# Likelihood modelling of the Space Geodesy Facility laser ranging sensor for Bayesian filtering


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## Outline

This work analyzes the data output of laser ranging data collected from the Space Geodesy Facility (Herstmonceux, UK), and integrates it in a Bayesian target tracking algorithm. The main contributions are:

1. Modelling of the sensor through a bespoke likelihood function
2. Generation of simulated scenarios to analyze the proposed algorithm
3. Testing of the proposed algorithm on real data generated from the SGF

## Space Geodesy Facility

- High precision, range-only sensor (SLR data)
- Unknown clutter characteristics:
  1. High density of points
  2. Heavily-skewed, towards higher ranges
  3. Time-varying

## SGF Data

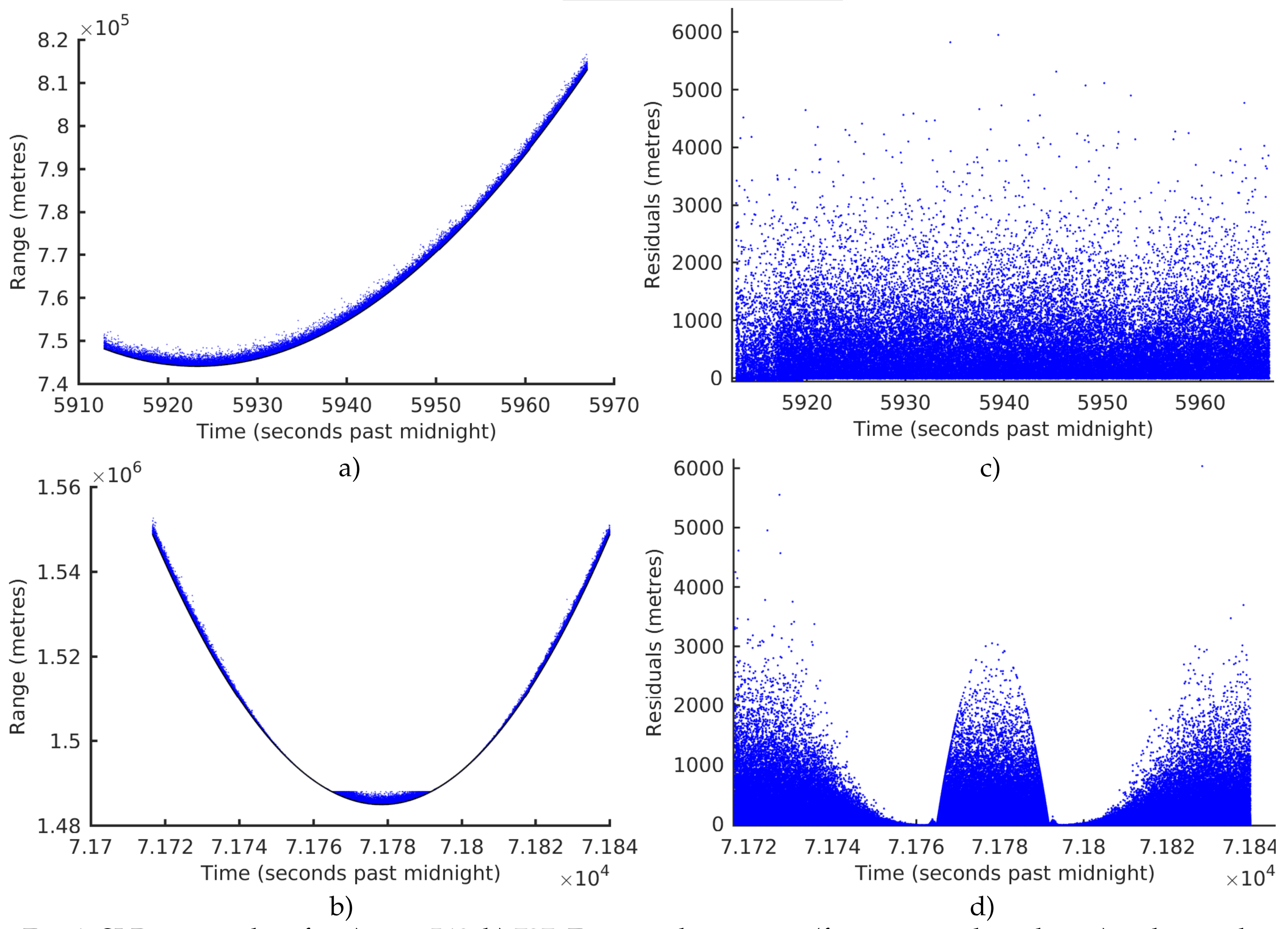


Fig. 1: SLR output data for a) pass 540, b) 737. Estimated trajectory (from external catalogue) is depicted with a black line, the data points are in blue. c) and d) are the estimated residuals of the respective passes.

## Sensor modelling

**Challenges:**

- Clutter distribution unknown: which points are clutter, which ones are target-generated?
- The data distribution is highly skewed in favour of higher ranges.

**Proposed approach:**

- Treat all data points as target-generated → residuals become observation noise
- Use a pass (batch 746) as training set to determine noise distribution.

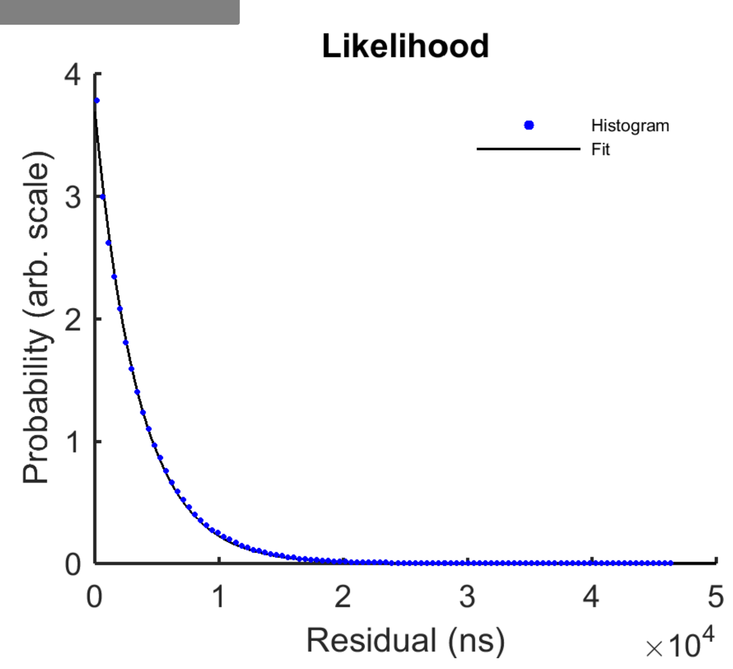


Fig. 2: Exponential fitted to the probability density of batch 746.

**Result:**

- Exponential form proved to be a good match ($R^2 = 0.9994$)
- Parametrization: $l(z|x) = \exp(-2.811^{-4}(0.5*c*z - r))$, where r is the object's range, z the measured range, and c the speed of light

## Filter design

**Features:**

- Target motion model: constant velocity model
- Sensor model: derived from testing batch
- Single-object filter:
  1. Kalman filter → fails because of highly-skewed noise distribution
  2. Standard bootstrap particle filter → affords flexibility in noise model

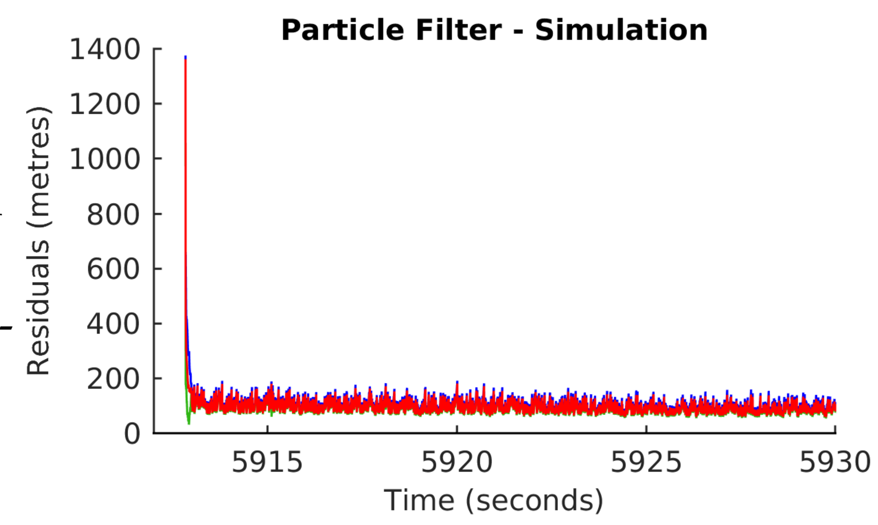


Fig. 4: Average RMSE for 30 MC runs (red line, +/- standard deviation are green and blue lines)

**Simulation:**

- Data points from catalogue trajectory (batch 540) with exponential noise

## Real-data analysis

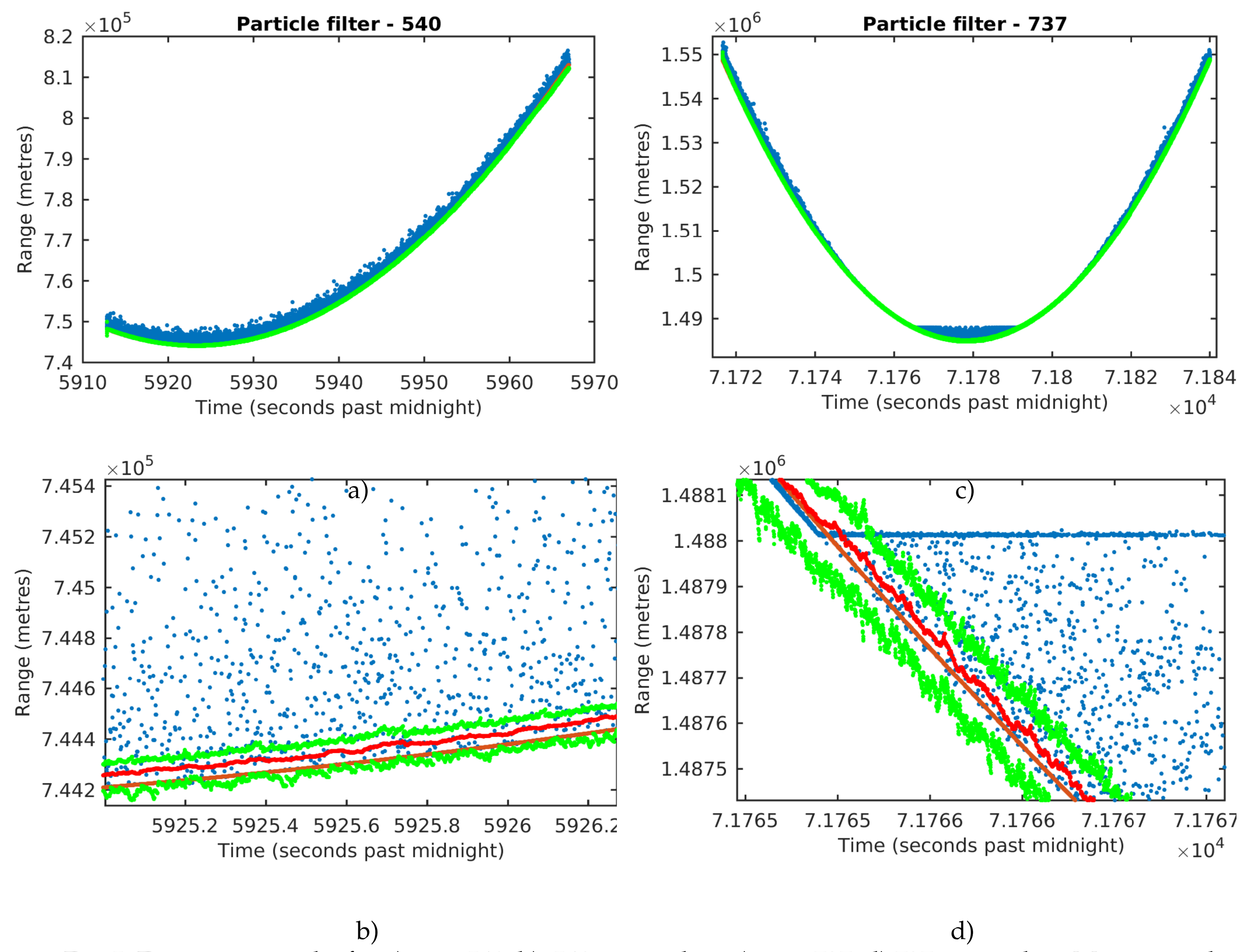


Fig. 5: Estimation results for a) pass 540, b), 540 zoomed-in, c) pass 737, d) 737 zoomed-in. Maxima and minima are in green, data is in blue, catalogue trajectory is in orange, and estimate in red.

**Results:**

- Pass 540 estimated with high accuracy (avg. RMSE: 50m)
- Pass 737 is estimated with similar accuracy in spite of sudden change in noise distribution
- Particle distribution accurately represents distribution shape

## Conclusion

We have developed a filtering solution to estimate the range of a satellite from SLR data:

- Capable of handling the noise profiles usually found in SLR data from the Space Geodesy Facility (Herstmonceux, UK)
- Tested on both real and simulated data
- Estimates are consistent with the orbital predictions obtained from external catalogues
- Provides uncertainty information


## Acknowledgements

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