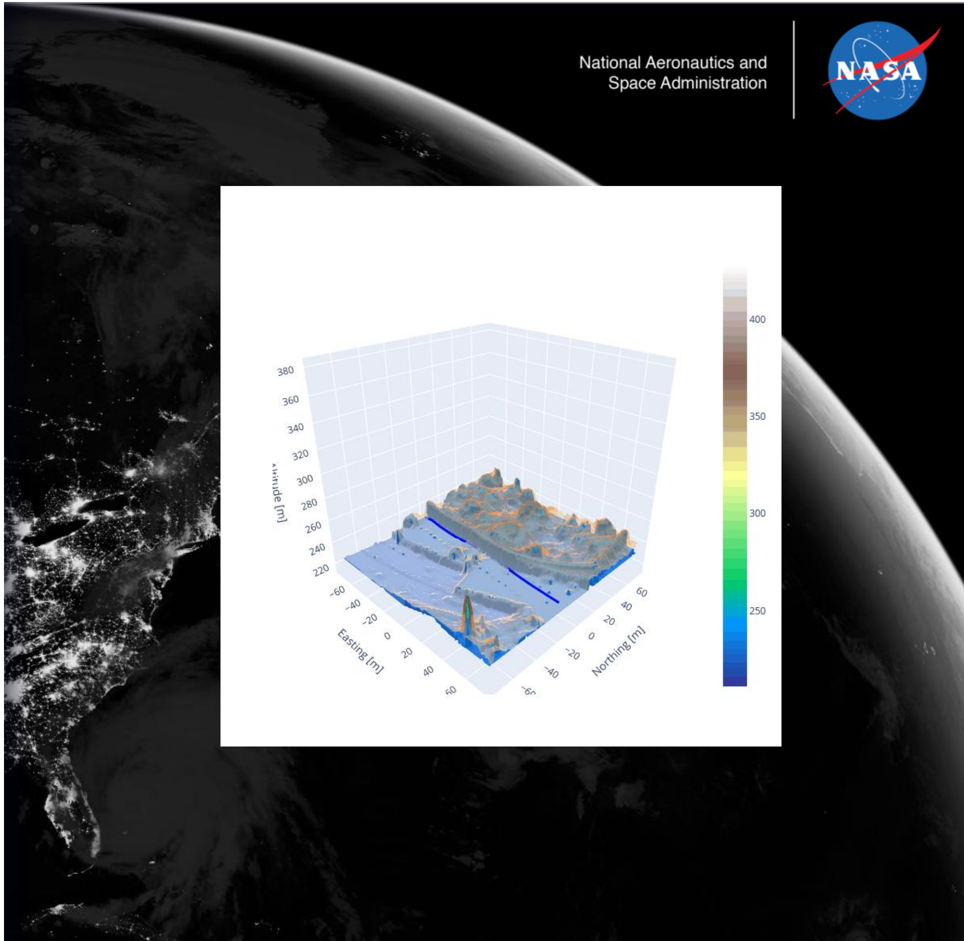
- Remove epochs where we injected an error into a keystone satellite
- We are unable to resolve all the errors
- **One of the problems**: too many signals affected by errors (more than correct signals)
- Should we have been able to fix up to 3 satellites?
- Low LOS satellites count results in fewer combinations of error-free satellites producing viable position solutions (with 9 total, this number can be 0)



Results

Real World

- Vehicle equipped with a GNSS receiver
- Collected data in downtown Columbus, Ohio
    - Moderate urban canyon
    - Representative of average city skyline
- 8 datasets collected over 2 days for a total of 5445 epochs (treated independently)



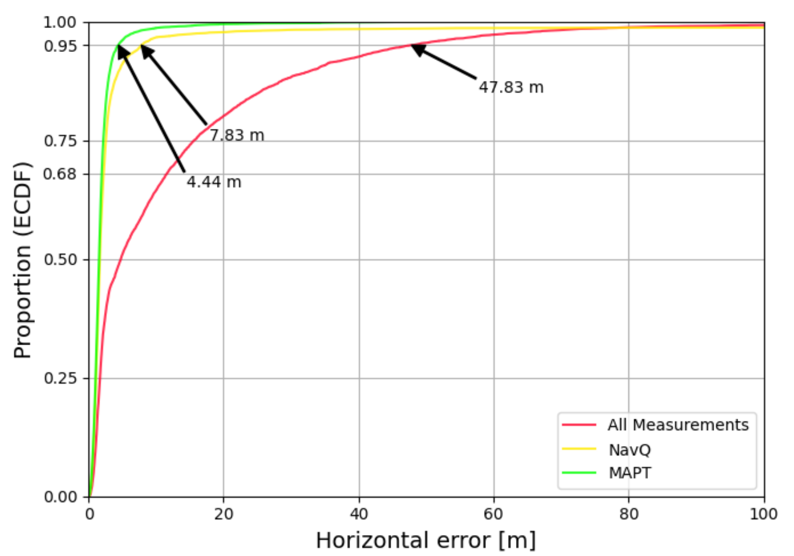
Results

Real World

- Results are as good as our prior work (which is good!)
- Why this is good:

Stage	Mean ET [ms]	Max ET [ms]
Stage 1: NavQ Execution	86.63	184.94
Stage 2: NavQ Multipath Model	163.6	210.04
Stage 3: Satellite Combinations	163.47	540.22
Stage 4: Clustering	149.44	774.29
Total Execution Time	232.71	1,360.8

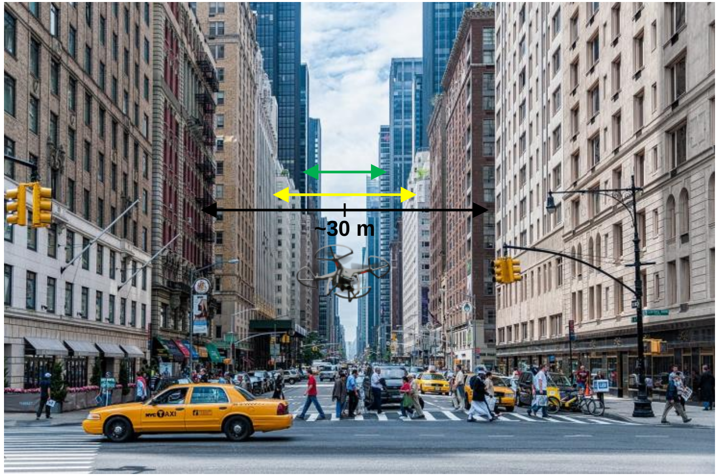
National Aeronautics and Space Administration



Method	95% error [m]	Max Error [m]	EWM50 [%]	EWNS [%]
All Meas.	47.84	206.14	3.98	0.55
NavQ	7.83	136.92	0.29	1.22
MAPT	4.44	64.76	0.07	0

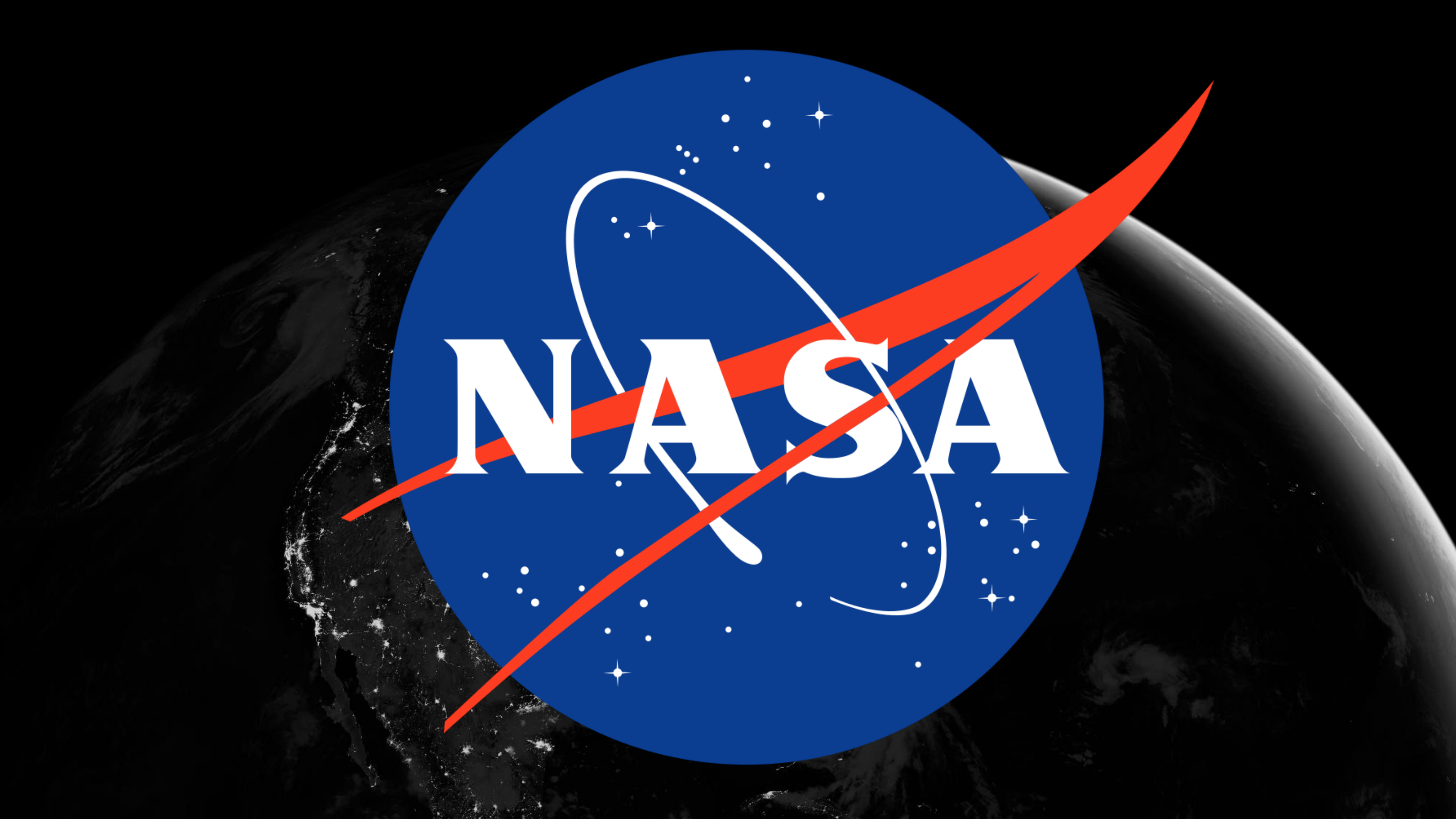
Conclusions

- We developed a novel approach to mitigate LOS multipath and enable better GNSS positioning in urban environments
- We decreased the 95th percentile of horizontal error from 47.8 m to 4.4 m
- Achieved similar performance to prior work while reducing average computational time from 6.1 s to 0.23 s
- Improved navigation accuracy: Reduce errors and improve situational awareness (especially in autonomous navigation) and reduces risk of path deviations
- Increased mission planner confidence: More reliable location information enables safer decision-making in complex environments



Thanks!

Any questions?


NASA

Examples

National Aeronautics and
Space Administration