‘Advances in AI for Positioning, Navigation and Timing Applications’

A joint event between the Cambridge Wireless Location SIG & The Royal Institute of Navigation

30 June 2026, Cambridge

Chair: Session 2

David Bartlett
Cambridge Wireless
SIG Champion

Agenda

13:55 **Bob Oates & Rebecca Middleton, Cambridge Consultants**
Robust and resilient AI for safety critical systems

16:00 **Dr. Iñigo Cortés, CTO and co-founder, RobNav**
Reinforcement learning-based adaptive control algorithm for PNT

16:15 **Freddy Saunders, Senior Consultant, Plextek**
IMU augmentation using Deep Learning

16:30 **Stephen Clemmet, Silogic Technology Limited**
Before GNSS Fails: Lessons from Ukraine

16:45 **Speaker Panel Session**
Chaired by **Ramsey Faragher, Royal Institute of Navigation** & Cambridge Wireless SIG Champion

17:15 Concluding Remarks & Event ends

Robust and resilient AI for safety critical systems

Dr Bob Oates
Associate Director
Cambridge Consultants

Rebecca Middleton
AI Assurance Specialist
Cambridge Consultants

CAMBRIDGE WIRELESS

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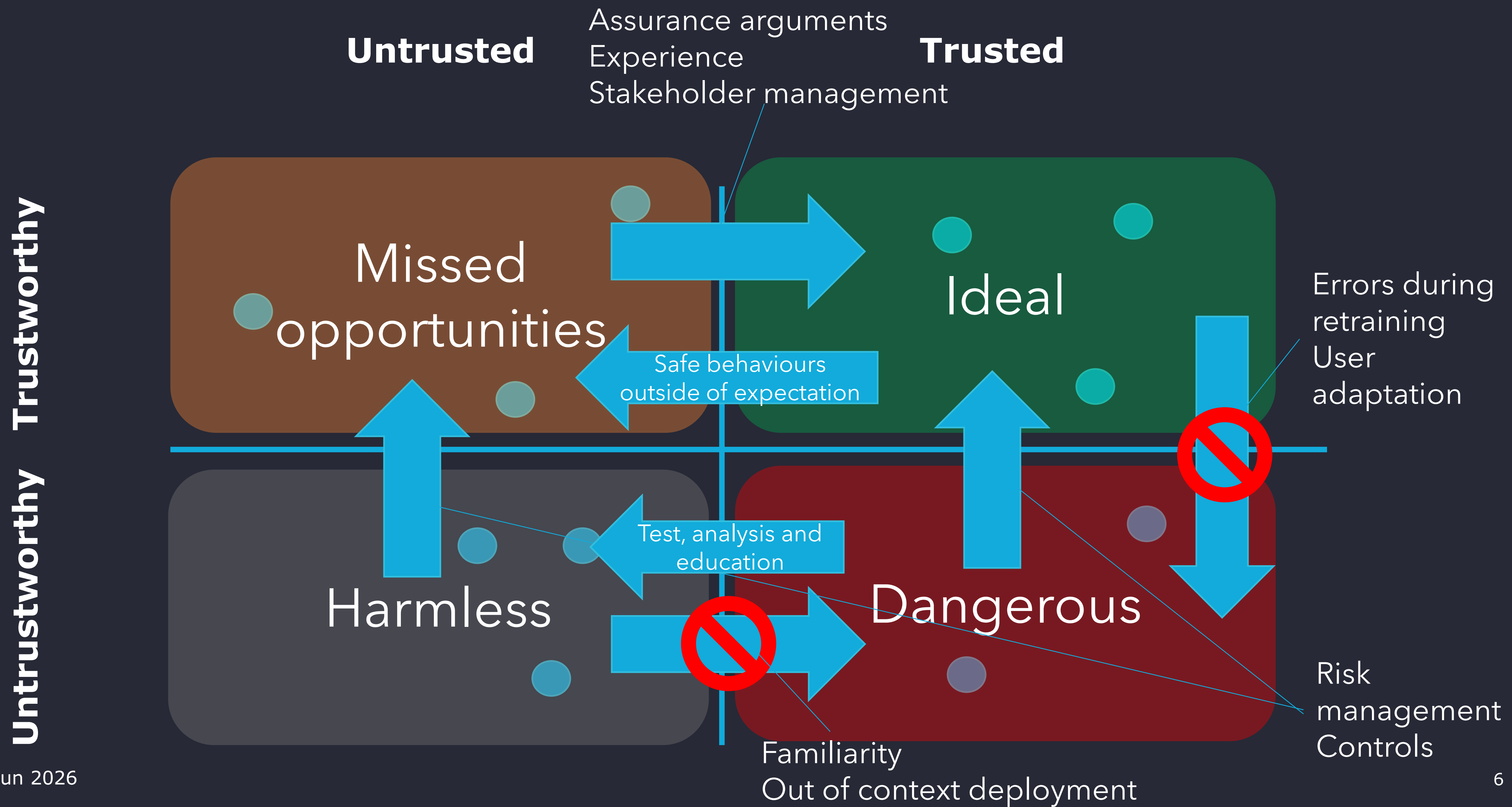
Robust and Resilient AI for Safety Critical Systems

Rebecca Middleton & Bob Oates

Embodied AI Safety



AI in PNT offers a wide range of significant benefits

Resilience
Maintains PNT when signals are degraded or attacked

Accuracy
Improves positioning precision beyond traditional methods

Adaptability
Learns and adjusts to new environments dynamically

Automation
Reduces reliance on human intervention and tuning

AI enabled PNT

Trustworthy position, navigation and timing

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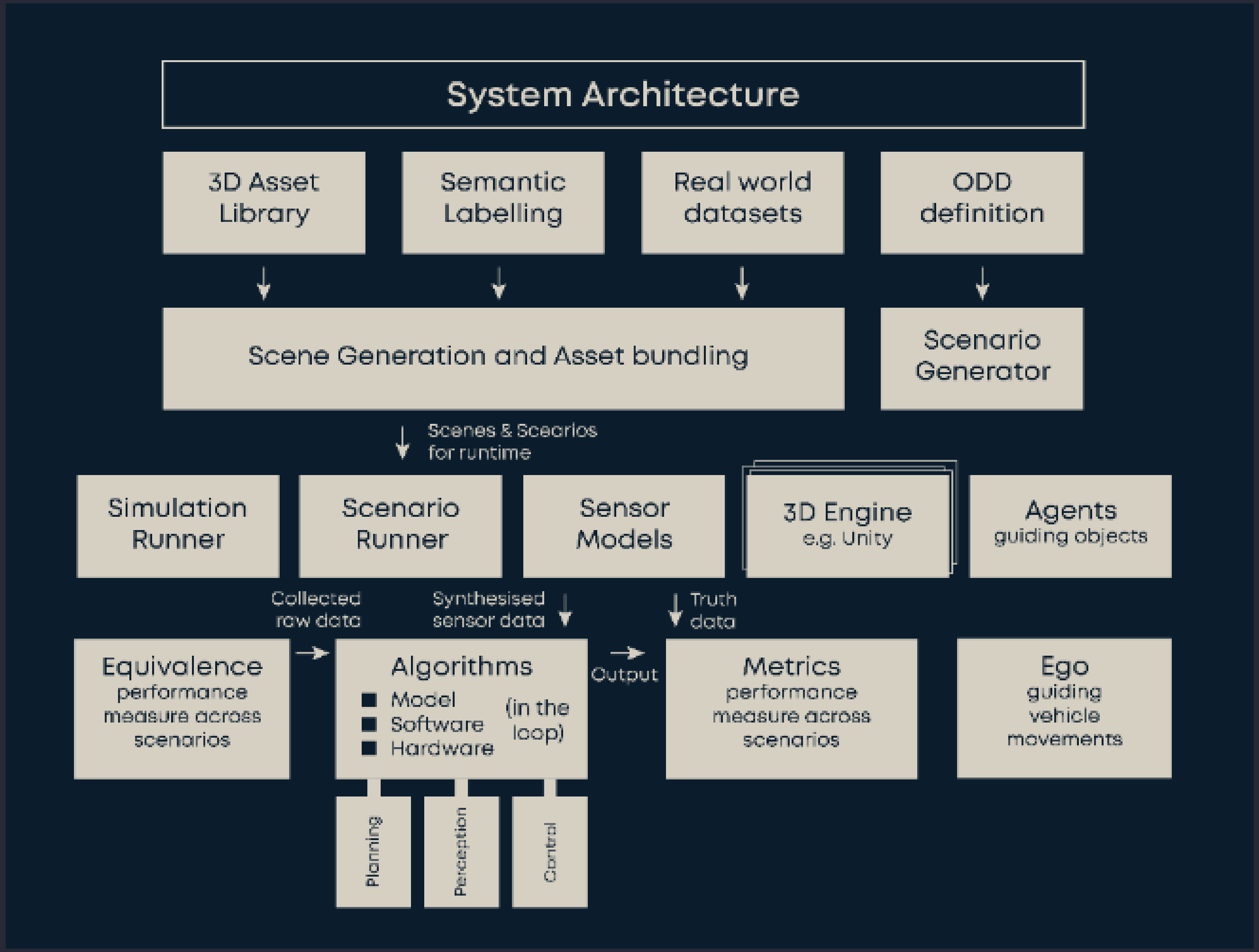
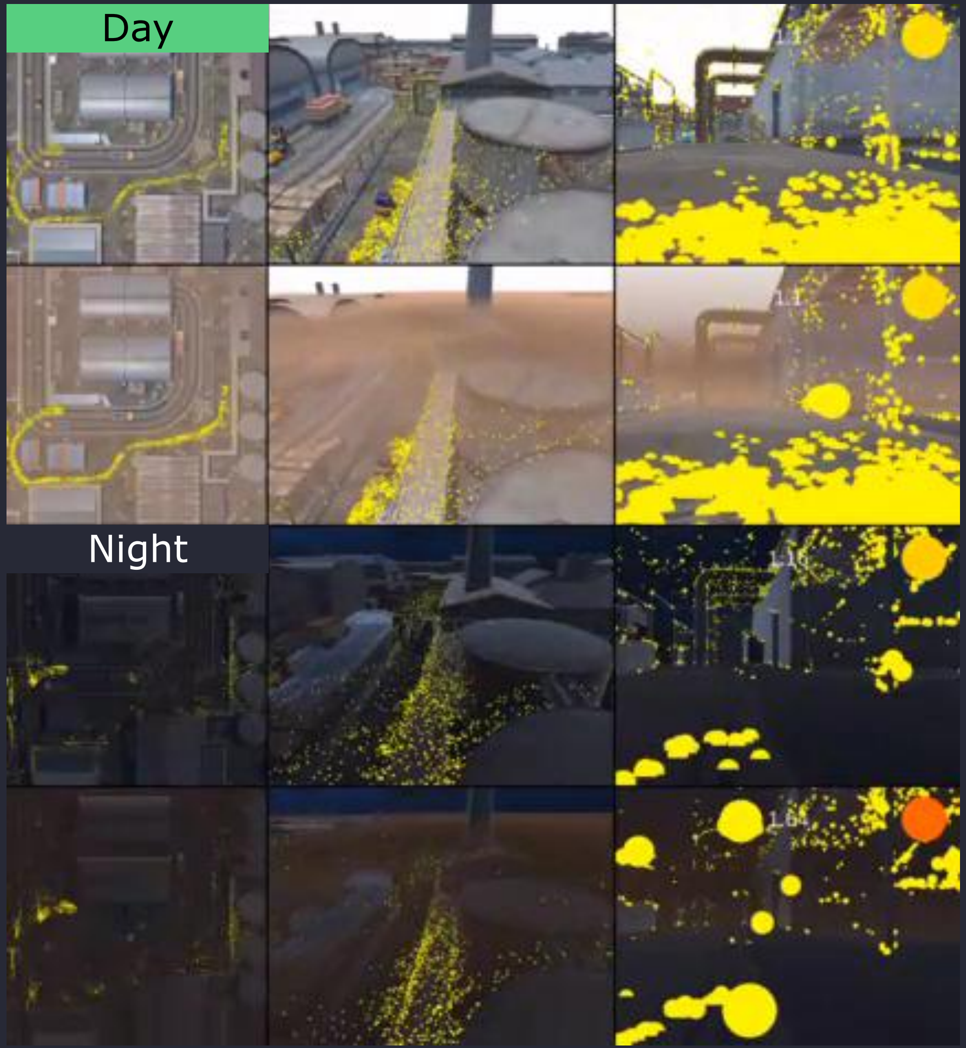
The second layer: AI must itself be robust, resilient to make PNT trustworthy

AI enabled PNT

Trustworthy position, navigation and timing

We need to test where AI breaks





Putting it all together

Simulation, Monitoring, Automated test harnesses, MLOps infrastructure

AI Governance

Assurance case: Adaptive, evidence-based argument

Enabling technologies

Test data | Analysis outcomes | Monitoring data | Training records | Error logs

User training | Surrounding processes | Security controls | Monitoring | Model retraining | Software Guardrails

Trust Calibration | Environment | Sensor Failure | Data Errors | Adversary Attack | Model Failure | Unknown unknowns

A hard problem but a solvable one

Robust and resilient AI in PNT is hard but it is **solvable**, and increasingly **necessary** to get right.

Simulation

Test edge cases
& failure modes

Assurance cases

Evidence-based,
through-life arguments

Governance

Risk management
across the lifecycle

Robust & resilient AI-enabled PNT

The methods exist. Applying them rigorously is how we unlock AI's benefits in PNT safely.

UK ▪ USA ▪ SINGAPORE ▪ JAPAN

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Reinforcement learning-based adaptive control algorithm for PNT

Dr. Iñigo Cortés
CTO and co-founder
RobNav

CAMBRIDGE WIRELESS

ROYAL INSTITUTE OF NAVIGATION

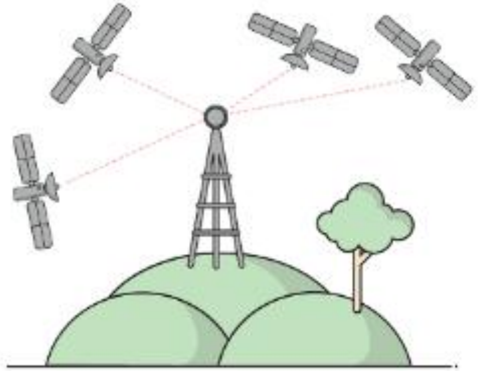
Reinforcement learning-based adaptive control algorithm for PNT

Dr. Iñigo Cortés

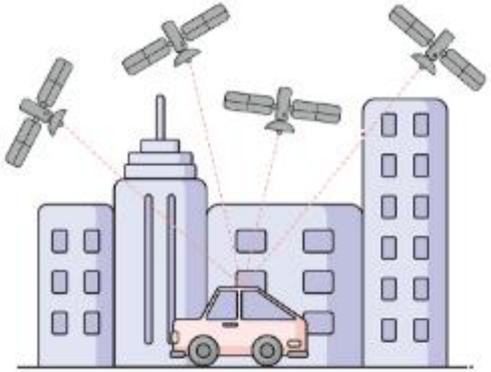
Advances in AI for Positioning, Navigation and Timing Applications
Cambridge, June 2026

Introduction

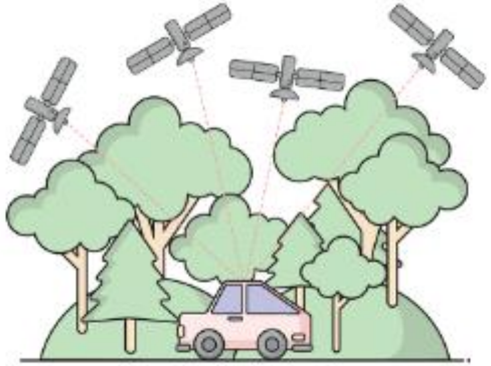
Base station



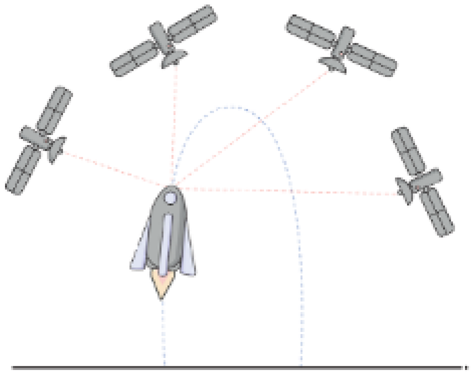
Urban



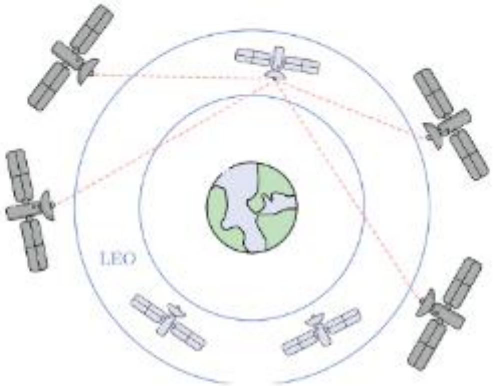
Forest



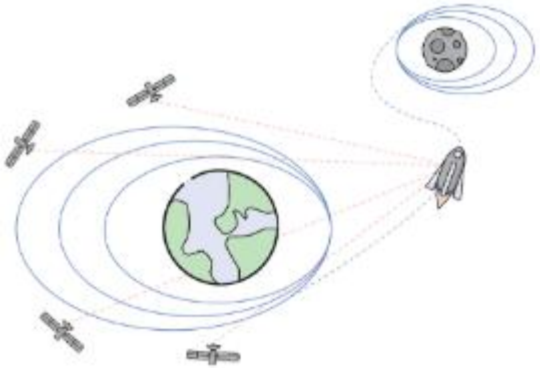
Sounding rocket



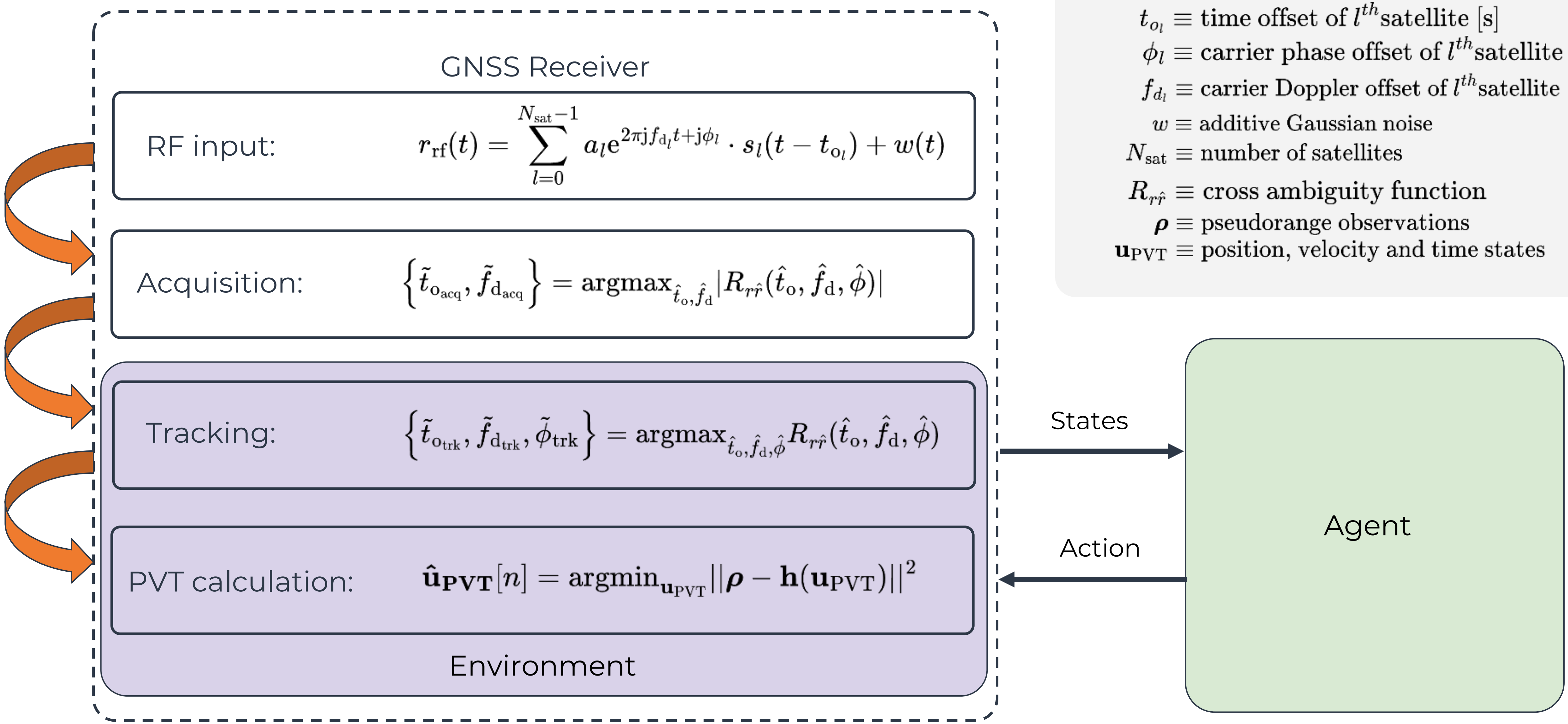
LEO



Lunar mission



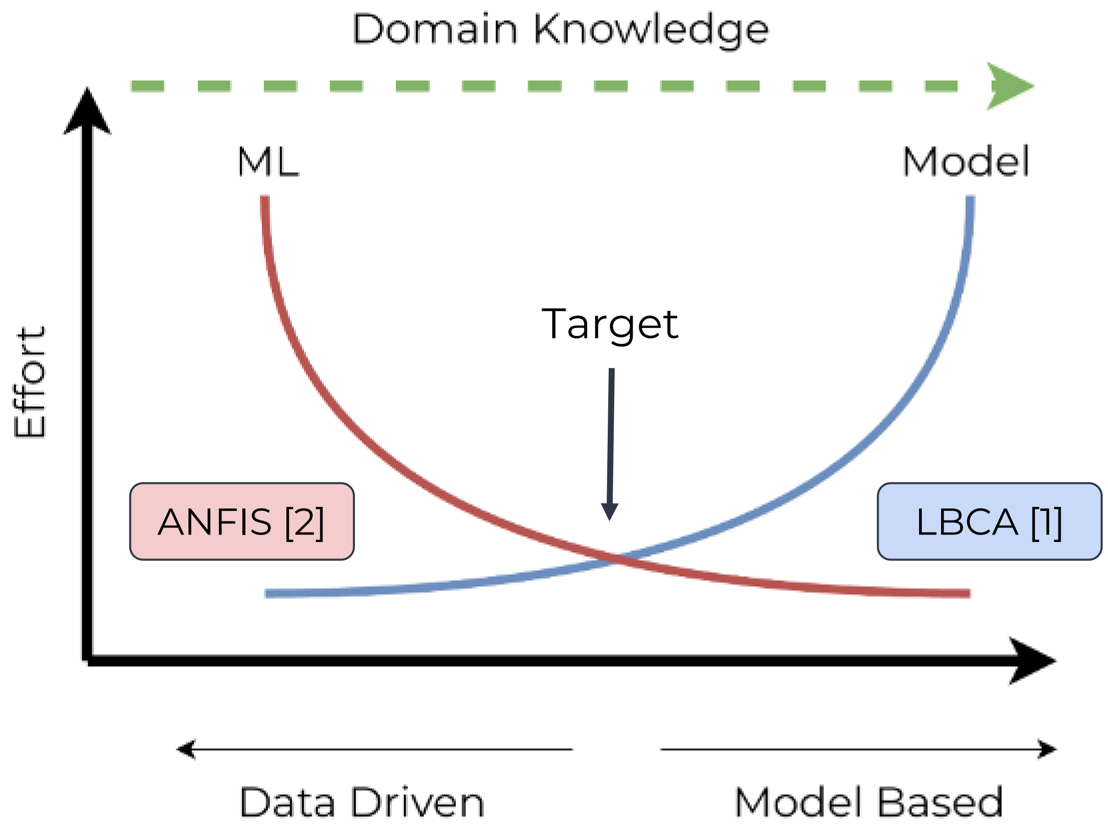
Introduction



$r_{\mathrm{rf}} \equiv$ received signal
$s_l \equiv$ transmitted signal of l^{th} satellite
$a_l \equiv$ attenuation factor of l^{th} satellite
$t_{o_l} \equiv$ time offset of l^{th} satellite [s]
$\phi_l \equiv$ carrier phase offset of l^{th} satellite [rad]
$f_{d_l} \equiv$ carrier Doppler offset of l^{th} satellite [Hz]
$w \equiv$ additive Gaussian noise
$N_{\mathrm{sat}} \equiv$ number of satellites
$R_{r\hat{r}} \equiv$ cross ambiguity function
$\boldsymbol{\rho} \equiv$ pseudorange observations
$\mathbf{u}_{\mathrm{PVT}} \equiv$ position, velocity and time states

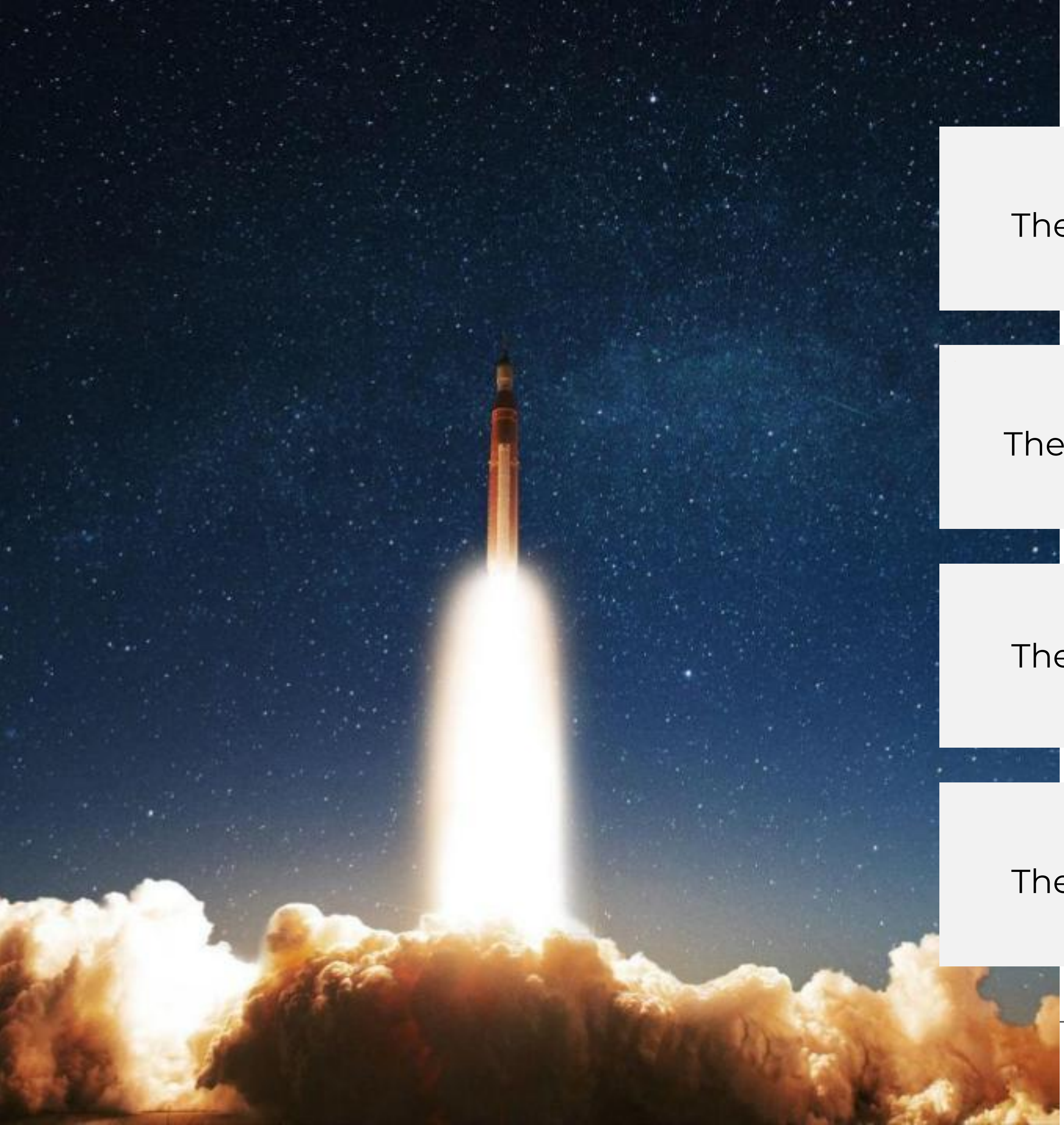
GNSS: Global Navigation Satellite System
PVT: Position, Velocity and Time

Introduction



[1] Cortés, I. (2024). Generalized robust adaptive control algorithm for GNSS receivers. PhD thesis, Tampere University, Tampere, Finland
[2] J.-S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," in IEEE Trans. Sys. Man, and Cybernetics, vol. 23, no. 3, pp. 665-685, 1993, doi: 10.1109/21.256541.

LBCA: Loop Bandwidth Control Algorithm
ANFIS: Adaptive Network based Fuzzy Inference System
ML: Machine Learning



1

The Origin: A controller a human had to tune

2

The Extension: A controller that tunes itself

3

The Potential: Tracking, navigation and beyond

4

The Takeaway: Model-based meets data-driven

The Origin: Adaptive Control Algorithm

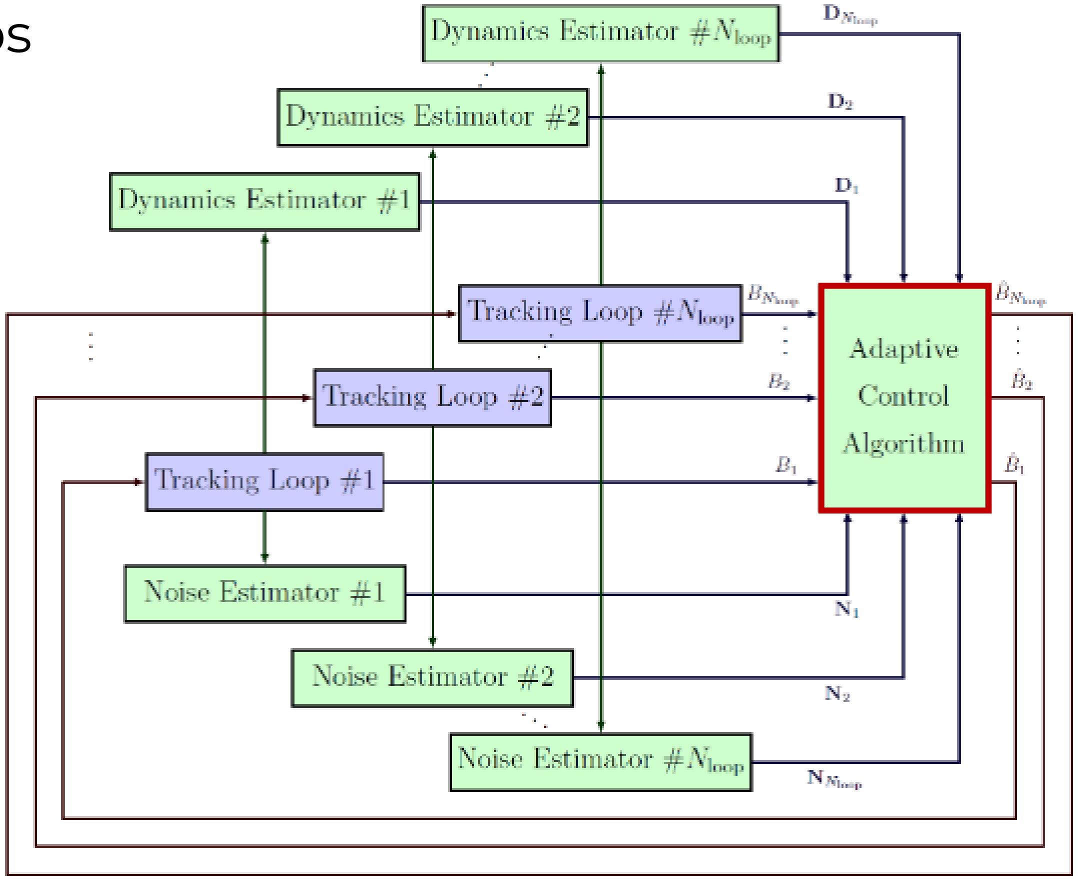
$\mathbf{N}_l \equiv$ noise features of l^{th}loop $\in \mathcal{R}^{1\times K}$

$\mathbf{D}_l \equiv$ dynamic features of l^{th}loop $\in \mathcal{R}^{1\times P}$

$\hat{B} \equiv$ updated response parameter

$B \equiv$ response parameter

- Adapts response of a plurality of loops in a GNSS receiver
- Input
  - Response parameter
  - Dynamic features
  - Noise features
- Output
  - Updated response parameter

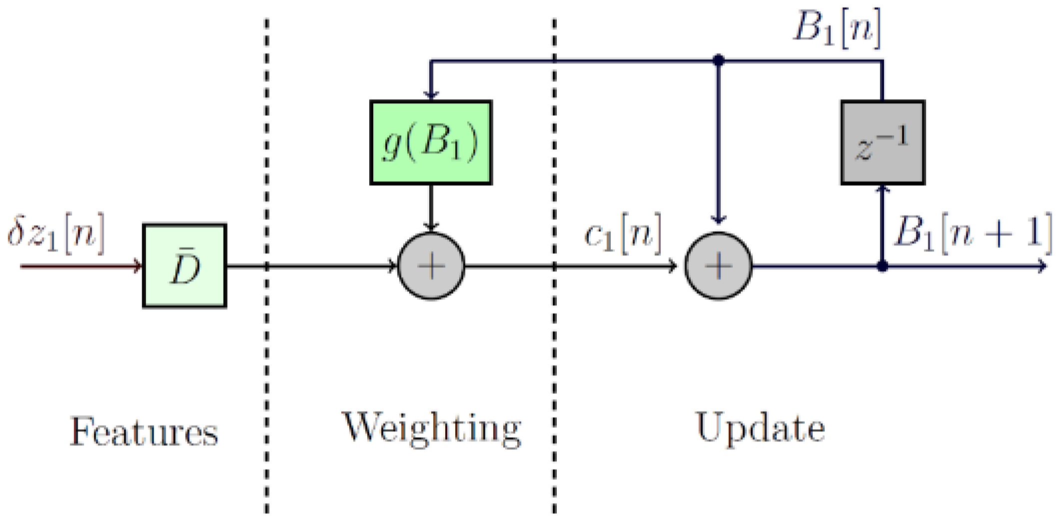


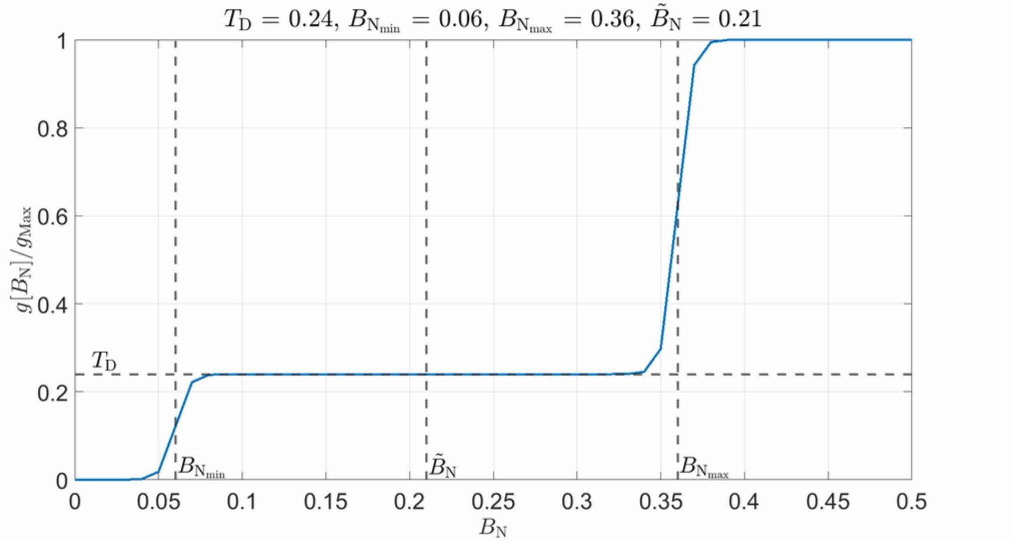
[3] I. Cortés et al. ADAPTIVE WEIGHTING MATRIX FOR ADAPTIVE TRACKING LOOPS. EU Patent, EP3816672. Oct. 2019

The Origin: Loop Bandwidth Control Algorithm (LBCA) [4]

- Assumptions
  - Single noise and dynamic feature from innovation
  - Bandwidth update
  - Single weighting function
  - No channel interdependency

$\bar{D} \equiv$ normalized dynamics
$c \equiv$ control value [Hz]
$B \equiv$ loop bandwidth [Hz]
$g \equiv$ weighting function
$\delta z \equiv$ innovation





[4] I. Cortés et al. Adaptive loop-bandwidth control algorithm for scalar tracking loops. 2020 IEEE/ION Position, Location and Navigation Symposium (PLANS). Portland, OR, USA, 2020, pp.1178–1188. doi:10.1109/PLANS46316.2020.9110182.

The Extension: RL Framework

$$\pi_\theta \equiv \text{policy function}$$
$$\mathbb{B} \equiv \text{stochastic bandwidth [Hz]}$$
$$\theta_\xi \equiv \text{model parameters}$$
$$\nabla_\theta J(\theta) \equiv \text{direction of steepest ascent}$$
$$\xi \equiv \text{trajectory}$$

Reward

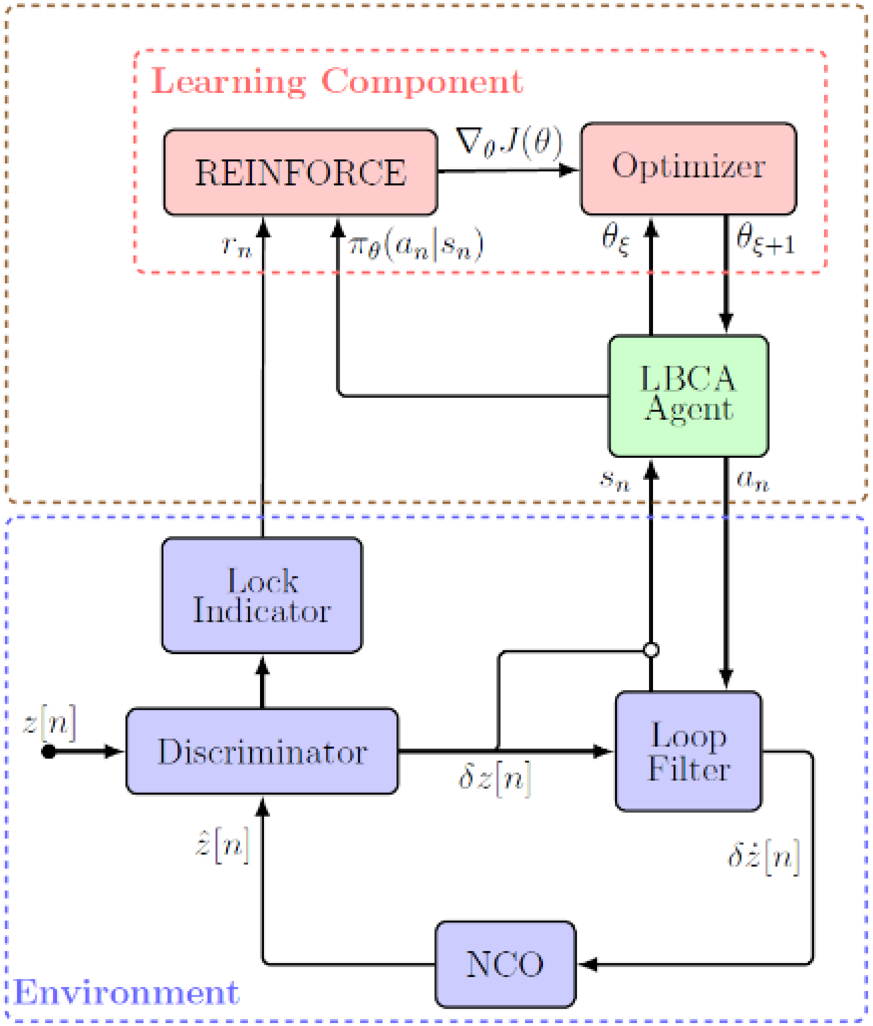
$$r[n] = ae^{b\text{PLI}[n]} + c$$

States

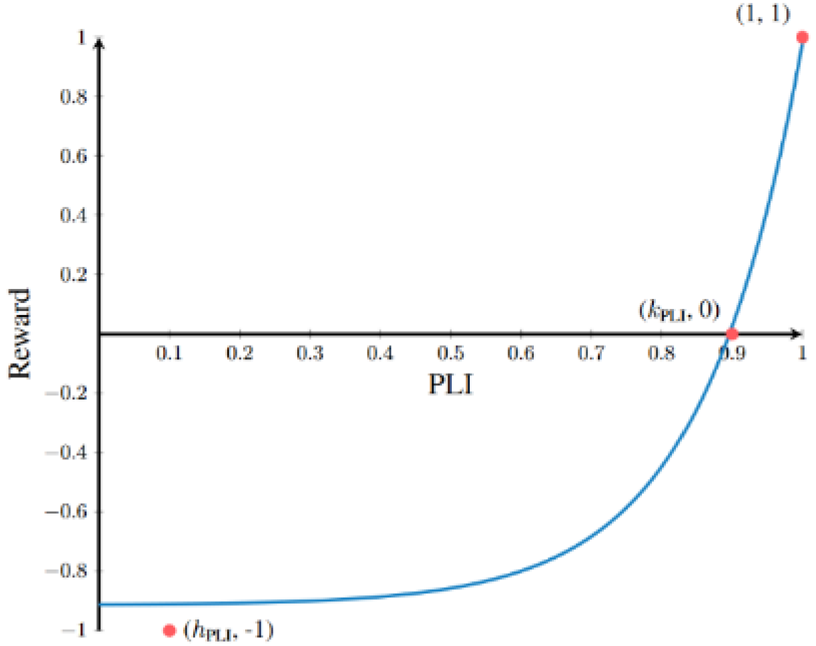
$$s[n] = \{\delta z, B[n]\}$$

Action

$$a[n] = \mathbb{B}[n+1]$$

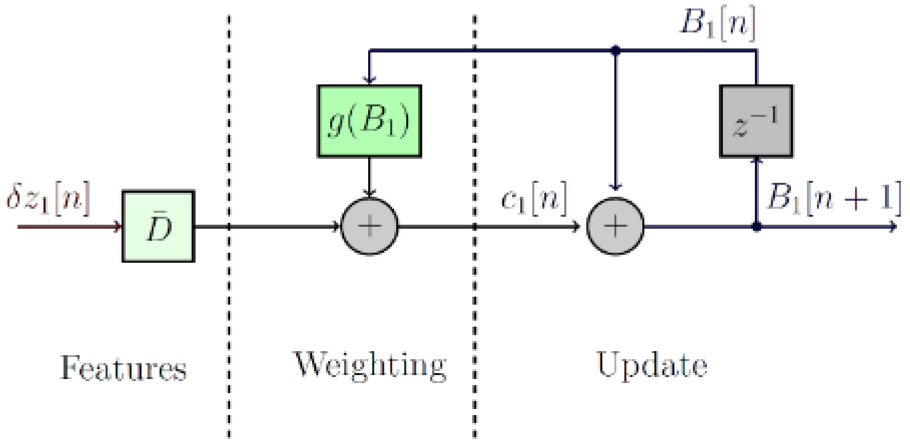


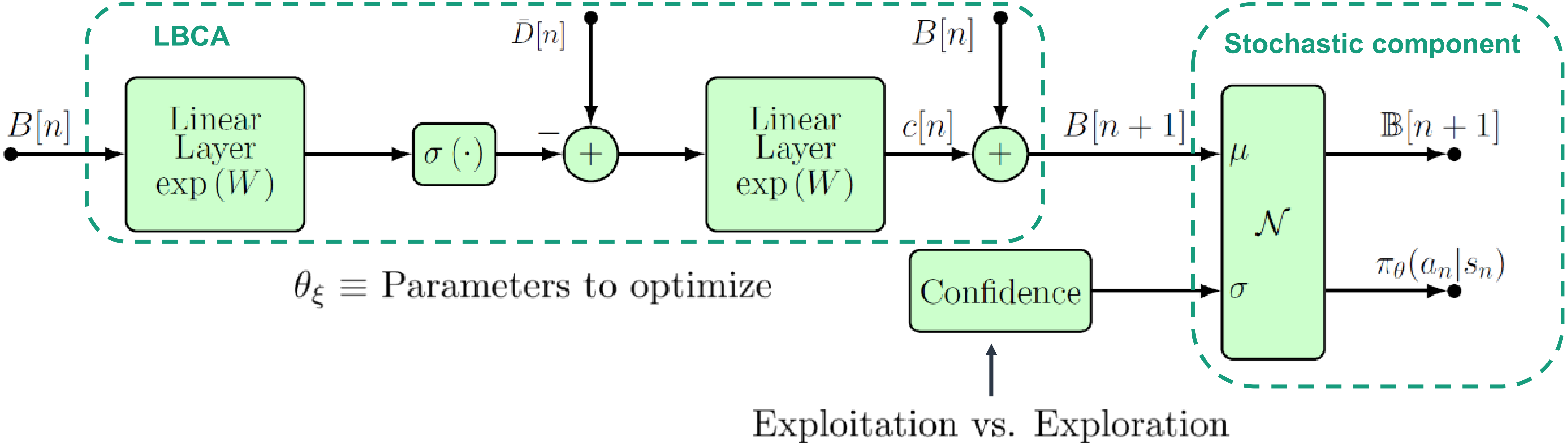
Reward



RL: Reinforcement Learning

The Extension: LBCA Agent

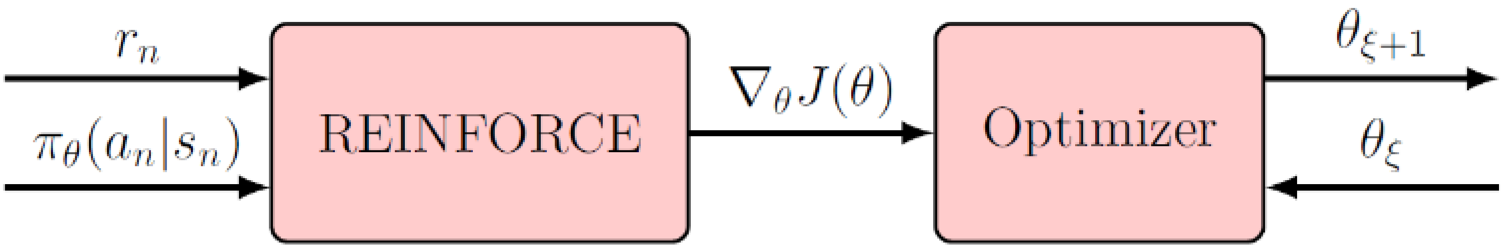




The Extension: REINFORCE

$\pi_\theta \equiv$ policy function
$\mathbb{B} \equiv$ stochastich bandwidth [Hz]
$\theta_\xi \equiv$ model parameters
$\nabla_\theta J(\theta) \equiv$ direction of the steepest ascent
$\xi \equiv$ trajectory

$R(\xi) \equiv$ cumulative return
$\gamma \equiv$ discount rate
$\alpha \equiv$ learning rate
$M \equiv$ number of trajectories
$K \equiv$ trajectory lenght



REINFORCE

$$\nabla_\theta J(\theta) \approx \frac{1}{M} \sum_{i=0}^{M} \sum_{k=0}^{K} \nabla_\theta \log \pi_\theta(a_k^{(i)}|s_k^{(i)}) R(\xi^{(i)})$$

$$R(\xi) = \sum_{l=k}^{K} \gamma^{K-l} r[l]$$

OPTIMIZER

$$\theta_{\xi+1} = \theta_\xi + \alpha \nabla_\theta J(\theta)$$

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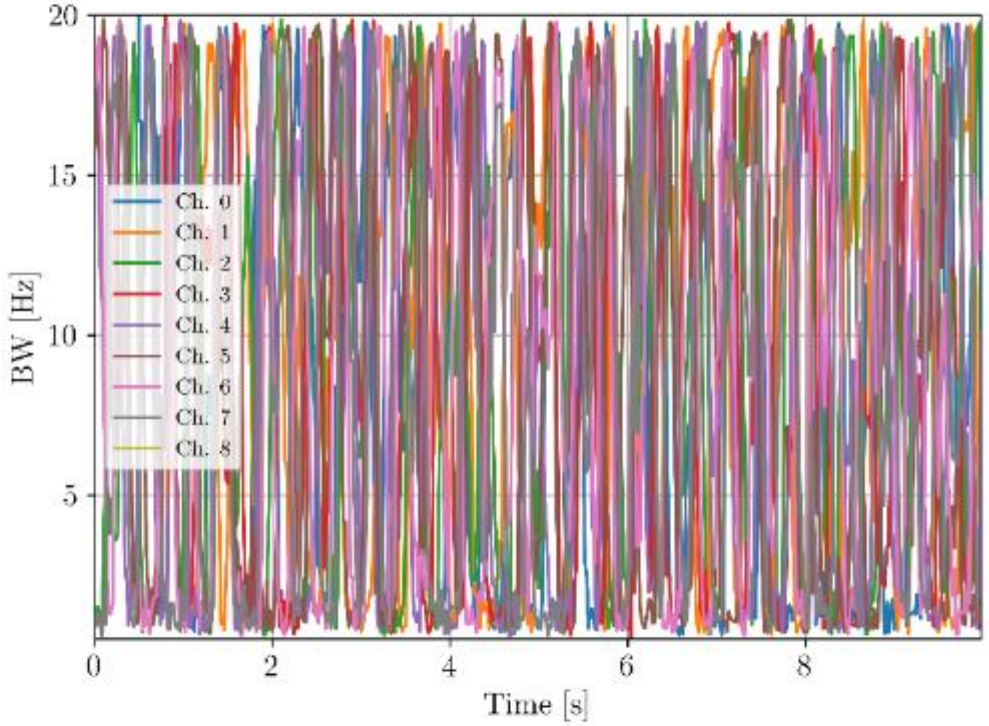
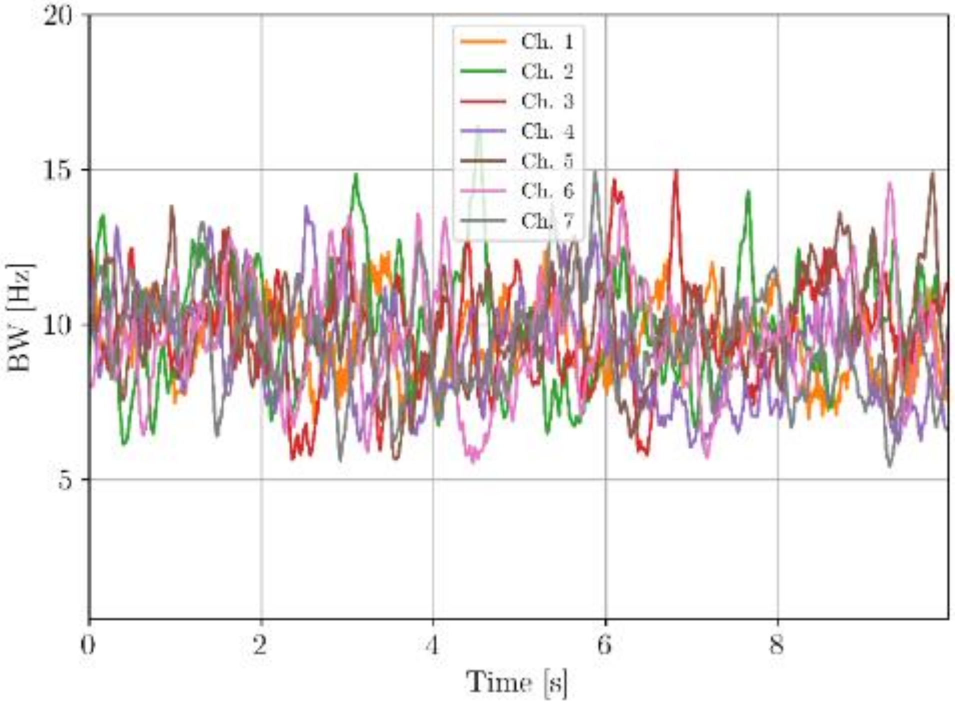
The Extension: Bandwidth Update

Start of training



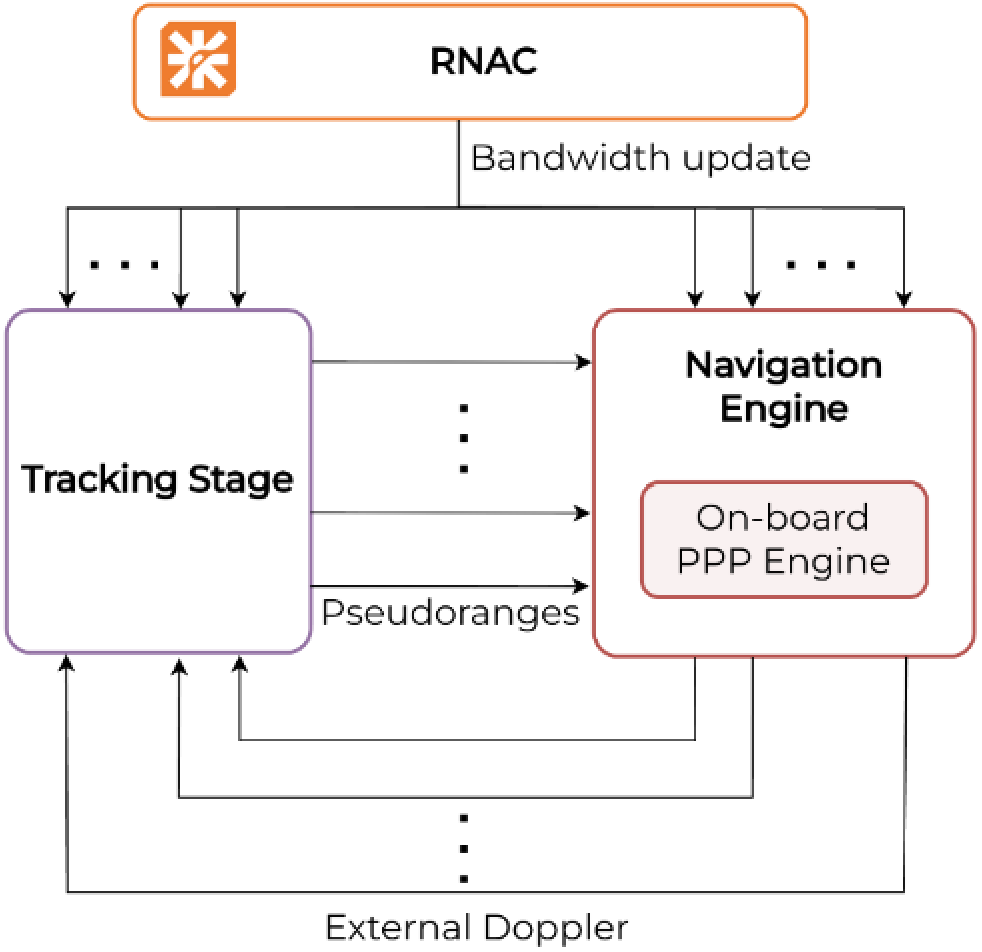
After training



The Potential: Adaptive Vector Tracking

- Use RNAC as:
  - SQM in navigation engine
  - Internal/external Doppler selection

- Advantages:
  - Faster PPP convergence
  - Valid across a broad range of scenarios



RNAC: RobNav Adaptive Control
SQM: Signal Quality Monitoring

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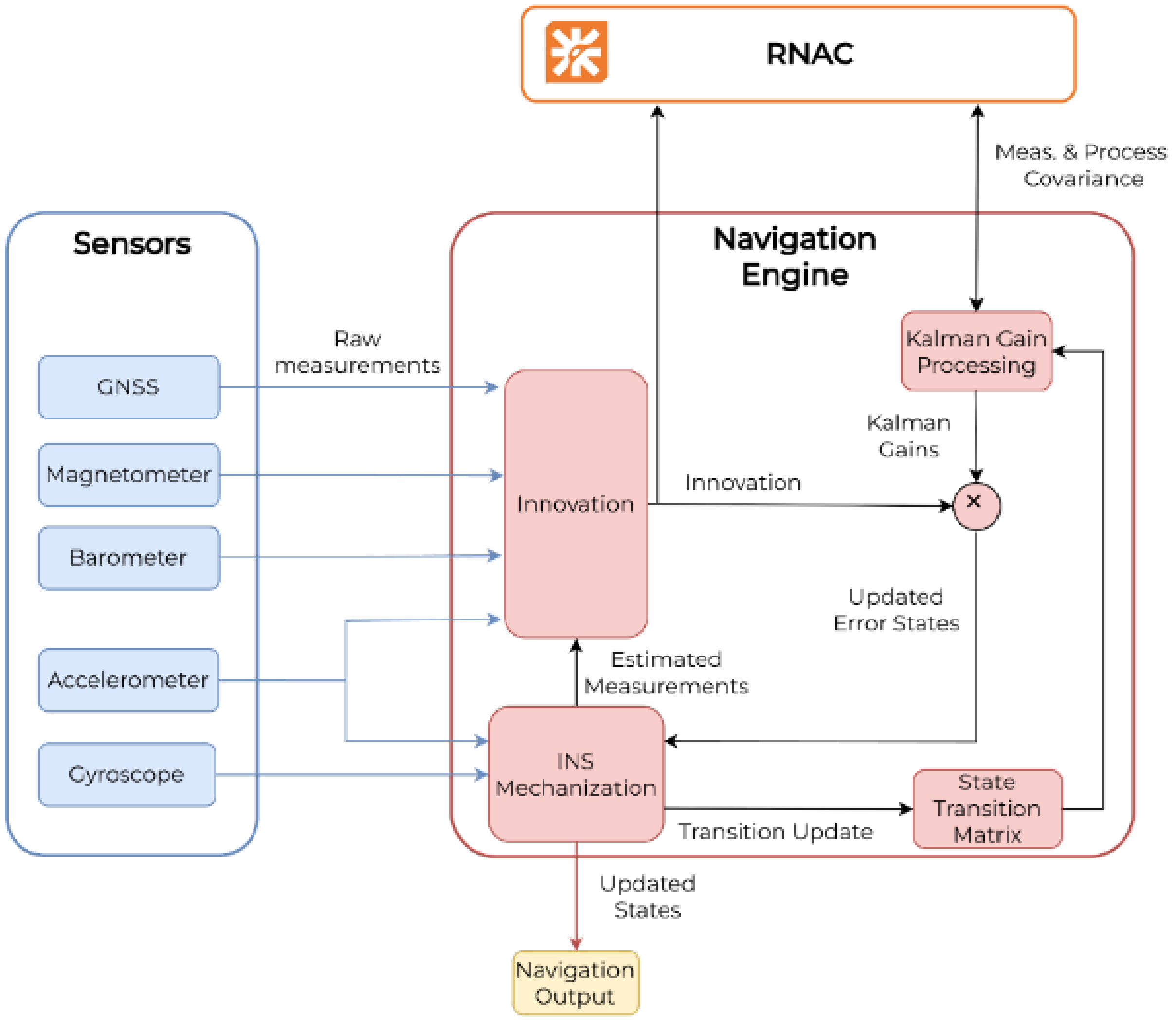
The Potential: Adaptive Navigation Engine

- Use RNAC as:
  - Response-time controller
  - Measurement gate

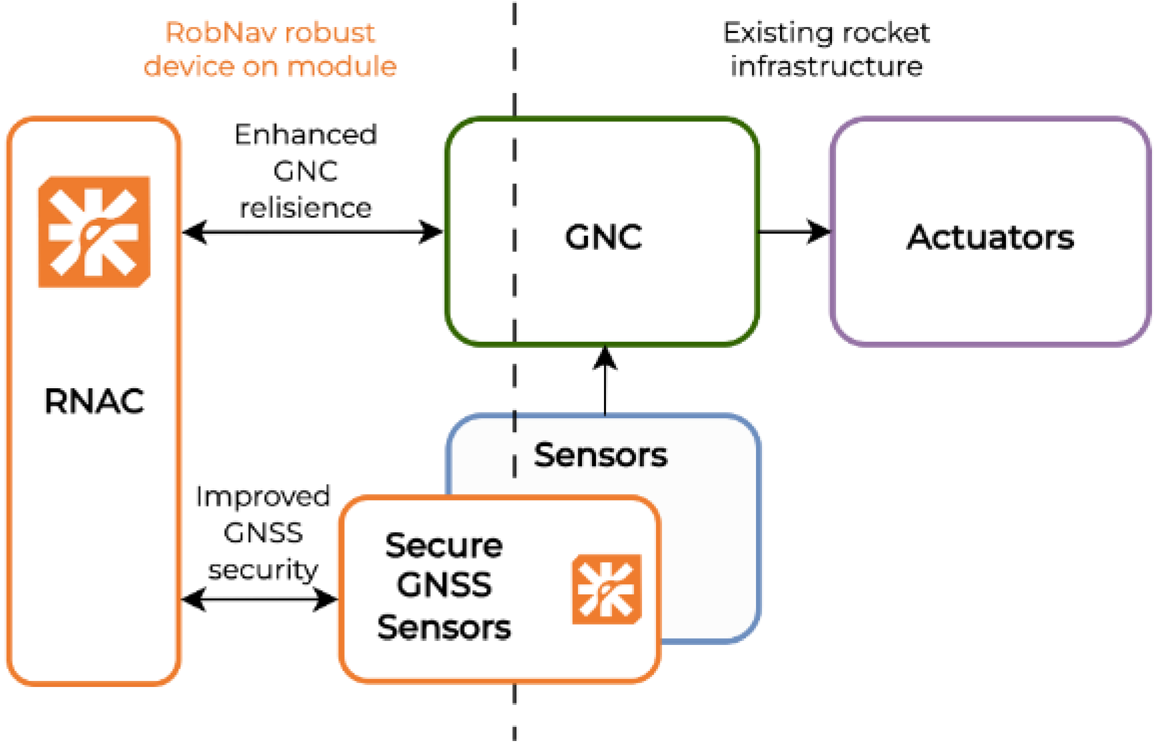
- Main advantages:
  - Trust the right sensor
  - Reject a faulty sensor entirely



The Potential: Towards Guidance, Navigation and Control (GNC)

- Use RNAC as:
  - GNC supervisory layer
  - Response-time controller
  - Control allocation

- Main advantages:
  - Enhance GNC resilience
  - Actuator-fault robustness



RNAC: RobNav Adaptive Control
GNC: Guidance, Navigation and Control

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The Takeaway

- RNAC can be trained within a learning system
- Confidence value: exploration and exploitation
- RL framework implemented in a GNSS receiver
- RobNav is expanding this concept to GNC

ROBNAV

ROBNAV

Reinforcement learning-based adaptive control algorithm for PNT

Advances in AI for Positioning, Navigation and Timing Applications
Cambridge, June 2026

IMU Augmentation Using Deep Learning

Freddy Saunders
Senior Consultant
Plextek

CAMBRIDGE WIRELESS

ROYAL INSTITUTE OF NAVIGATION

IMU Augmentation Using Deep Learning for Personnel Tracking

Benjamin Griffin, Freddy Saunders

30th June 2026

The Problem


NO GNSS
NO SIGNAL
INTERNAL
NAVIGATION
ONLY
27
INTERNAL NAVIGATION
YOU ARE
HERE
RECOMMENDED
ROUTE
TARGET: FIRE
ROOM 214
STAIR
213
216
STAIR A
STAIR A
214
LEVEL 2
KNOW WHERE TO GO.
SAVE LIVES.
LOCATE
NAVIGATE
REACH
REUNITE

Inertial Measurement Units (IMUs)

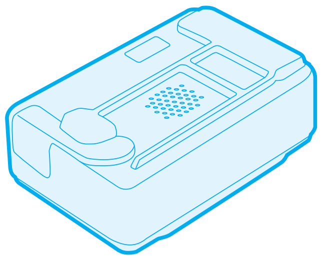
Micro Electro-Mechanical System (MEMS)

Low size, weight, power and cost.

Widely deployed for robust sensing with a high dynamic range.

Lower accuracy limits use in precision applications and industries.

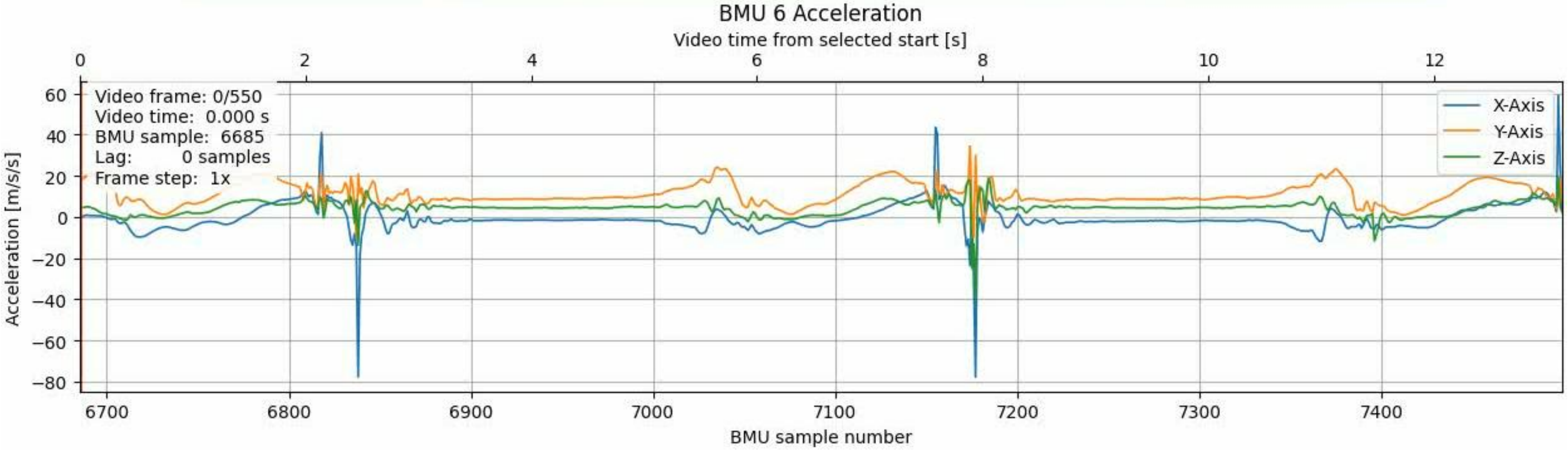
Concept



Personnel Navigation Tracker

Boot Mounted Unit

Zero Velocity Update Dead Reckoning



Real-time Pedestrian Tracking

Personnel Navigation Tracker

Boot Mounted Unit

MEMs based boot mounted IMU that takes the place of, or augments, a GNSS receiver, when no signal available

Low position error over distance traversed typically 2% over distance travelled.

Size	58mm x 38 mm x 19 mm
Weight	58g
Power	At least 8 hour battery life Up to 2.5W Internal Li-Polymer Rechargeable Battery 320 mAh 3.7V
Interfaces	Battery Charging – wireless QI RF Bluetooth LE
User Device	Standard Android Handset

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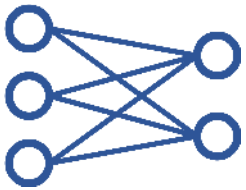
The Opportunity

Machine Learning Augmentation



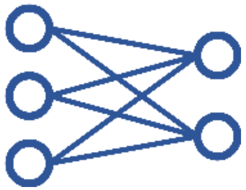
→ ML and AI have improved greatly over the last few years.

→ Data driven calibration of complex nonlinear error terms.

→ Enhances performance without hardware modification to IMU.

The Opportunity

Machine Learning Augmentation



→ ML and AI have improved greatly over the last few years.

→ Data driven calibration of complex nonlinear error terms.

→ Enhances performance without hardware modification to IMU.

Aim: Enhance low-cost MEMS based IMUs by applying ML techniques to reduce both accelerometer and gyroscope errors while maintaining low size, weight and power.

Literature Review

1) Purpose

→ Identify ML architectures and models that enhance IMU performance while maintaining low Size, Weight and Power.

→ Focus on ML models applied to low-cost MEMS IMUs.

2) Initial Review:

Review based on research by Cohen *et al.,* identified several key ML architecture for IMU calibration and denoising [1].

→ Multilayer Perceptron's,

→ Convolutional Neural Networks,

→ Recurrent Neural Networks,

→ Transformers.

3) Review Criteria

→ Effectiveness in reducing IMU errors.

→ Quality of training/ testing methodology,

→ Inference time,

→ Model size < 100 MB.

4) Down Selection:

→ Convolutional Neural Network,

→ Temporal Convolutional Network,

→ Hybrid (CNN, LSTM, Attention),

→ Multilayer Perceptron.

Implemented Models

Implemented Models: Multilayer Perceptron (MLP)

Model Description:

→ Simple full connected network containing multiple dense layers.

→ Operates on a single inertial measurement (temperature, acceleration, angular rate).

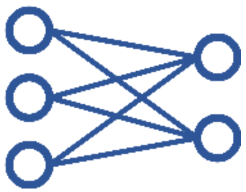
  > No temporal context.

Reason for Selection:

→ Low computational and memory requirements.

→ Provides a light-weight benchmark against which to baseline other models.

→ Contains 13 thousand trainable parameters requiring 52 KB of memory.



Hyperparameters	Value
Number of dense layers	4
Number of neurons per dense layer	64

Implemented Models: Convolutional Neural Network (CCN)

Model Description:

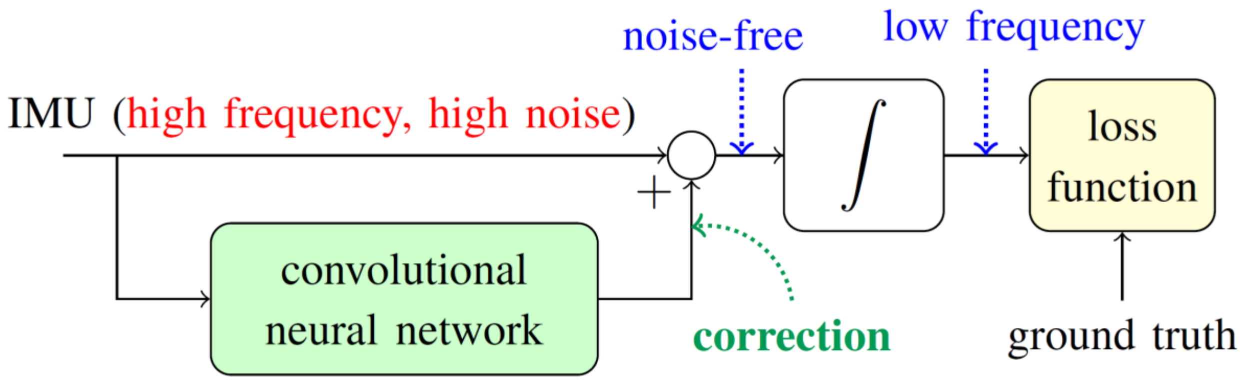
→ Employ's multiple convolutional layers, batch normalisation and GeLU activation functions [2].

→ Orientation error used as a loss function.

Reason for Selection:

→ Achieved the best published reduction in attitude error on the TUM-VI dataset [3].

→ Convolutions very efficient on GPU.



Hyperparameters	Value
Input window length	500 samples
Number of convolutional layers	2
Number of filters per convolution	64
Filter width	7
Dilation base	2.0

Implemented Models: Temporal Convolutional Network (TCN)

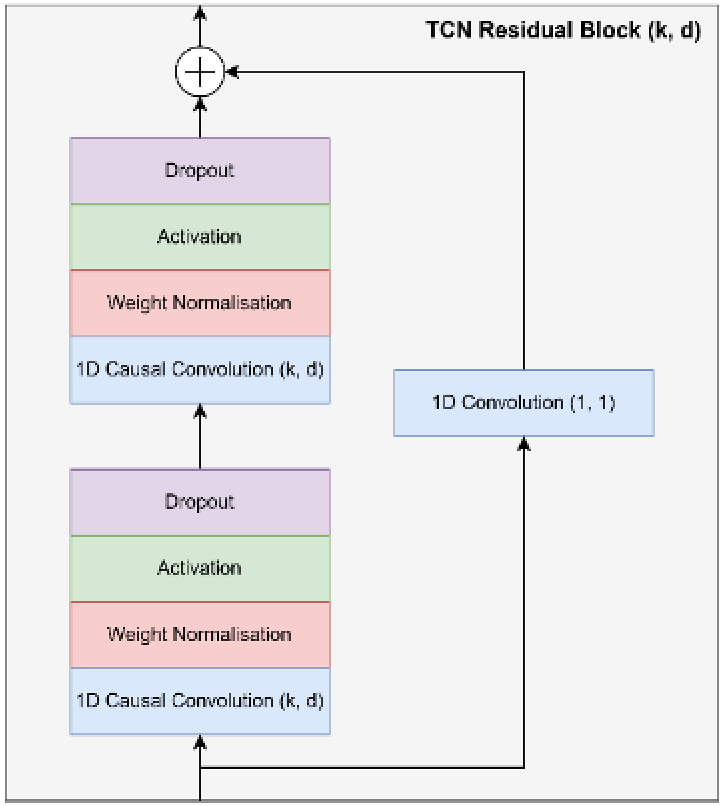
Model Description:

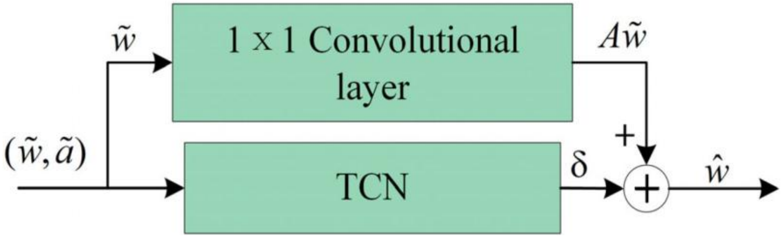
→ Builds on CNN, a full TCN is composed of multiple TCN Residual Blocks [4] [5].

Reason for Selection:

→ Achieve state of the art performance on both the EuRoC MAV [6] and TUM-VI [3] dataset and generalised well across both aerial and automotive datasets.

Hyperparameters	Value
Input window length	500 samples
Number of TCN blocks	2
Number of filters per convolution	64
Filter width	5
Dilation base	2.0





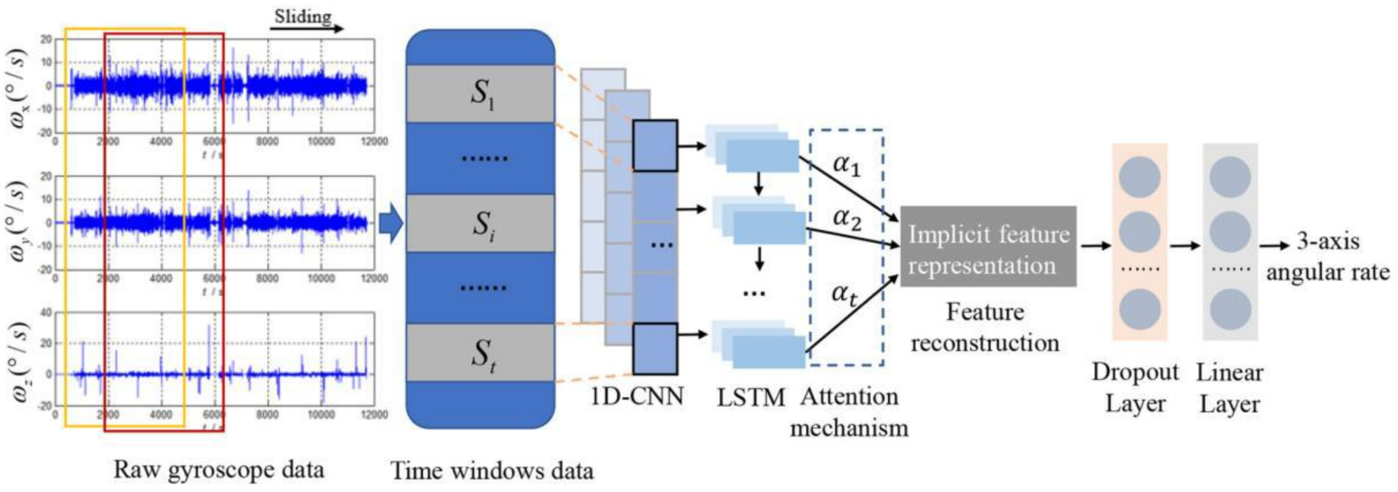
Implemented Models: CNN + LSTM + Attention (Hybrid)

Model Description:

→ This hybrid approach combining CNNs for local feature extraction, LSTM for long-term temporal dependencies and an Attention block to weight extracted features [7].

Reason for Selection:

→ Potential to capture both short and long-term temporal features.



Hyperparameters	Value
Input window length	100 samples
Number of convolutional layers	1
Number of filters per convolution	256
Number of LSTM layers	1
Number of LSTM units per layer	128
Number of Attention blocks	1
Number of Attention units per block	8

Collected Datasets and Model Evaluation

Collected Datasets and Model Evaluation

Civitanavi Dataset:

→ MMU-M: Low SWaP-C MEMS based IMU.

→ ARGO 4000: High SWaP-C fibre optic based IMU.

→ IMUs mounted in a 3-Axis rate chamber, temperature, acceleration and angular rates were logged from both IMUs.

→ Dataset collected over 48 hours; temperature was varied from -40°C to +80°C.

→ **Model Input:** MIMU-M acceleration, angular-rate and temperature

→ **Target Output:** ARGO4000 acceleration and angular-rate.

IMUs

MIMU-M

→ Low SWaP-C IMU,

→ MEMS based.

ARGO 4000

→ High SWaP-C IMU,

→ Fibre optic gyro.

Collected Datasets and Model Evaluation

BMU Dataset:

→ Plextek Boot Mounted Unit (BMU) contains an ensemble of MEMs IMUs.

→ The BMU is a component of Dismounted Position and Navigation System.

→ Dataset collect over 8 different 30-minute walks at 100 Hz.

→ Dataset contains acceleration, angular-rate and temperature for each IMU in the ensemble.

→ **Model Input:** Single IMU in the ensemble.

→ **Target Output:** Average of all IMUs in the ensemble.

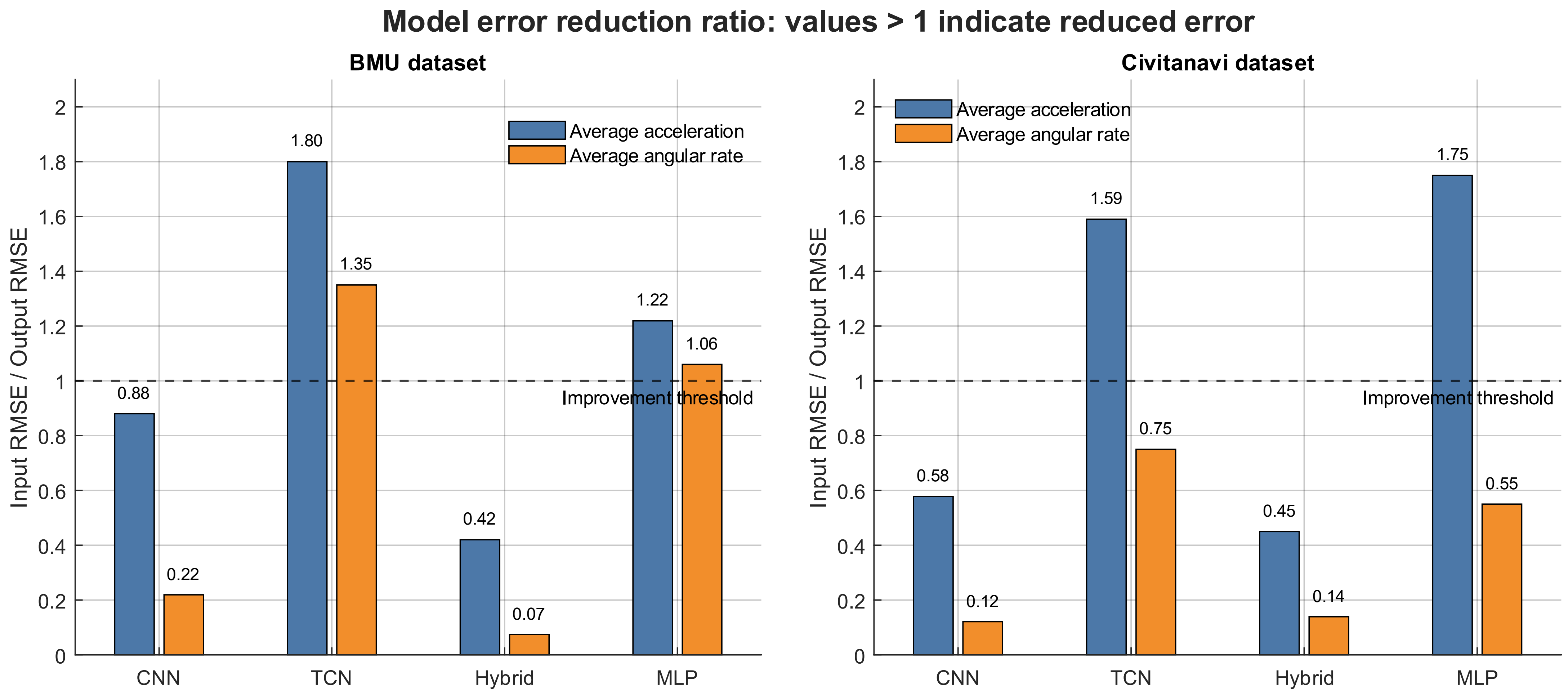
Plextek BMU

Plextek BMU

→ Low SWaP-C IMU,

→ MEMS based.

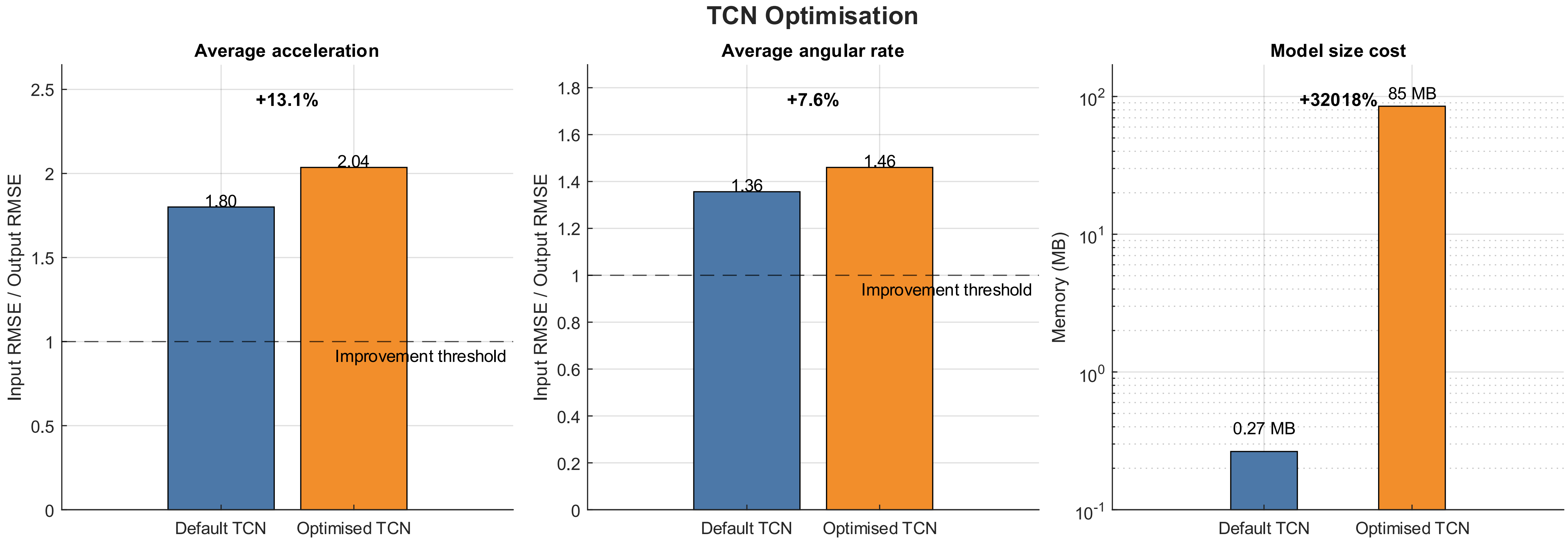
Results



CNN: Convolutional Neural Network.
TCN: Temporal Convolutional Network.

Hybrid: Convolutional + LSTM + Attention.
MLP: Multilayer Perception.

Refined Model Performance Results



→ The initial model contains 70 thousand trainable parameters requiring 271 KB of memory, the optimised model is 300 times larger containing 22 million parameters, requiring 85 MB of memory.

→ The increase in model performance is much smaller with an average acceleration improvement of 1.13 and average angular rate improvement of 1.08.

Conclusion and Further Work

Conclusion and Further Work

Conclusions and Results Summary:

→ Overall TCN based model performed best.

→ Performance on BMU dataset generally better than Civitanavi dataset.

→ Performance on Civitanavi Dataset lower than expected. Possibly due to physical characteristics between components (MEMS vs Fibre Optic) and synchronisation challenges, further investigation needed.

Further Data Collection and Analysis:

→ Training Improvements:
- > Investigate alternative loss functions, e:g integrated position,
- > Investigate a split model for sperate accelerometer and gyroscope,
- > Optimisation over context window length during training.

→ Implementation:
- > Export TCN model to run on embedded hardware.
- > Implementation on Plextek's BMU.

IMUs Tested

MIMU-M

→ Low SWaP-C IMU,

→ MEMS based.

ARGO 4000

→ High SWaP-C IMU,

→ Fibre optic gyro.

Plextek BMU

→ Low SWaP-C IMU,

→ MEMS based.

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Thank you

Benjamin Griffin

Freddy Saunders

benjamin.griffin@plextek.com

freddy.saunders@plextek.com

Plextek
Exceptional Engineering Solutions

www.plextek.com | hello@plextek.com

+44 (0) 1799 533200

The Plextek Building, London Road, Great Chesterford,
Saffron Walden, CB10 1NY, United Kingdom

Before GNSS Fails: Lessons from Ukraine

Stephen Clemmet

CEO

Silogic Technology Limited

CAMBRIDGE WIRELESS

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Before GNSS Fails: Lessons from Ukraine

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TECHNOLOGY

BELARUS
POLAND
RUSSIA
SLOVAKIA
HUNGARY
ROMANIA
MOLDOVA
UKRAINE
RUSSIA
SEA OF AZOV
CRIMEA
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Shostka
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Nizhyn
Romny
Novohrad-Volynskyy
Zhytomyr
Kyiv
Pryluky
Lebedyn
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Myrhorod
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Luhansk
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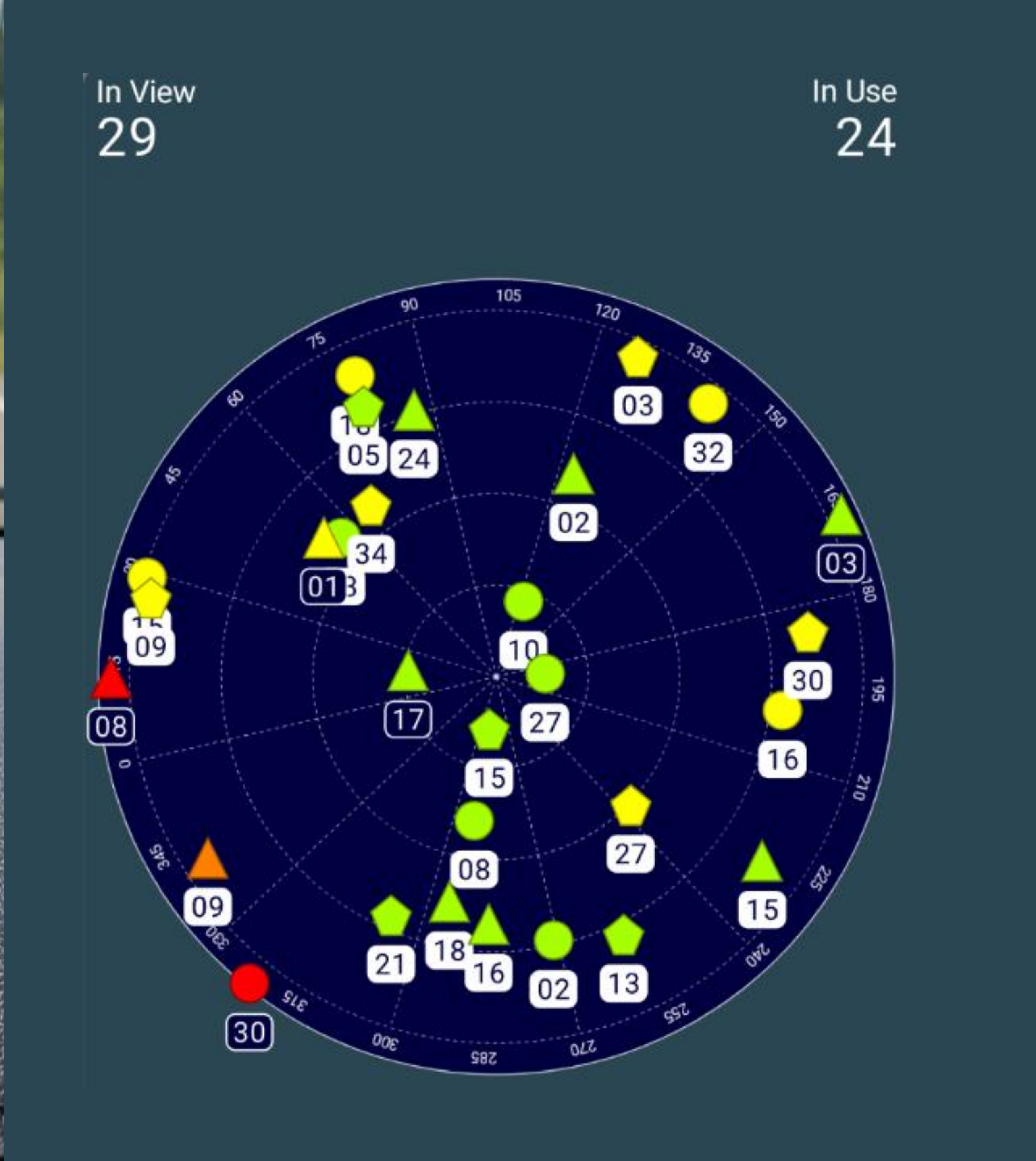
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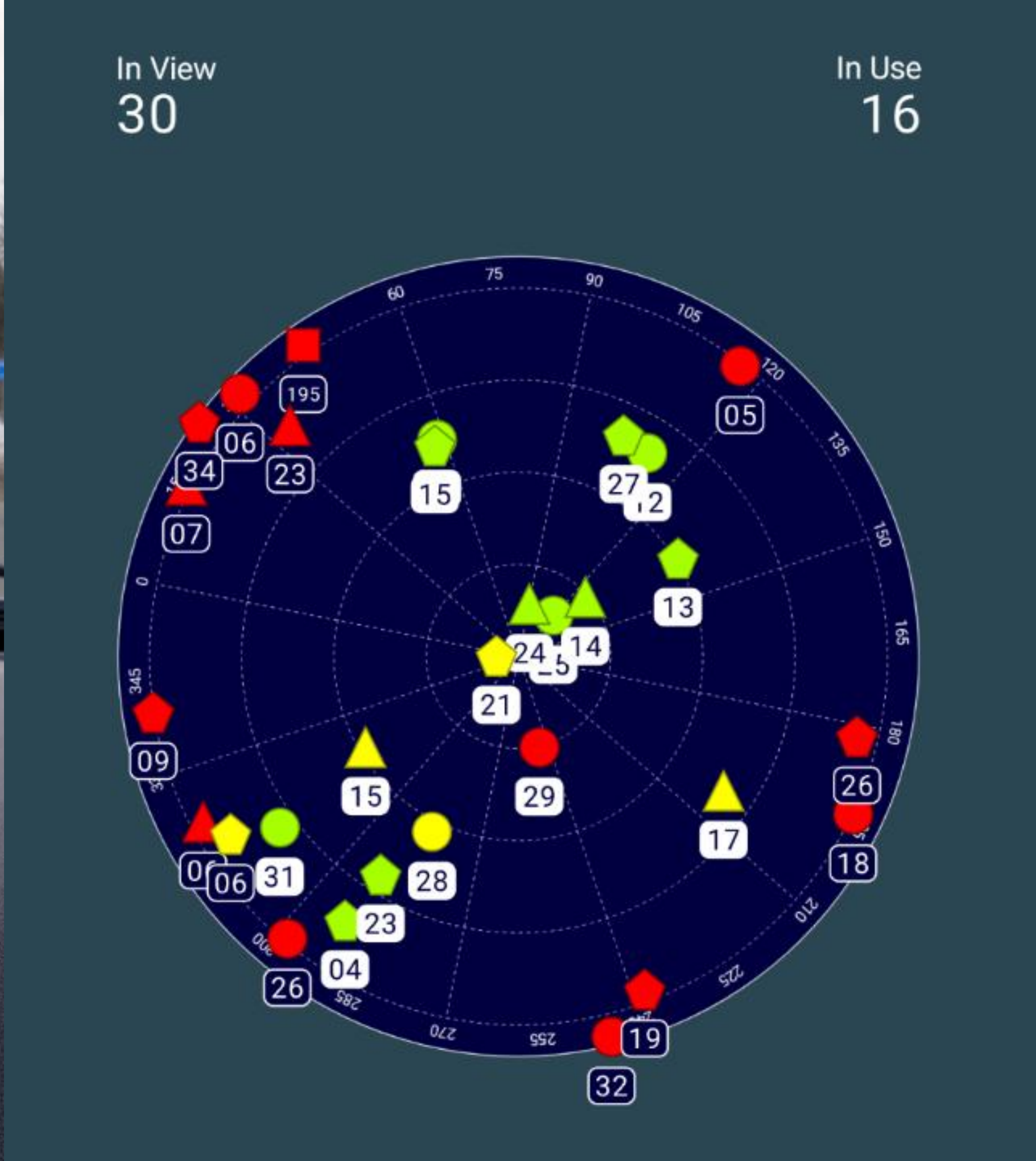
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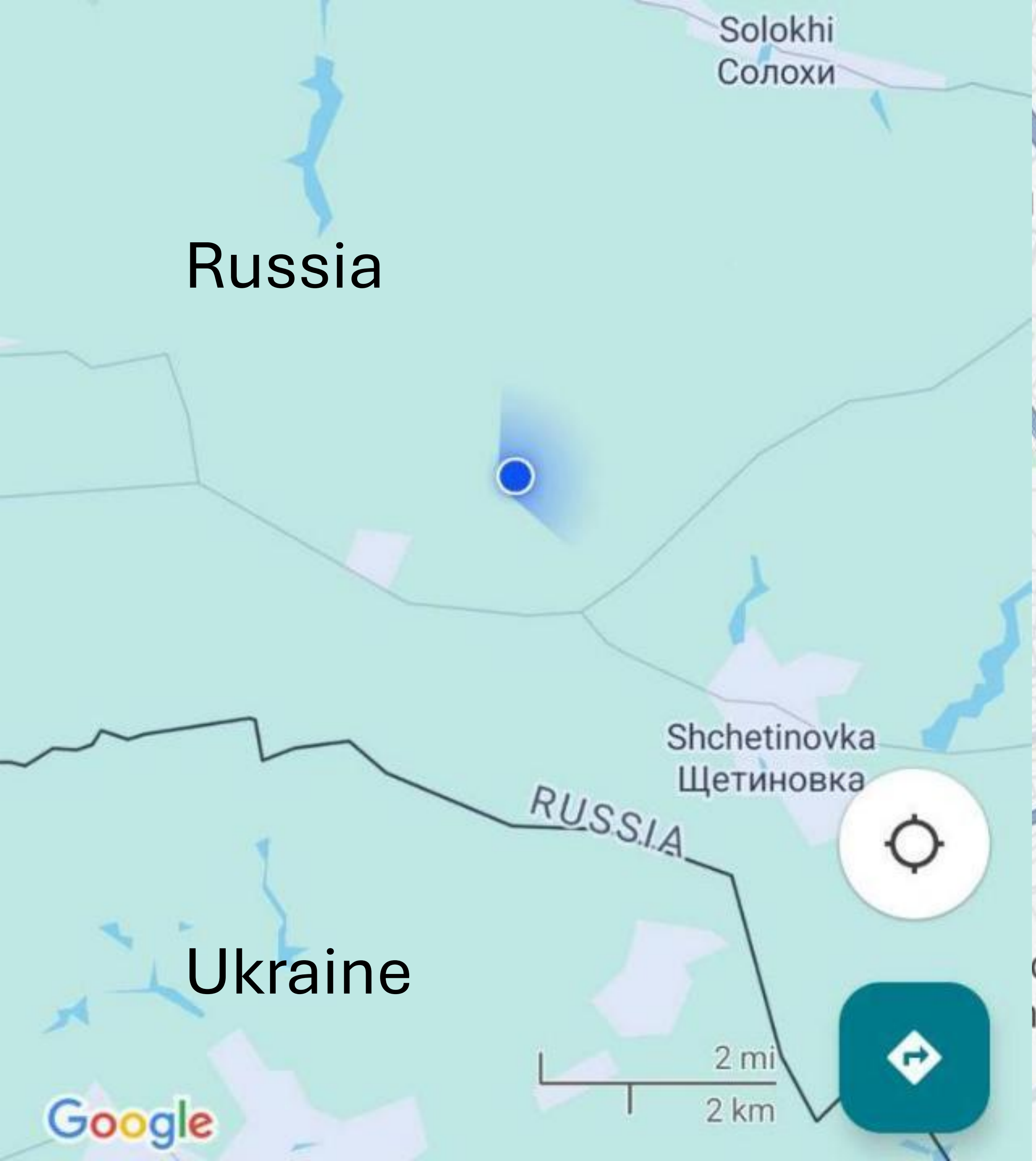
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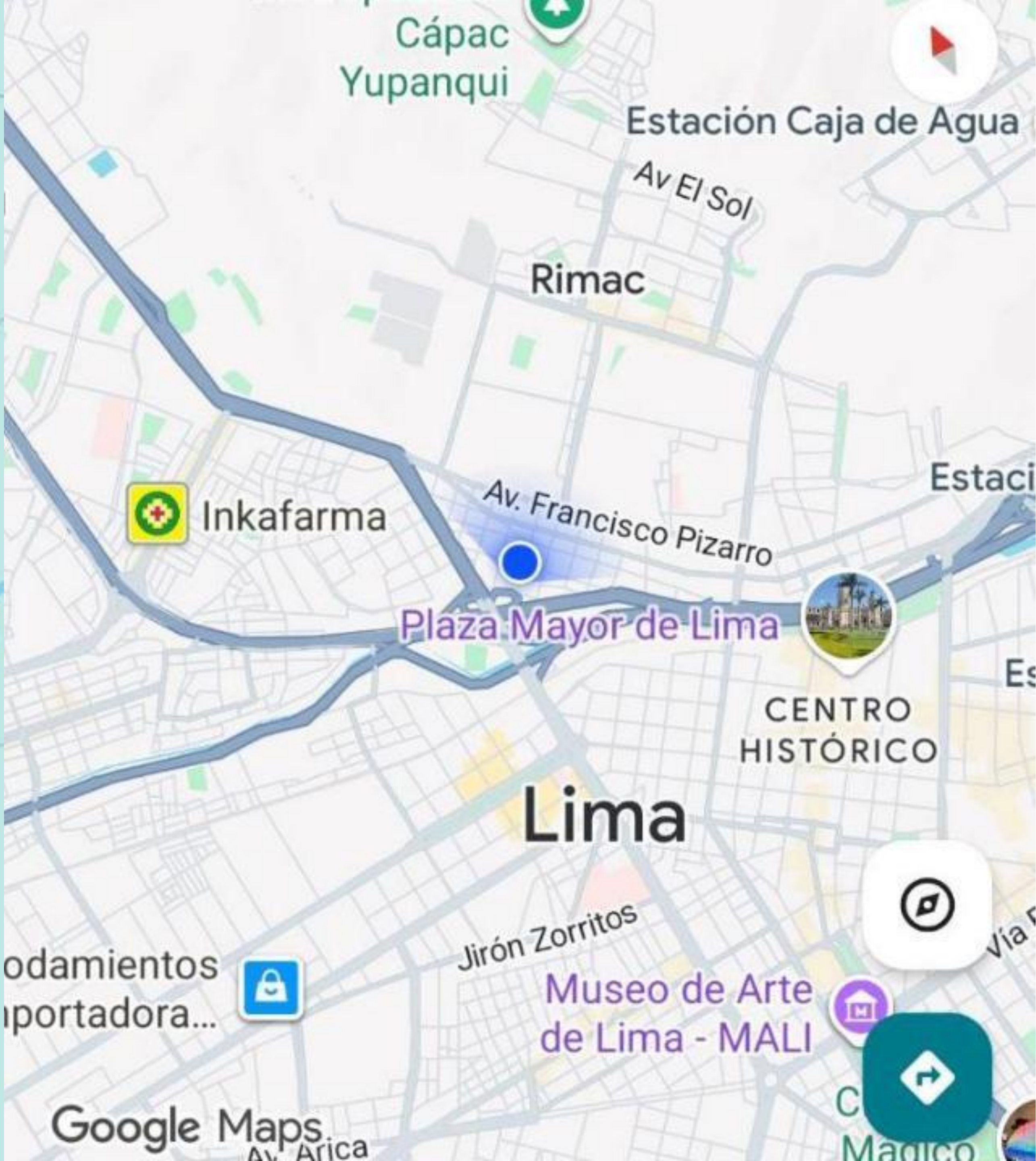
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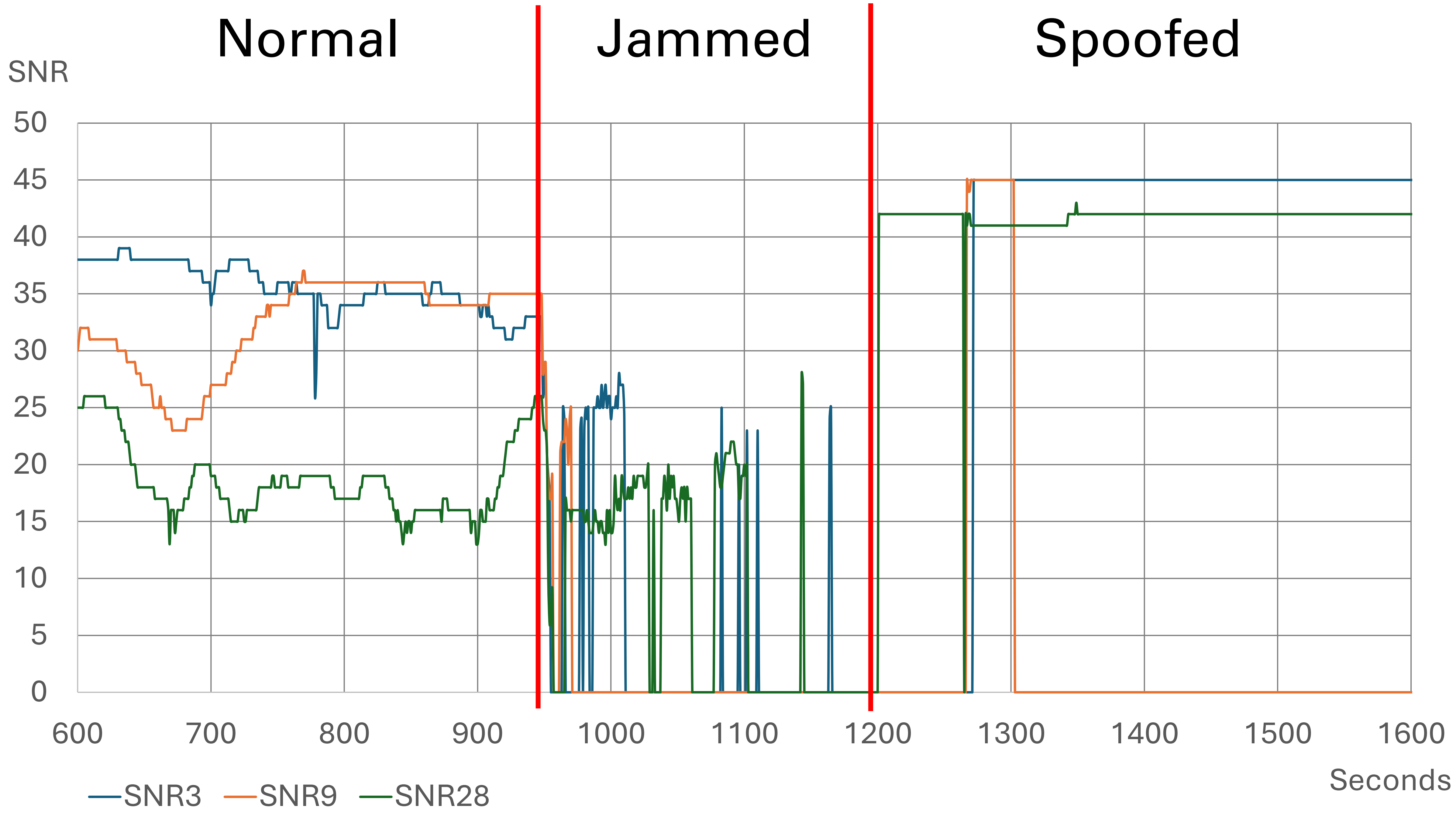
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Seconds
SNR3
SNR9
SNR28

Trust state is operational intelligence

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Stephen Clemmet · CEO
sclemmet@silogictechnology.com