Deep Learning Assisted Kalman Filter for GNSS/MEMS IMU Integration in GNSS Denied Environments

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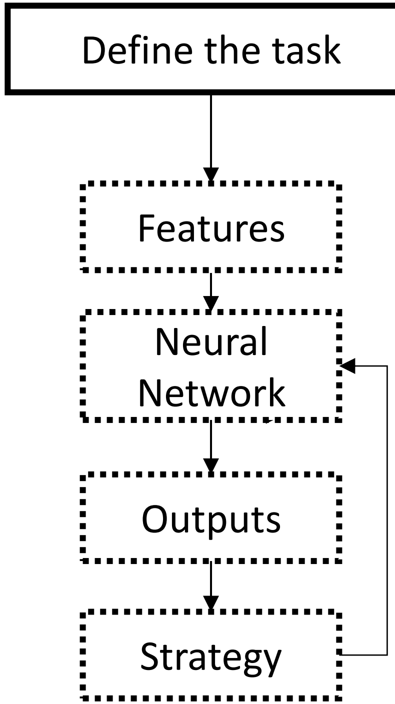
Deep Learning Assisted Kalman Filter

Key elements in Deep Learning

- Deep Learning in GNSS/INS Integration is **NOT** a standardized Problem. In order to apply the Deep learning to this specific application, we need to consider those elements and define the task.



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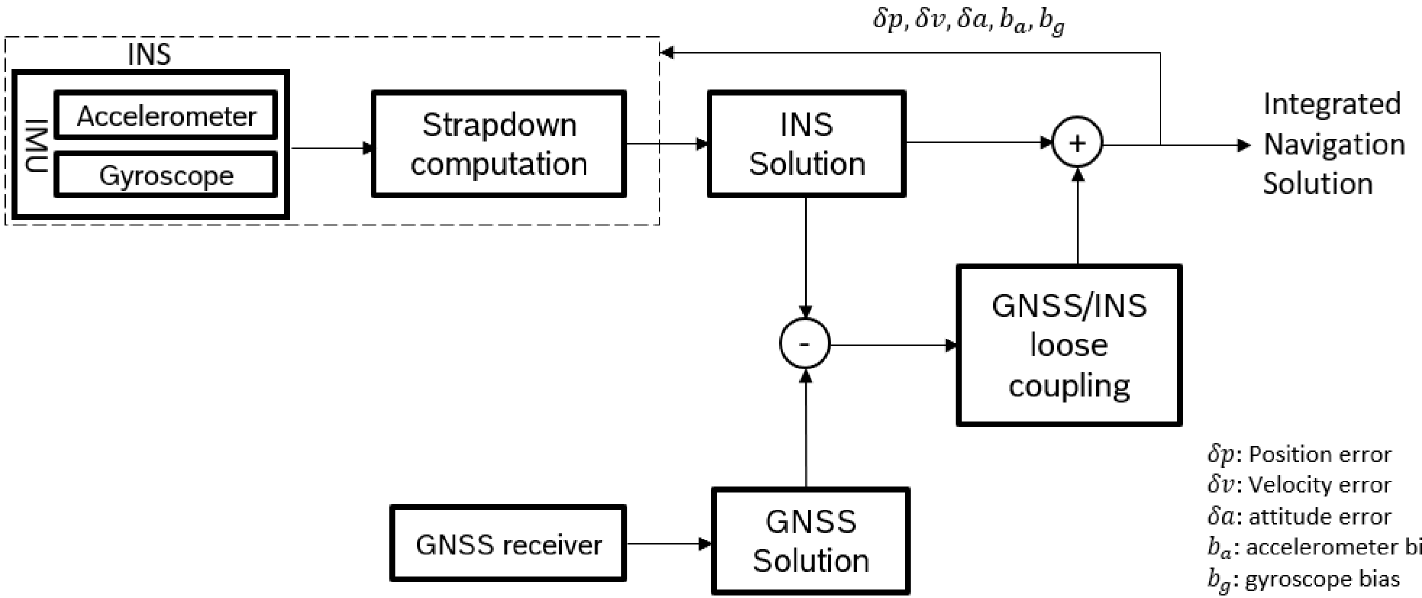
Define the task

- The GNSS and INS can be loosely coupled



δp: Position error
δv: Velocity error
δa: attitude error
b_a: accelerometer bias
b_g: gyroscope bias

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Define the task

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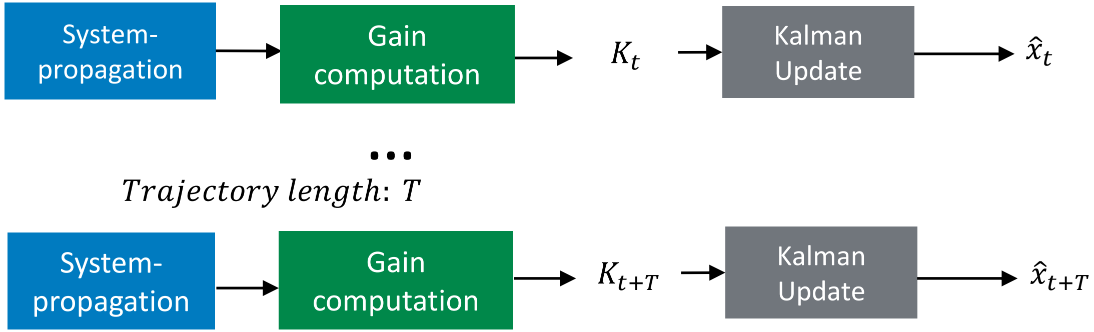
- In GNSS/INS integration, model-based Kalman Filter (MBKF) is one of the most widely used integration algorithms



System propagation

Predicted error state estimate	$\delta x_{t\|t-1} = f(\delta x_{t-1\|t-1})$
Predicted covariance estimate	$P_{t\|t-1} = F_t P_{t-1\|t-1} F_t^{\top} + Q_t$

Measurement Update

Kalman gain	$K_t = P_{t\|t-1} H_t^{\top} H_t P_{t\|t-1} H_t^{\top} + R_t$
Innovation	$\tilde{y}_t = y_t - h(x_{t\|t-1})$
Updated error state estimate	$\delta x_{t\|t} = \delta x_{t\|t-1} + K_t \tilde{y}_t$
Updated covariance estimate	$P_{t\|t} = (I - K_t H_t) P_{t\|t-1}$

https://en.wikipedia.org/wiki/Extended_Kalman_filter

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Define the task

- As a model-based algorithm, the MBKF estimates the accumulated error in the strapdown computation based on **a priori system models** and **noise statistics**. The performance of the conventional MBKF is influenced by the **system model deficiencies**, **noise model assumptions.**
- The IMU error is **complex especially for the MEMS IMU**.

System propagation

Predicted error state estimate	$\delta x_{t\|t-1} = \boxed{f(\delta x_{t-1\|t-1})}$
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Output

- In MBKF and DL, they both combine approaches from **statistics, recursion and optimization theory**.
- By **hybridizing** them, the advantage of DL can assist MBKF to overcome the model deficiency and the unknown process and measurement noise.

- How?

System propagation

Predicted error state estimate	$\delta x_{t\|t-1} = \boxed{f(\delta x_{t-1\|t-1})}$
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Measurement Update

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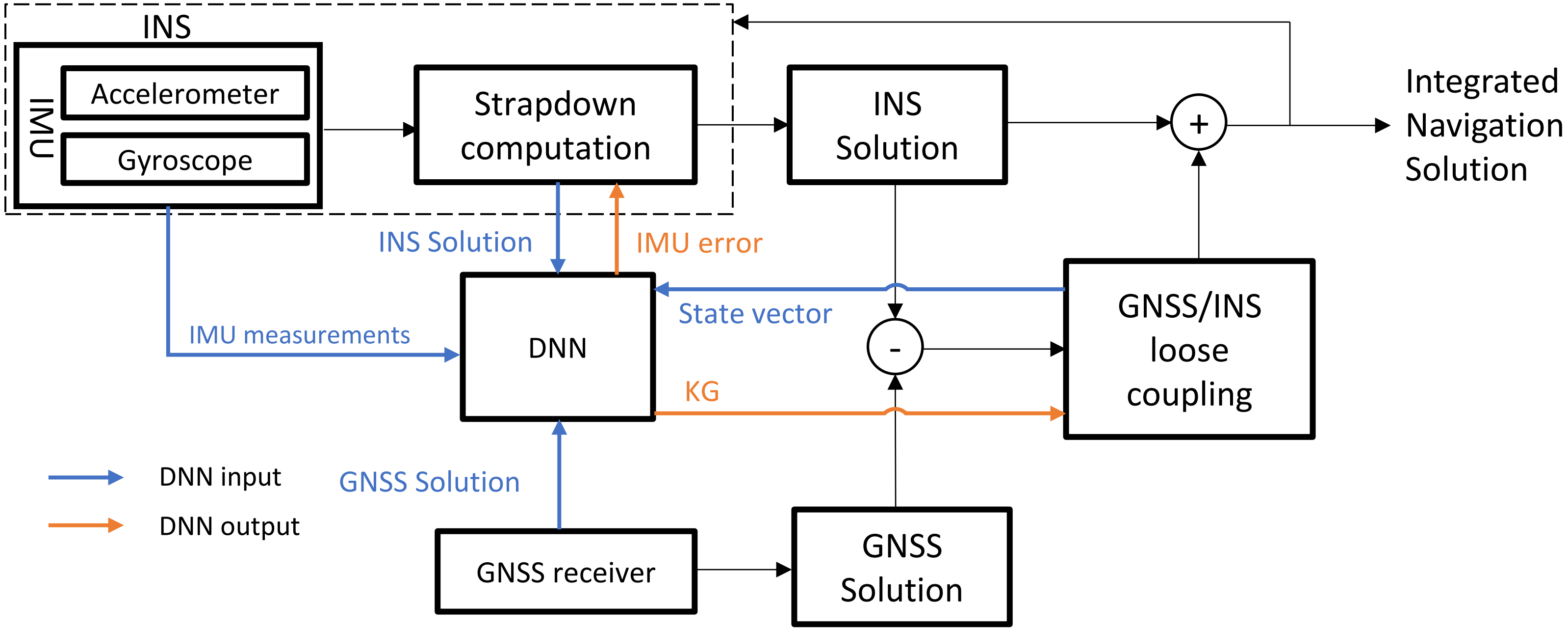
Implicitly tracked

IMU error

Define the task → Features → Neural Network → Outputs → Strategy

Deep Learning Assisted Kalman Filter
High-level Structrue and Features

- We propose a deep learning-assisted Kalman Filter (DLKF) that incorporates a deep neural network (DNN) to overcome the limitations of MBKF. This DNN is tightly integrated into the GNSS/INS integration system



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Neural Network Design

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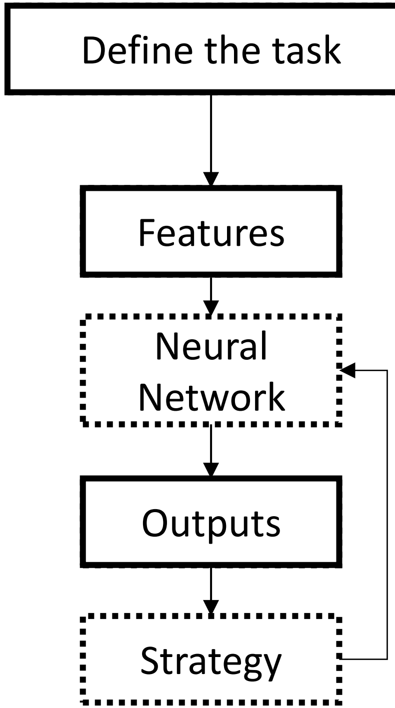
- To enable effective learning of the Kalman gain and IMU errors by the DNN, it is crucial to select the proper network type and provide input features that contain the necessary information.

- Features
  - INS solution
  - GNSS solution
  - IMU measurements
  - State vectors



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Neural Network Design

- Convolutional neural network (CNN)
  - IMU measurements and INS solutions operate in high frequency have complex interdependencies.
  - By sliding the convolutional filters over time windows, the CNN can capture **short-term** temporal information and identify temporal features such as motion dynamics.
- Long short-term memory (LSTM)
  - Both the KF and LSTM are designed to predict future states based on historical data.
  - Learn **long-term** dependencies, retain and leverage the information over the long sequence through the large memory cell.
- CNN-LSTM
  - This combination can help to enhance filter quality and learn the complex integration system.

[1] S. Li, M. Mikhaylov, N. Mikhaylov, and T. Pany, "**Deep learning based Kalman filter for GNSS/INS integration : Neural network architecture and feature selection**," *2023 International Conference on Localization and GNSS (ICL-GNSS)*, Castellón, Spain, 2023, pp. 1-7
[2] S. Li, M. Mikhaylov, T. Pany, and N. Mikhaylov, "**Exploring the Potential of Deep Learning Aided Kalman Filter for GNSS/INS Integration : A Study on 2D Simulation Datasets**," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 60, no. 3, pp. 2683-2691, June 2024.

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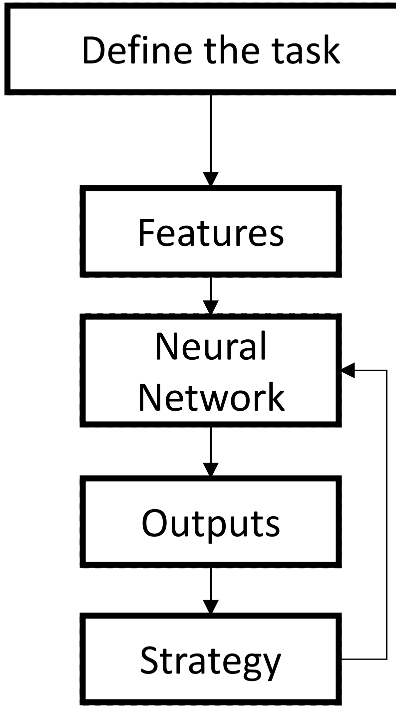
Training strategy



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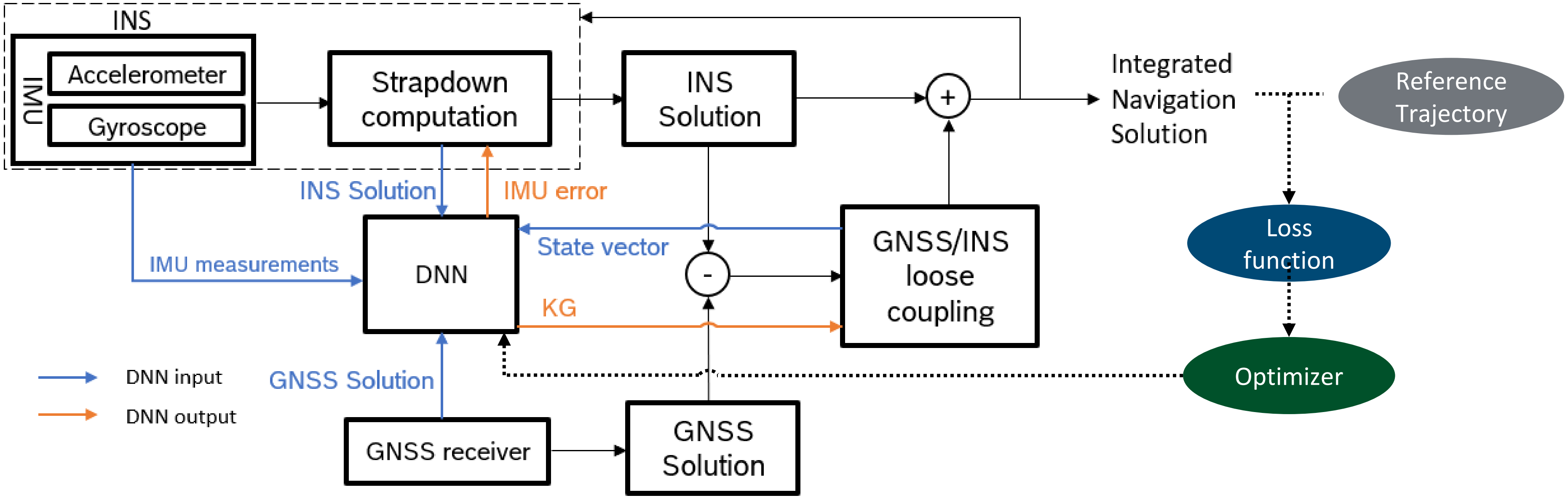
Training strategy

- End to End



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Training strategy

- Gradient explosion and vanish
  - Truncate trajectory: long trajectory is truncated into multiple sub-trajectories
  - Shuffle the sub-trajectories and use batch_size number trajectories to train
- Accuracy of the IMU error estimates
  - Decrease GNSS measurement frequency
  - Add GNSS outage in training dataset
- Loss function
  - Weighted sum of the respective losses

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Experiments and Results

- Simulated dataset
- Real dataset

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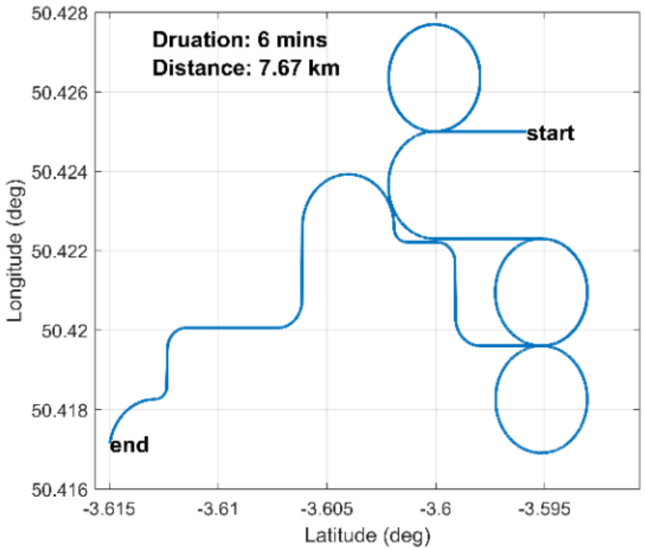
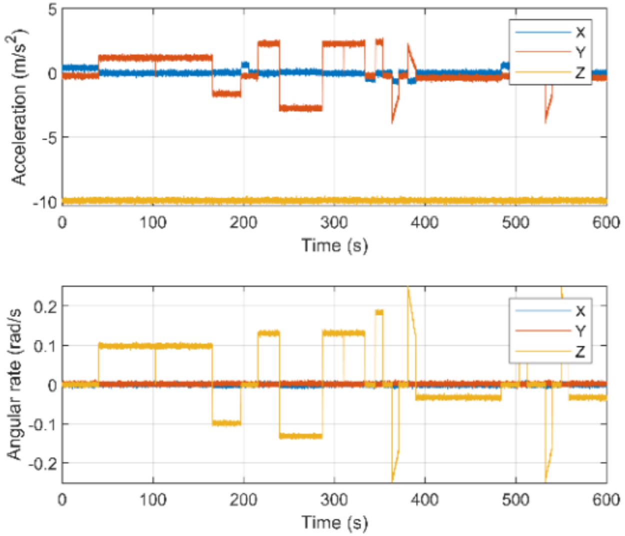
Simulation

- The vehicle motion was manually designed with a variety of maneuvers, including acceleration, straight driving, turns, 8-shape patterns, and halts.
- Accelerations and angular rates were calculated considering Earth's rotation and gravity and different types of IMU errors were simulated for various evaluation and analysis purposes
- No GNSS outage in simulated dataset





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Performance analysis

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- IMU error estimation analysis
  - We simulated IMU measurements with a constant bias and Gaussian noise. The scale factor, misalignment error, and g-dependent gyroscope errors were not simulated

Sensor	Constant Bias	Gaussian Noise
Accelerometer X	0.0883 m/s^2	0.0098 $m/s^{1.5}$
Accelerometer Y	-0.1275 m/s^2	0.0098 $m/s^{1.5}$
Accelerometer Z	0.0785 m/s^2	0.0098 $m/s^{1.5}$
Gyroscope X	-0.0175 rad/s	0.0003 $rad/s^{0.5}$
Gyroscope Y	0.0252 rad/s	0.0003 $rad/s^{0.5}$
Gyroscope Z	-0.0296 rad/s	0.0003 $rad/s^{0.5}$

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Performance analysis

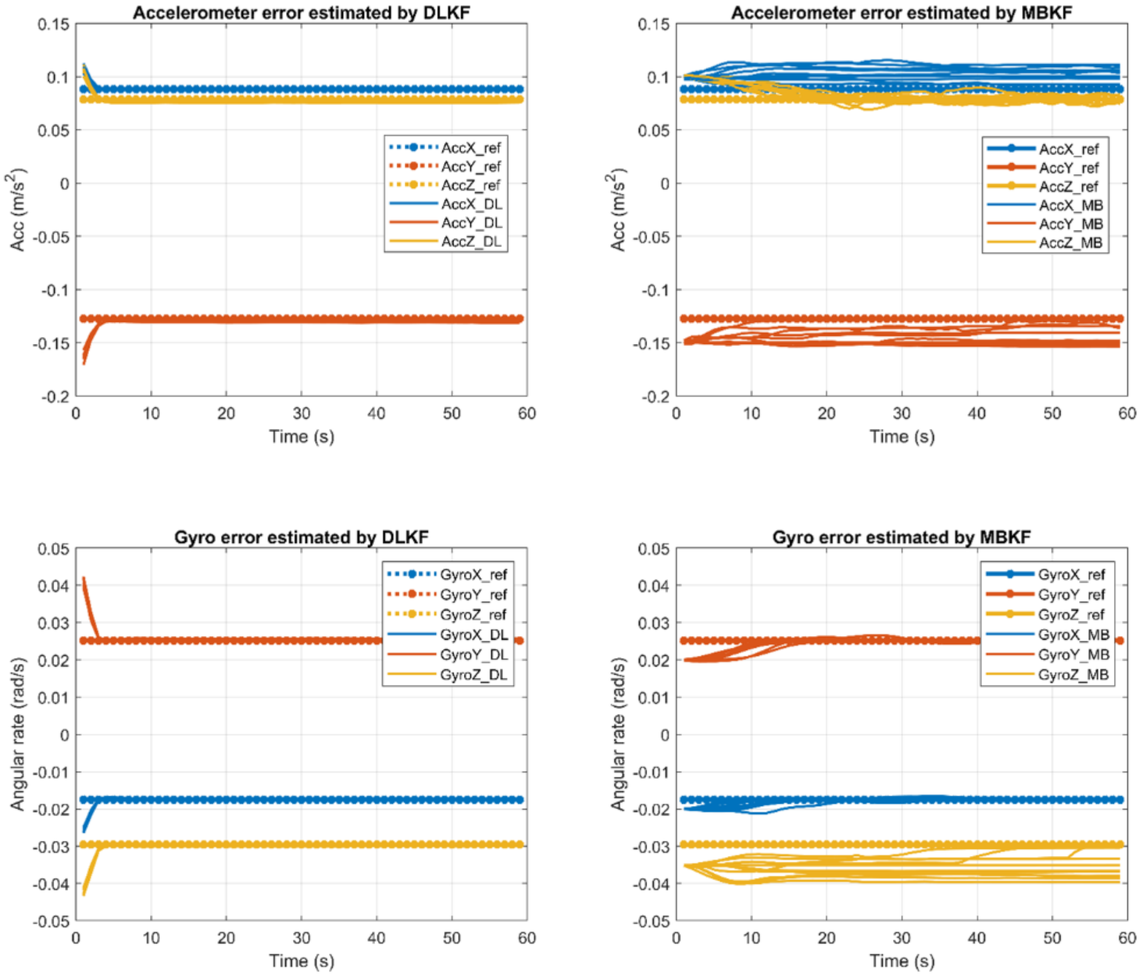
- IMU error estimation analysis

Results of 10 sub-trajectories, the duration of each is 60 seconds

GNSS measurements are in centimeter level

Short converge time and no intial value requires in DLKF

Position accuracy (0.45 m for DLKF and 0.49m for MBKF)
Velocity accuracy (0.02 m/s for DLKF and 0.04 m/s for MBKF).



Deep Learning Assisted Kalman Filter
Performance analysis

- KG analysis
  - If the KG value is close to 0, it means the filter will rely primarily on the prediction, whereas if the KG value is close to 1, the filter will rely primarily on the measurements.
  - We simulated normal distributed Gaussian noise scaled by the specified factors and added it to the GNSS position and velocity solutions to change the measurement quality:

$$\tilde{y_p} = y_p + SFP \cdot \mathcal{N}(0,1)$$
$$\tilde{y_v} = y_v + SFV \cdot \mathcal{N}(0,1)$$

Set	Pos Scale Factor	Vel Scale Factor
1	0	0
2	1	0
3	5	0
4	0	0.1
5	0	0.5
6	2	0.2

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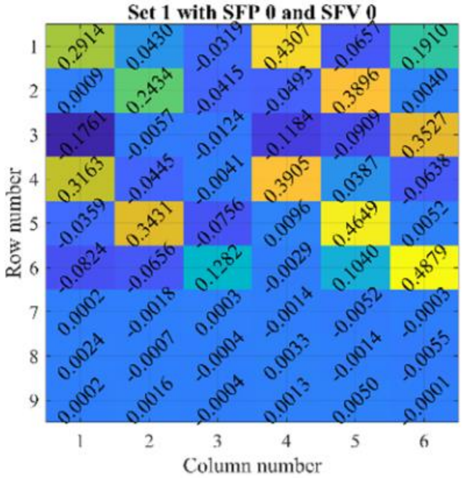
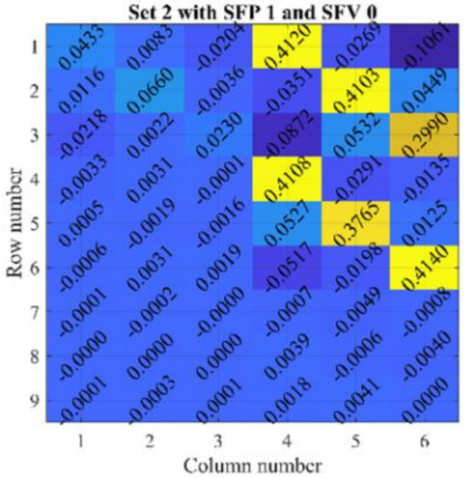
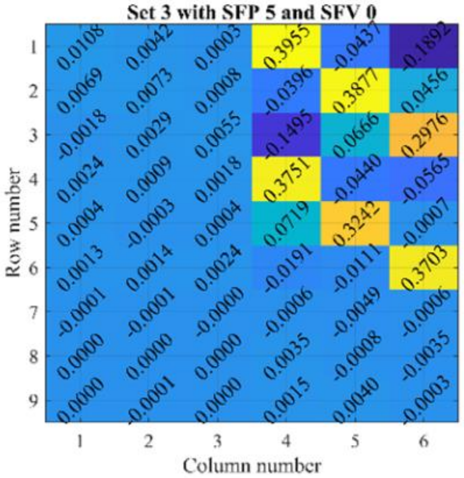
Performance analysis

- KG analysis
  - Set 1,2,3
  - Position Error increase
  - SFP (0, 1, 5)
  - DLKF (up)
  - MBKF(Down)

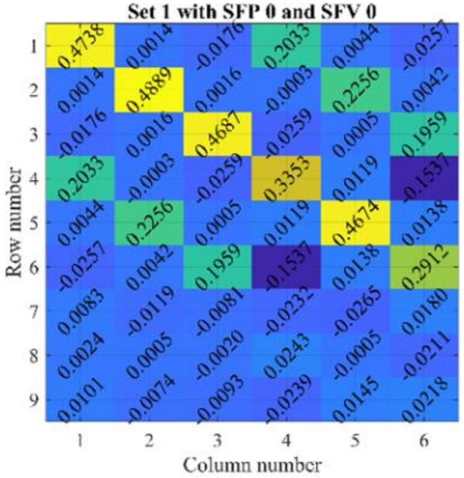
Deep Learning based Kalman filter (DLKF)

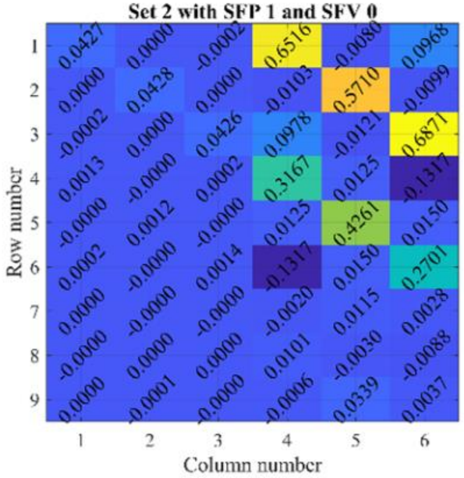


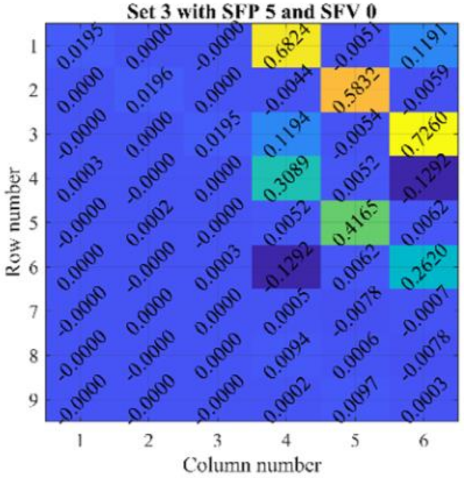




Model based Kalman filter (MBKF)





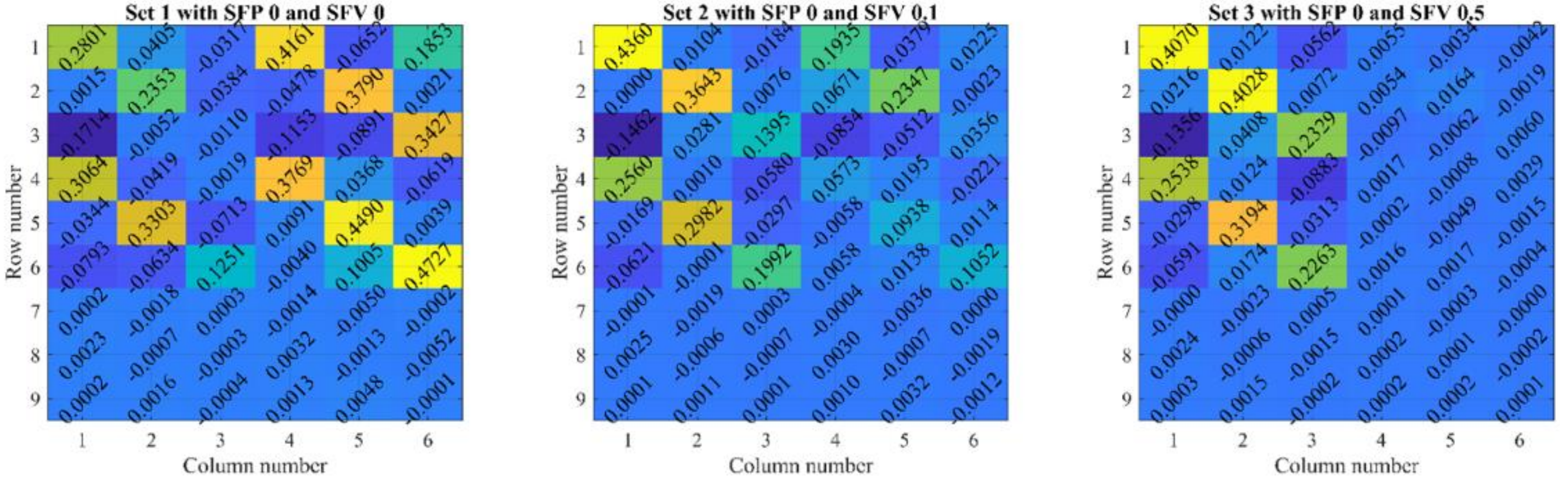


Deep Learning Assisted Kalman Filter

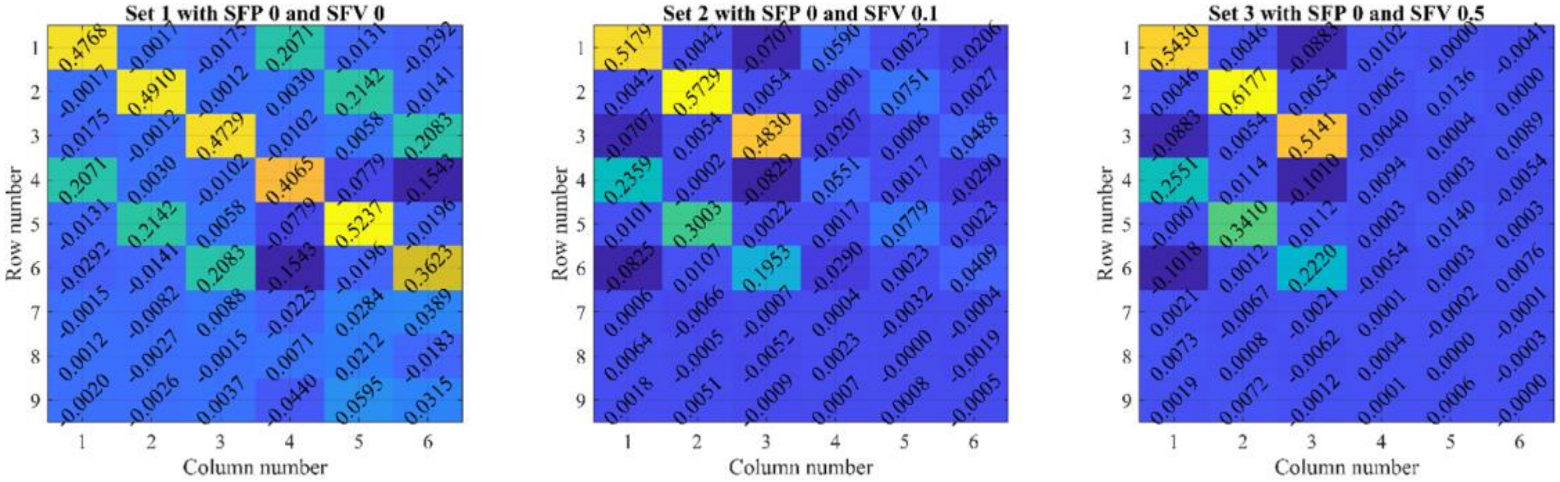
Performance analysis

- KG analysis
  - Set 1,4,5
  - Velocity Error increase
  - SFV (0, 0.1, 0.5)
  - DLKF (up)
  - MBKF(Down)

Deep Learning based Kalman filter (DLKF)



Model based Kalman filter (MBKF)



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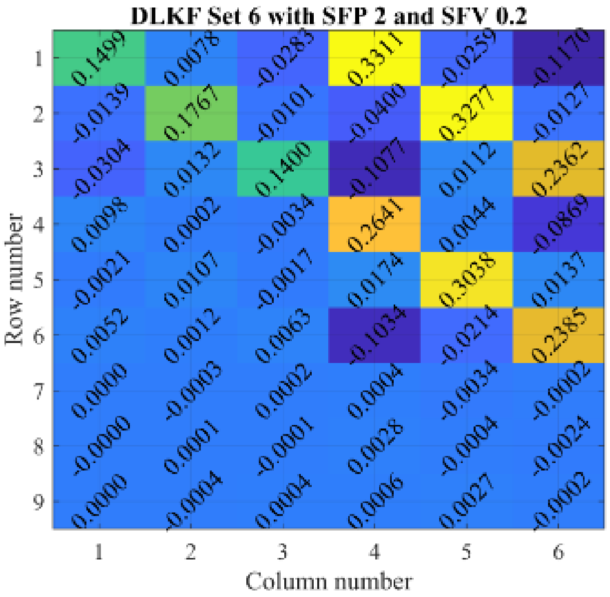
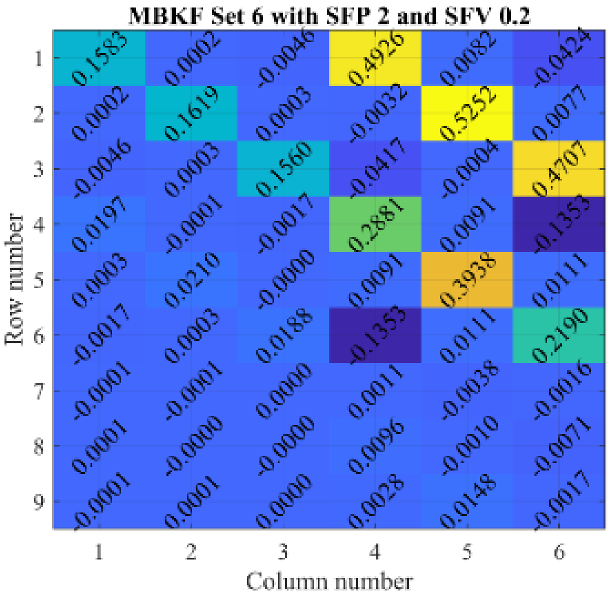
Performance analysis

- KG analysis
  - Set 6
  - Position error 2
  - Velocity error 0.2
  - DLKF (left)
  - MBKF(Right)





Deep Learning Assisted Kalman Filter

Experiments and Results

- Simulated dataset
- Real dataset

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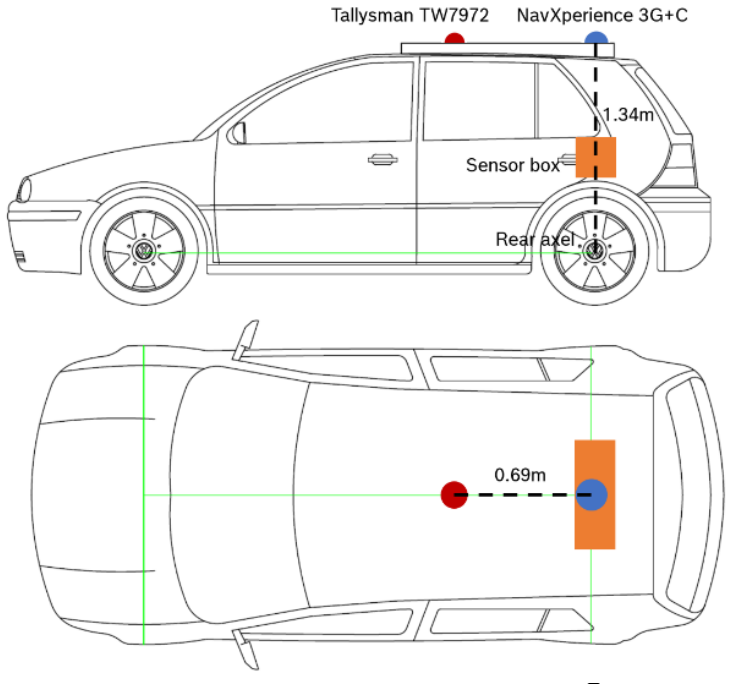
Data collection

- The real data recorded in various scenarios, including urban canyons, highways, short tunnels, and underground parking lots. A total of 75 test drives were conducted in 2021, 2022, and 2023, generating data with a total duration of approximately 42 hours and covering 1300 km. The raw sensor data was collected by a control area network (CAN bus) and recorded in ROS bag format.

Sensor	Type of Data	Description	Sample Rate	Antenna
Genesys ADMA G-Pro+ (Novatel OEM7720)	Ground Truth/ Reference System	The reference system includes position, velocity, and attitude.	100Hz	NavXperience
Ublox F9p (RTK)	Precise GNSS	RTK mode, GNSS solutions in centimeter level	10Hz	NavXperience
Ublox F9p (Standard)	Non-Precise GNSS	Standrad mode, GNSS solutions in meter level.	10Hz	Tallysman
Bosch BNO055	IMU	This sensor includes accelerometer and gyroscope.	50Hz	—



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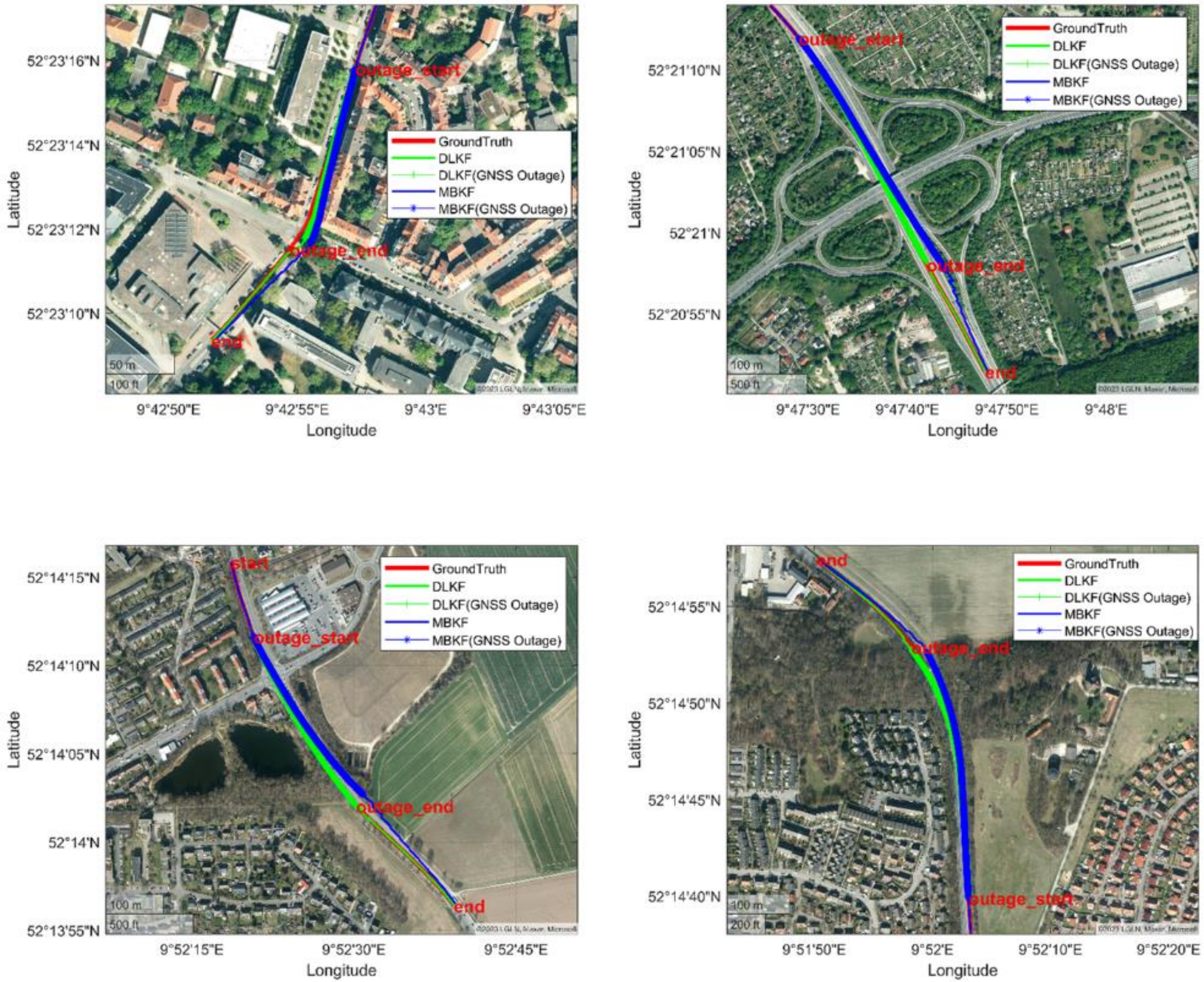
Performance analysis

- GNSS outage condition
  - Sub-trajectory length: 60s
  - GNSS outage Start: 30s
  - GNSS outage End: 50s
  - Basic strapdown computation



Deep Learning Assisted Kalman Filter

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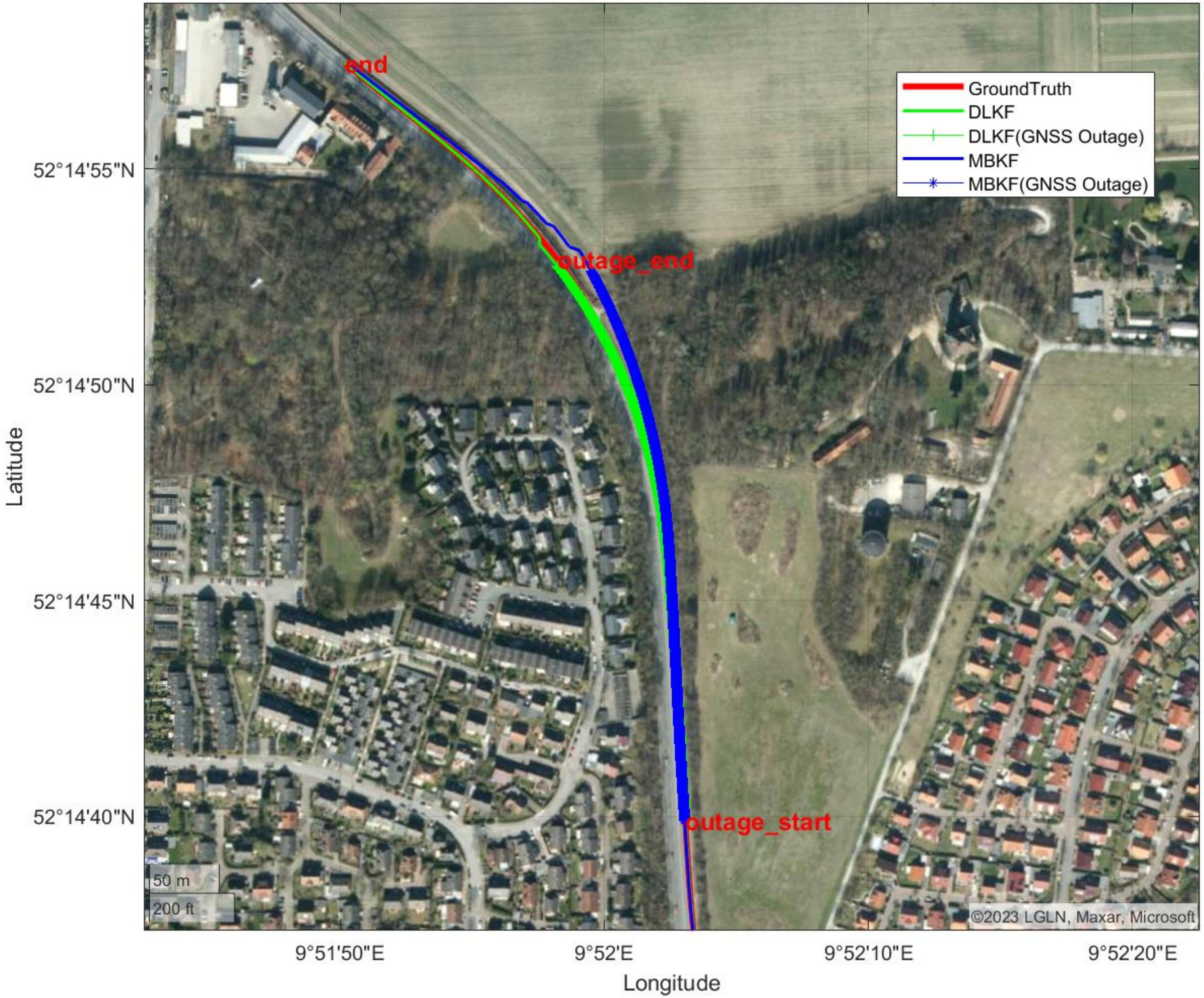

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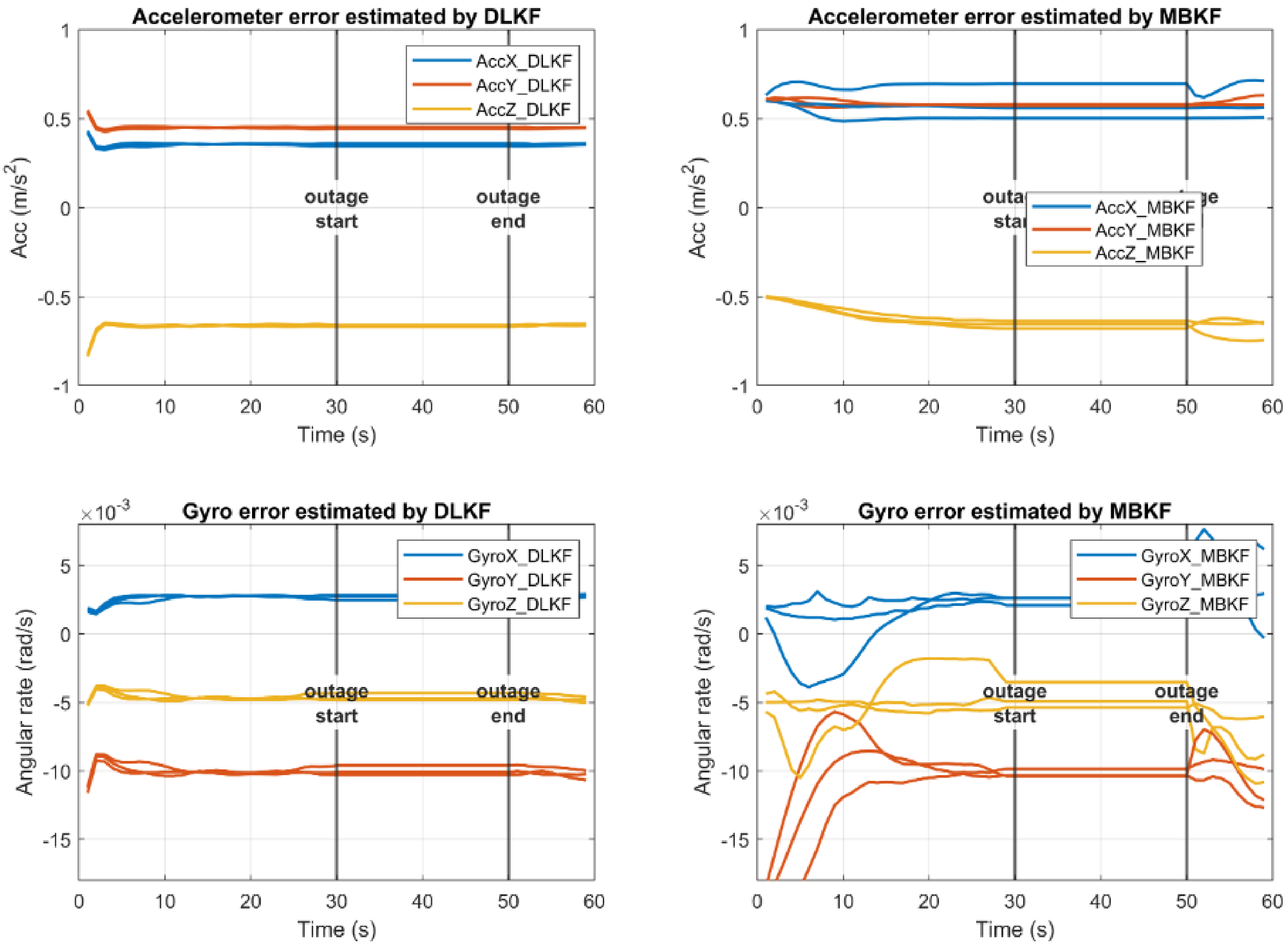
Performance analysis

- GNSS outage condition
  - IMU error estimation
  - Results on **3** sub-trajs



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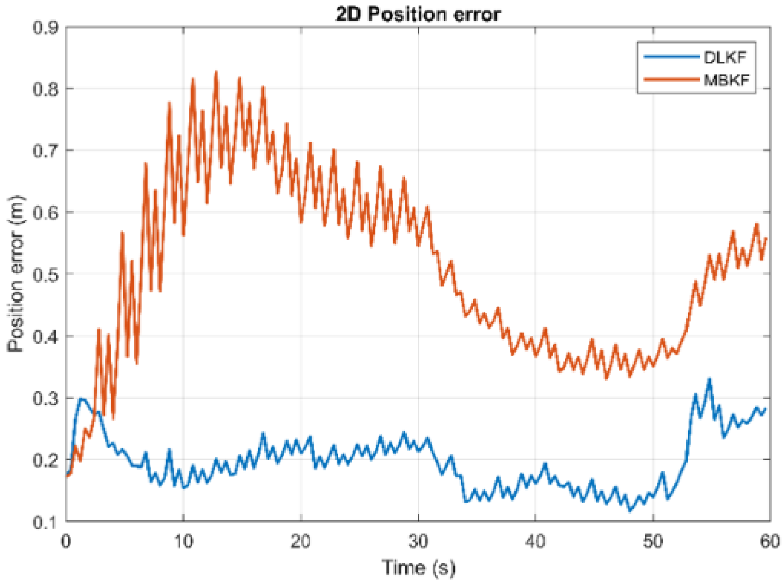
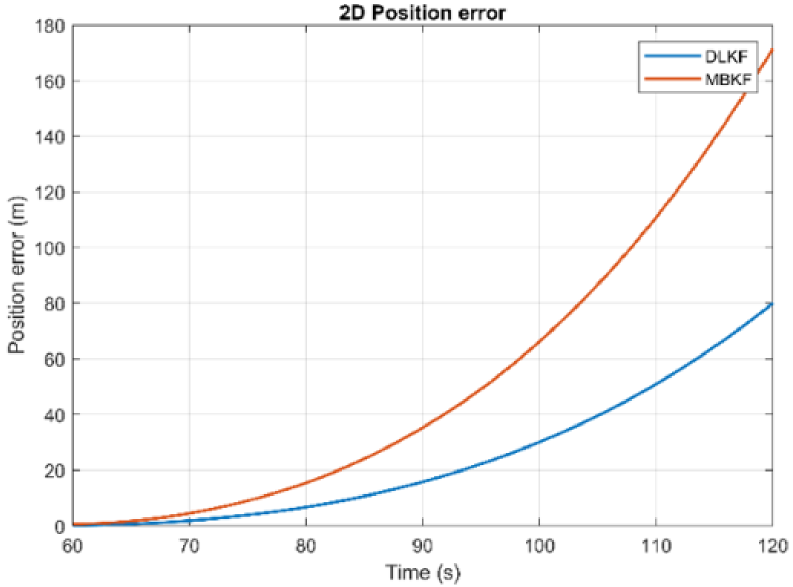
Performance analysis

- GNSS outage condition
  - Increase the sub-trajectory length to 120s
  - The GNSS outage start from 60s to 120s (1 minute outage)

Outage (s)	DLKF	MBKF
10	1.89	4.46
20	6.72	15.45
30	15.83	35.32
40	30.11	66.25
50	50.97	110.88
60	80.05	171.55



GNSS/INS(0-60s)



INS only (60-120s)

Deep Learning Assisted Kalman Filter

Conclusion and Future Work

- We implemented a deep learning assisted Kalman filter to enhance the performance of GNSS/INS integration.
- The proposed DL algorithm can learn system dynamics and noise statistics, leading to improved GNSS/INS navigation solution accuracy
- It can estimate IMU errors more precisely, thereby maintaining the navigation solution quality during GNSS outage conditions
- We can further extend the structure to learn the covariance separately for safety augmentations (integrity monitoring)

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Thank you!

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