Multitask Deep Neural Network for IMU Calibration, Denoising and Dynamic Noise Adaption for Vehicle Navigation

presentation for the respective conference paper

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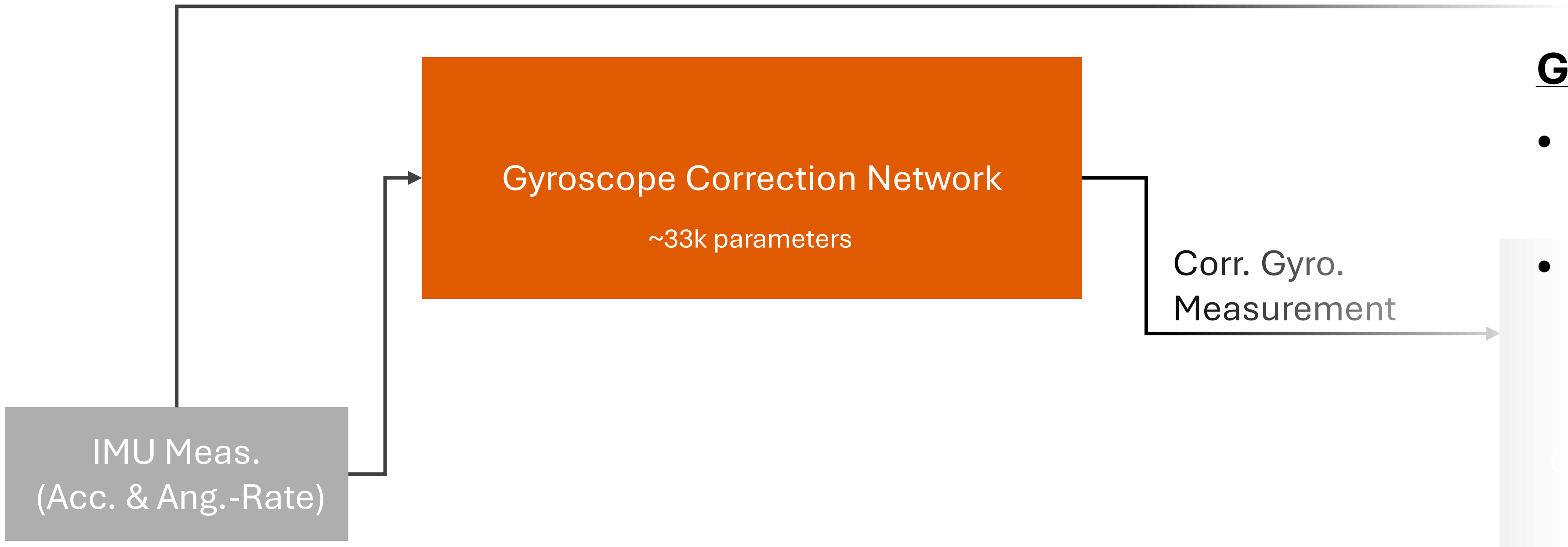
European Navigation Conference 2025

Motivation

- Work conducted within the DREAM project which aims to enhance localization and perception for public transport through robust, AI-based navigation modules.
- Vehicle navigation during **GNSS outage** relies on information from further sensors & auxiliary modules, for which often **AI solutions** exist.

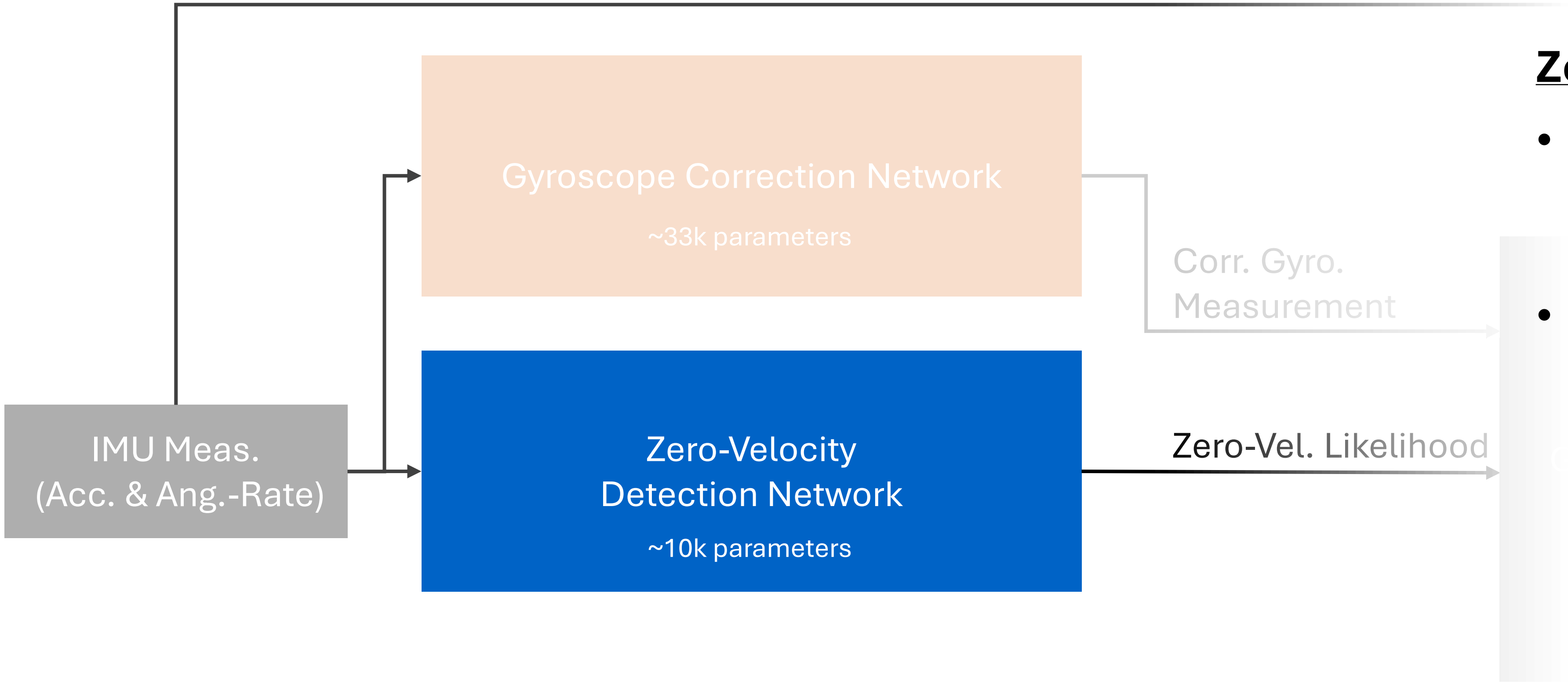
Motivation



Gyroscope Correction

- Network „corrects“ gyroscope measurements.
- Better at handling non-Gaussian and non-linear errors than traditional methods.

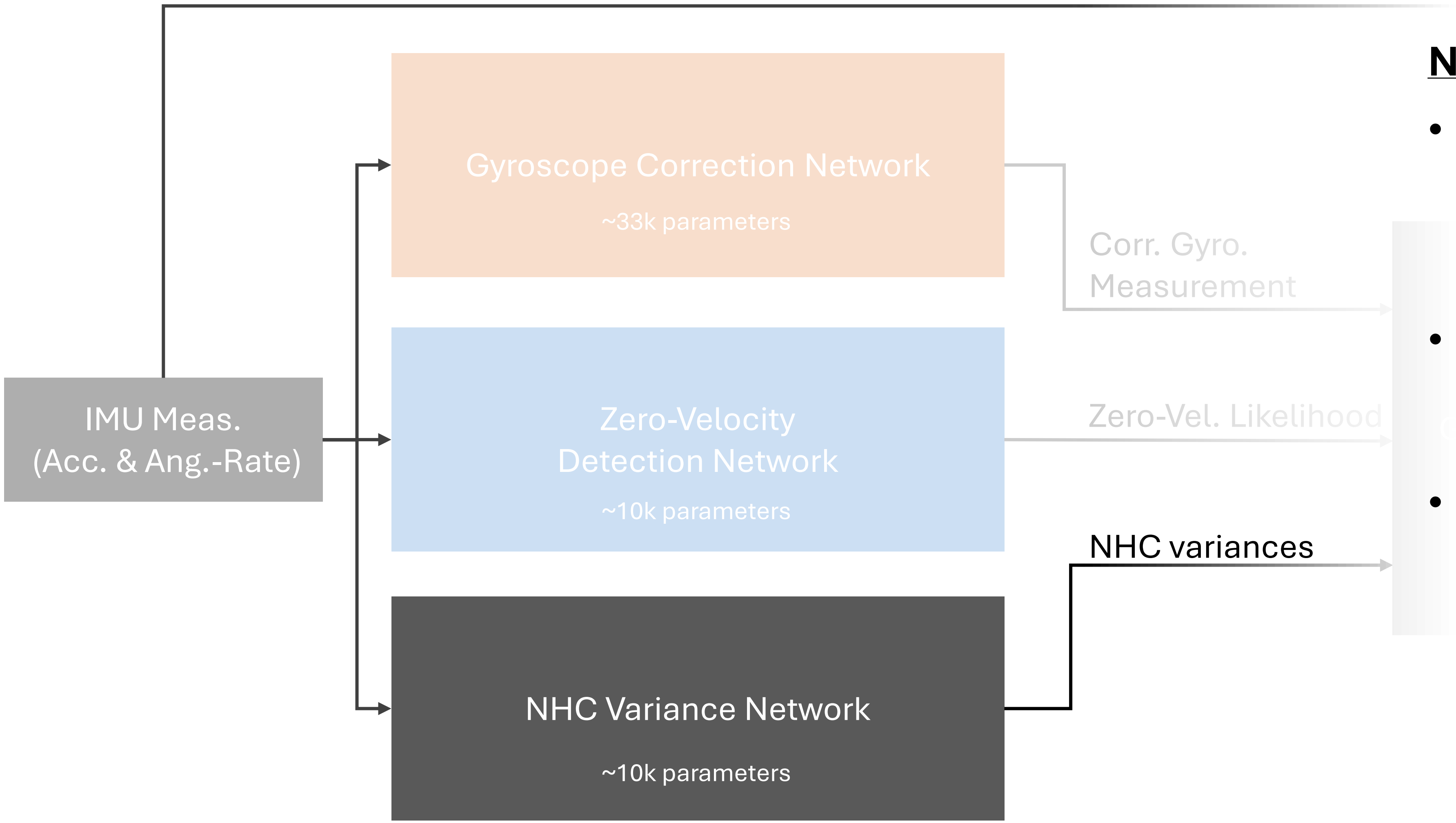
Motivation



Zero-Velocity Detection:

- Detection of standstill allows for „freezing“ of states and therefore no drift.
- Network estimates binary zero-velocity detection via likelihood.

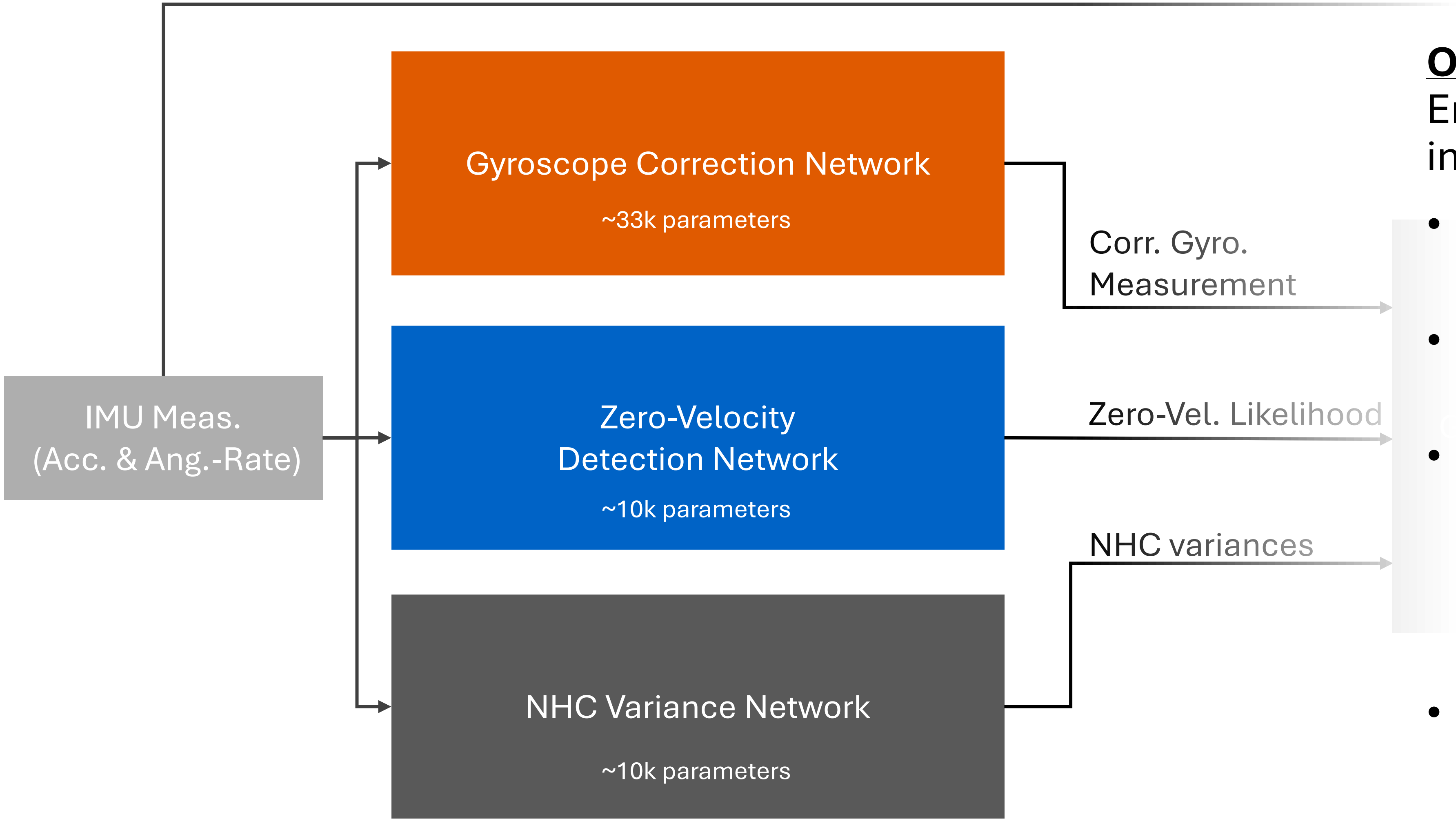
Motivation



<u>NHC Variance Network:</u>

- Non-Holonomic Constraints state that a vehicle on a road has neither lateral or vertical velocity.
- Due to constraint violations (e.g. slip) additional noise is introduced.
- Network estimates variances of NHC noise for Kalman Filter.

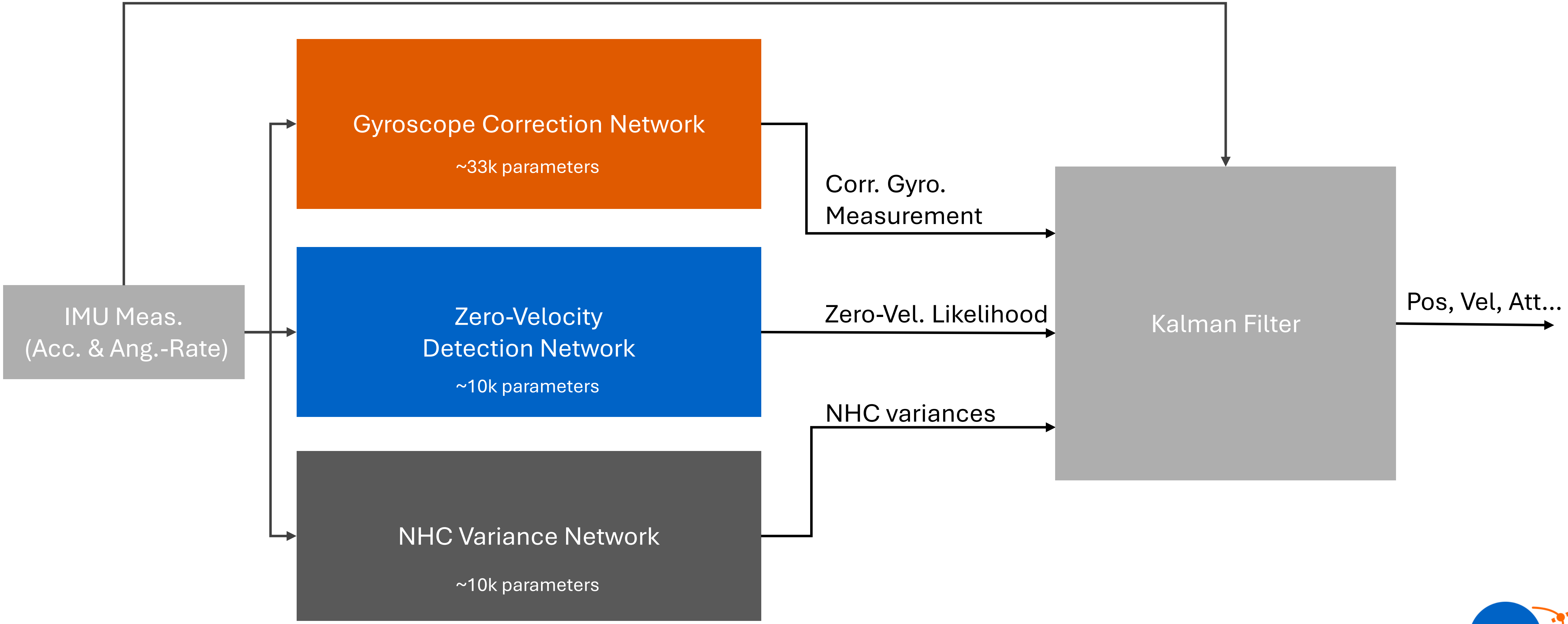
Motivation



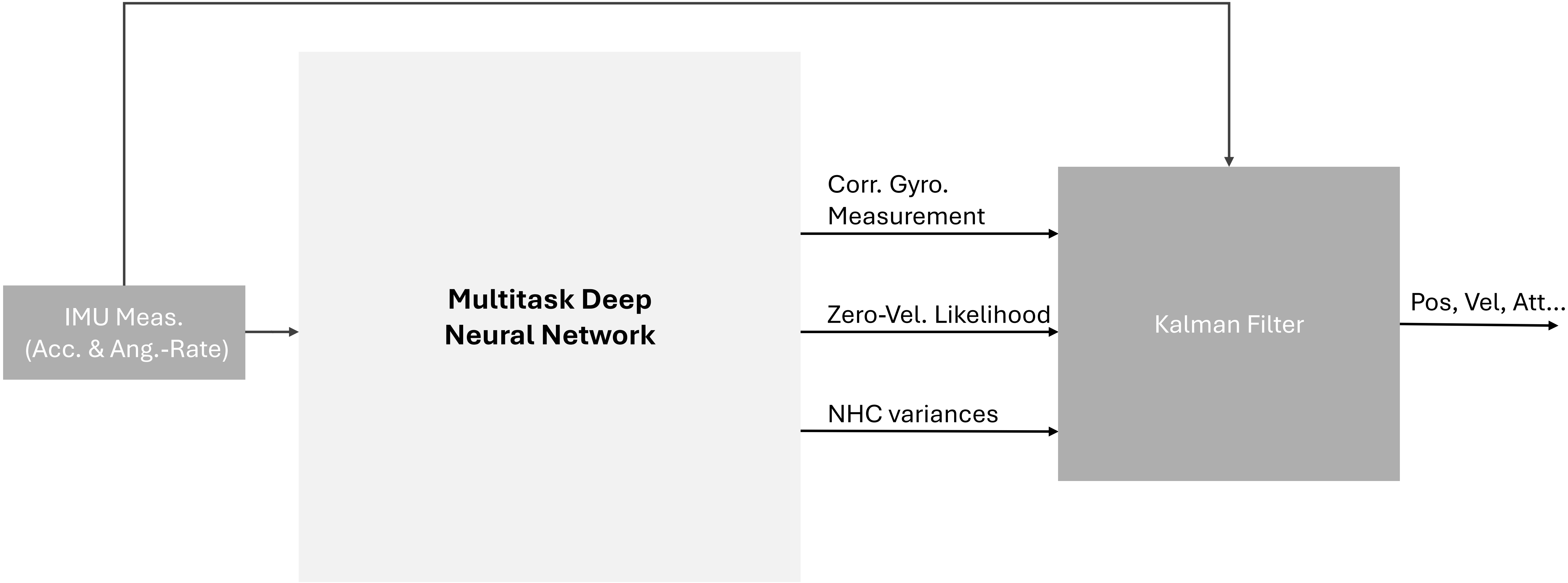
<u>Our Goal:</u>
Enhance navigation performance in GNSS denied situations.

- Build upon existing solutions and further develop those.
- Adapt and enhance models to further datasets.
- Make the system small, efficient and therefore fast enough to be able to be run on a embedded device (e.g. Raspberry Pi) in real-time.
- Enhance robustness and generalization of system.

Motivation


IMU Meas.
(Acc. & Ang.-Rate)
Gyroscope Correction Network
~33k parameters
Zero-Velocity
Detection Network
~10k parameters
NHC Variance Network
~10k parameters
Corr. Gyro.
Measurement
Zero-Vel. Likelihood
NHC variances
Kalman Filter
Pos, Vel, Att...

Motivation


IMU Meas.
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Multitask Deep
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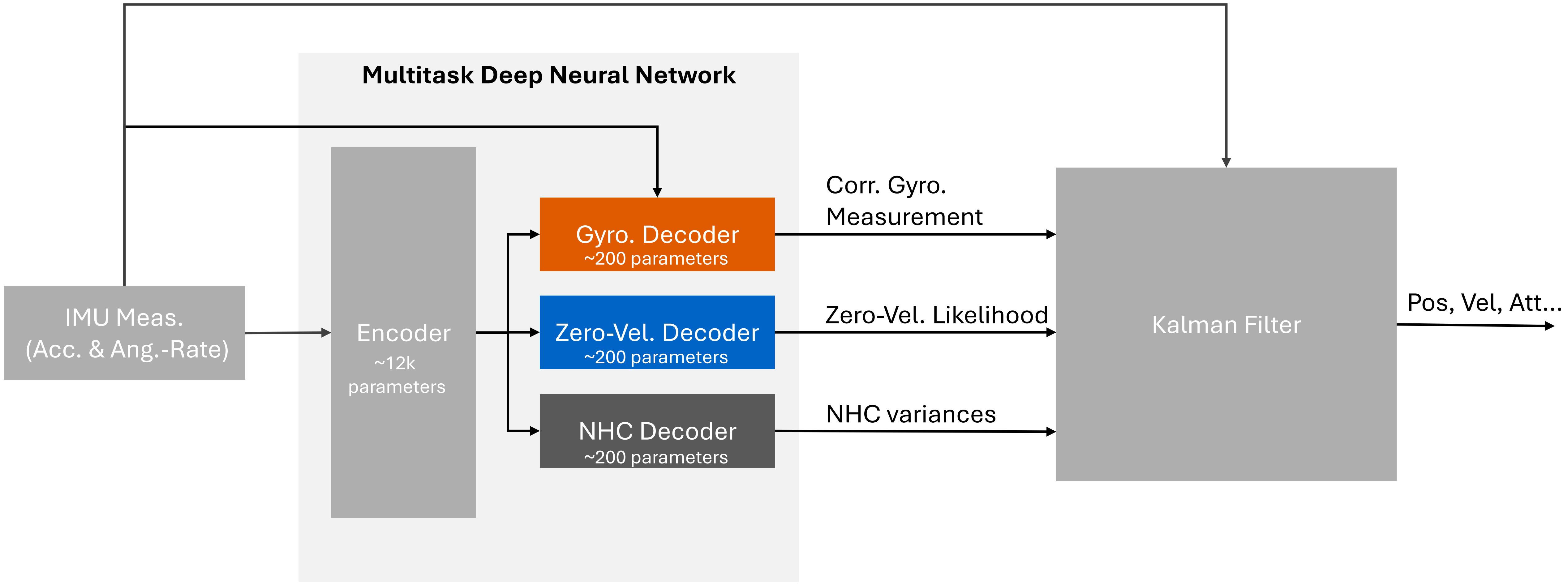
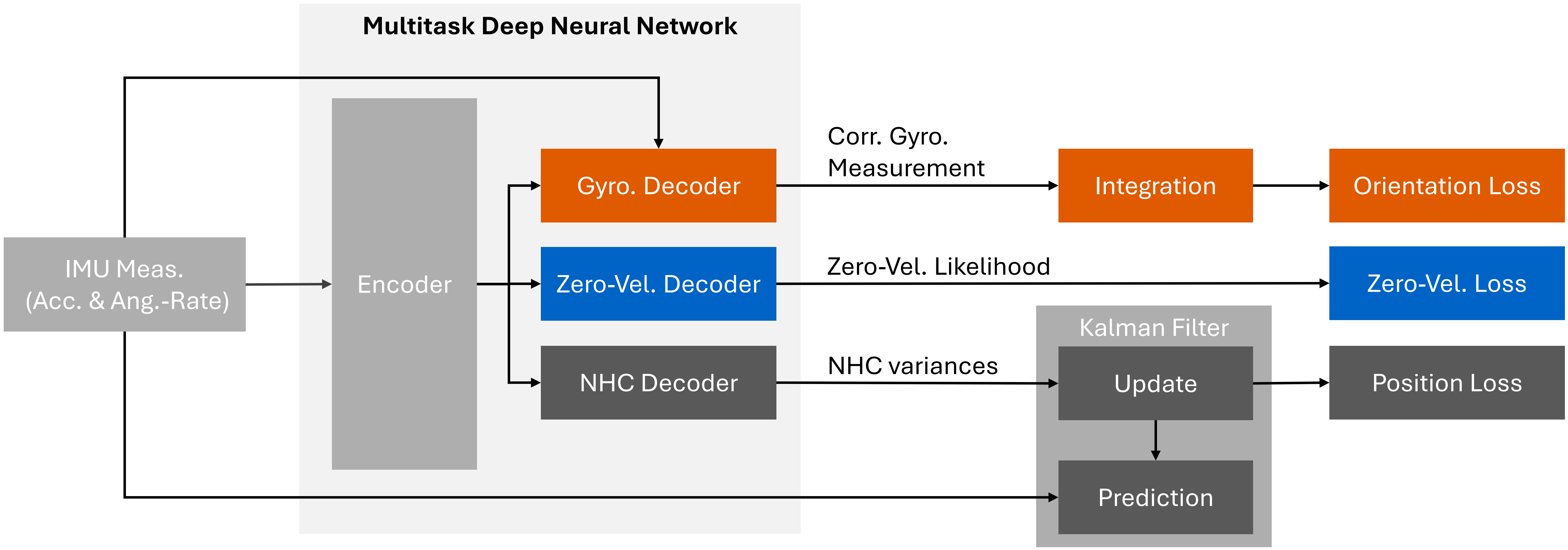
Network Architecture

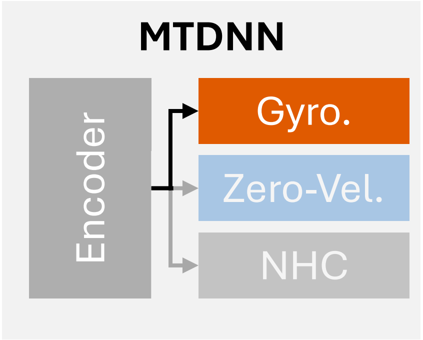


Training: Datasets

- 4Seasons dataset from Technical University of Munich.
  - Public benchmark dataset.
  - GNSS-RTK & Visual-Inertial-Odometry fused Ground Truth.
  - Various driving scenarios, surfaces & weather conditions.
  - ~1hr of data used.
- In-house ANavS dataset, evaluation in paper.

Training Process





Results of Gyro.-Correction

- Major improvement between 27% and 90.4%
- Orientation remains static during standstill
- Shows that network captures both dynamic and static behavior of the IMU signals

Performance Improvement over all data

Axis	RMS	95-Percentile
Roll	27.5 %	34.8 %
Pitch	41.4 %	49.1 %
Yaw	90.4 %	87.0 %

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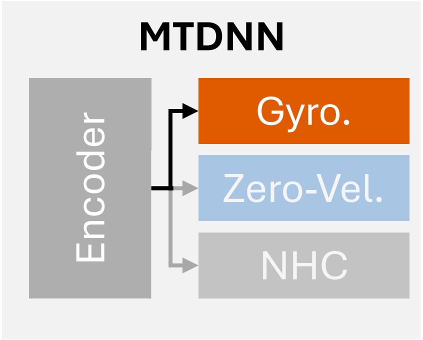

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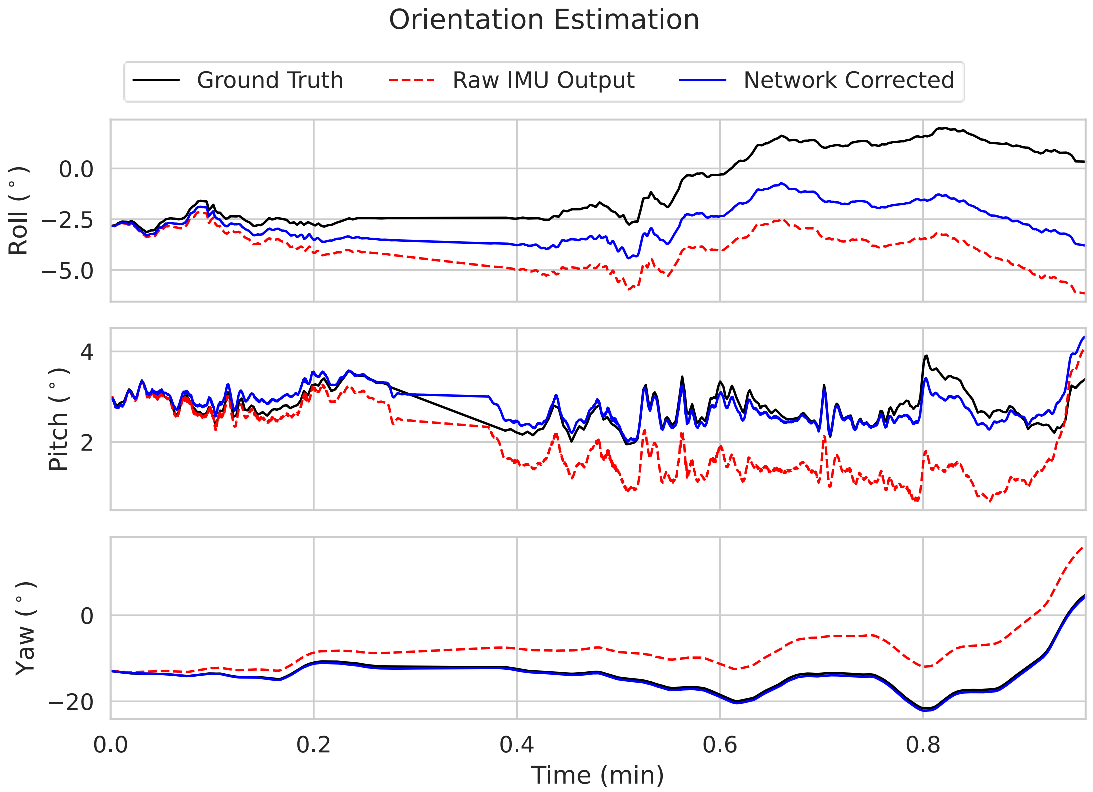
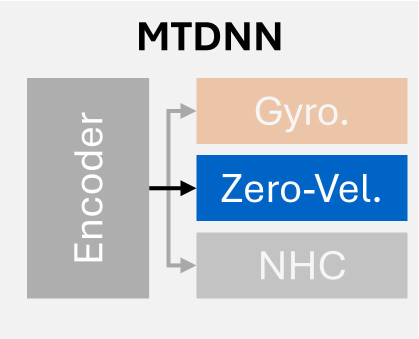
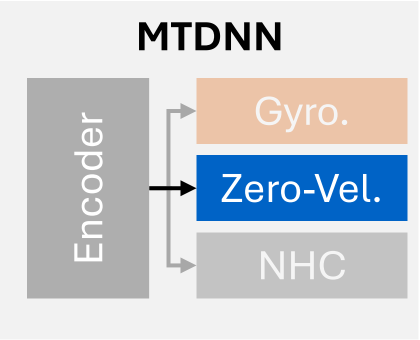


***Figure**: Exemplary result for one sequence.*

Results of Zero-Vel. Detection



- Network output closely matches ground truth with minimal delay and avoids false positives during motion
- Statistics:
  - 94.7 % precision
    → **few false positives**
  - 96.0 % recall
    → few missed detections
  - 95.3 % F1-score
    → balanced system



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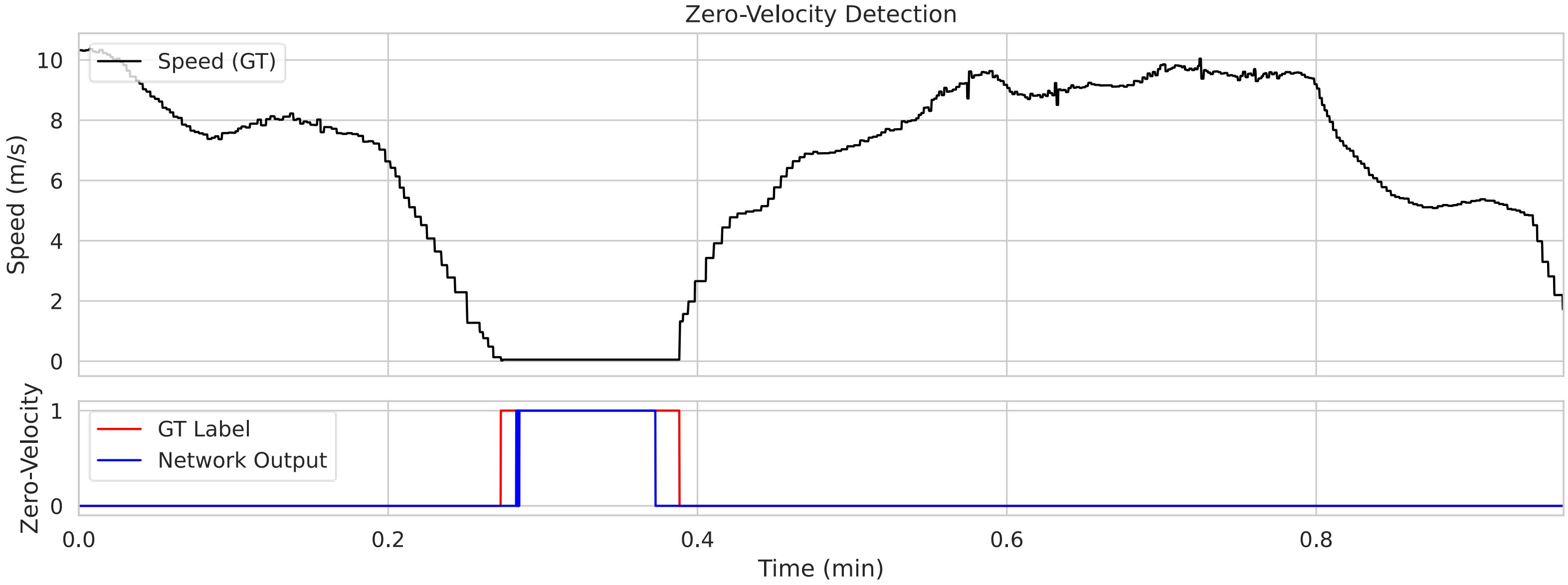
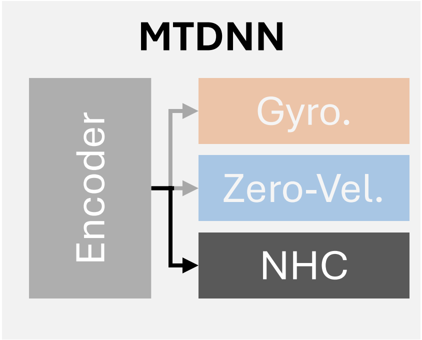


***Figure**: Exemplary result for one sequence.*

Results of NHC Variance Estimation



- Position error reduced by **29.9 %** (RMS) and **25.7 %** (95th percentile) through adaptive NHC variance estimation
- **No manual tuning needed** – the network learns to adapt constraints based on motion context
- Stable performance over time, reducing drift and improving Kalman filter accuracy in GNSS-degraded environments

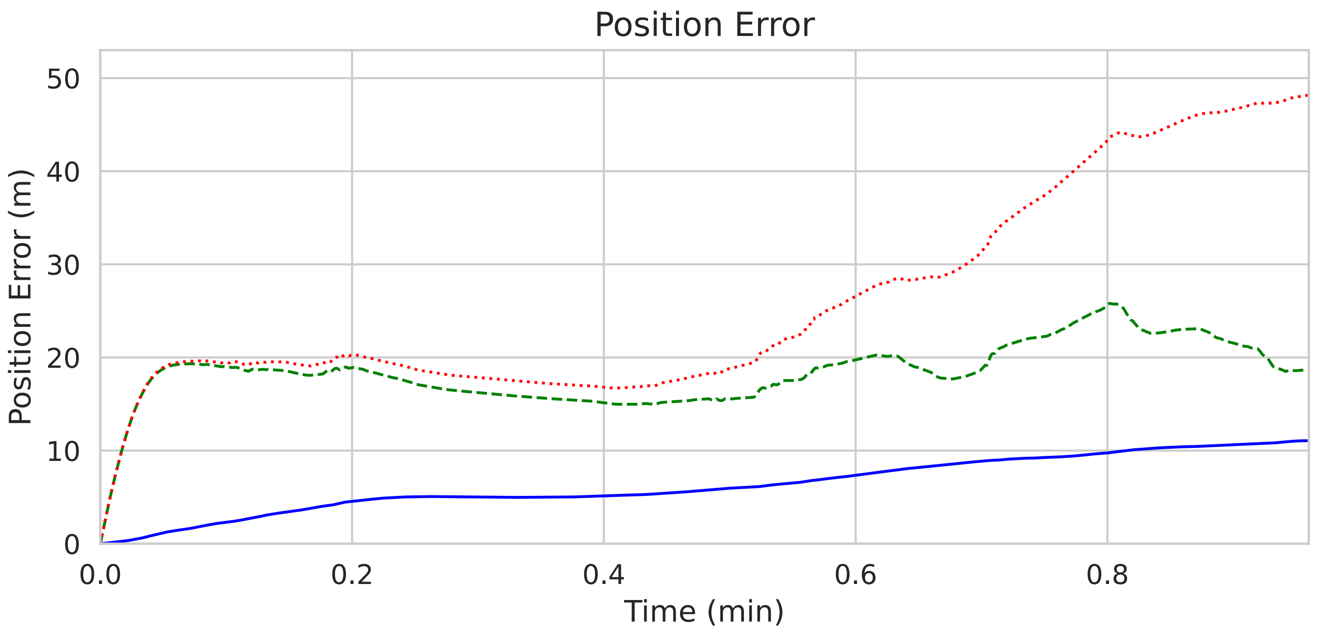
Scalar Position Error over all data

	RMS [m]	95-Percentile [m]
Static (Base)	36.79	81.05
MTDNN	25.80	60.24

Summary & Outlook

- Full integration of all auxiliary modules reduces the position error very effectively
- Each task contributes to improvement
- Smallen down the computational needs by ~75%
- No manual tuning required

→ Extend to multimodal inputs
→ Explore self-supervised training
→ Integrate MTDNN into a Multisensor System (with GNSS, LiDAR...)



	Gyro	NHC	Zero-Vel.
IMU only	Raw	Static	-
Gyro. Corr.	MTDNN	Static	-
All. Corr.	MTDNN	MTDNN	MTDNN

Contact & Project Information

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- Email: frieder.schmid@anavs.de
- Code and dataset will be published at https://github.com/anavsgmbh/MTDNN
- ANavS GmbH - Advanced Navigation Solutions, Munich (www.anavs.com)

DREAM Project

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- contract number: EUSPA/GRANT/03/2022.
- https://dream-project-eu.com/

DRIVING AIDS POWERED BY E-GNSS, AI AND MACHINE LEARNING