ESA NAVISP EL 1-034

AInGNSS: *ARTIFICIAL INTELLIGENCE IN GNSS RECEIVERS*

FINAL PRESENTATION

30/05/2023
ESA NAVISP EL1-034

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AINGNSS PROJECT OBJECTIVES

- AInGNSS investigated ***a new paradigm in the design of GNSS algorithms, leveraging artificial intelligence to design and test algorithms able to enhance raw measurements, along with quality indicators related to the local environment***

- The AI algorithms where tested on different GNSS datasets, covering several kinds of data and hybridization scenarios. Most promising algorithms were selected not only in terms of global added PVT accuracy but also regarding their overall efficiency and performances in specific use cases.

- The project's key objectives are listed below:
  - A review of the state of the art on the AI enhanced GNSS receivers
  - A AI GNSS testbed allowing to investigate, test and benchmark various AI algorithms,
  - A collection of relevant training data (both simulated and real)
  - An implementation of three selected AI algorithms on the testbed
  - An analysis & benchmark of these three algorithms based on extensive field trials

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AGENDA

/// AInGNSS project meta data

/// AInGNSS project context and methodology

/// Challenges raised by evolving & stringent user needs

/// How AI may fill the gap

/// AInGNSS major results

/// Conclusions and perspectives

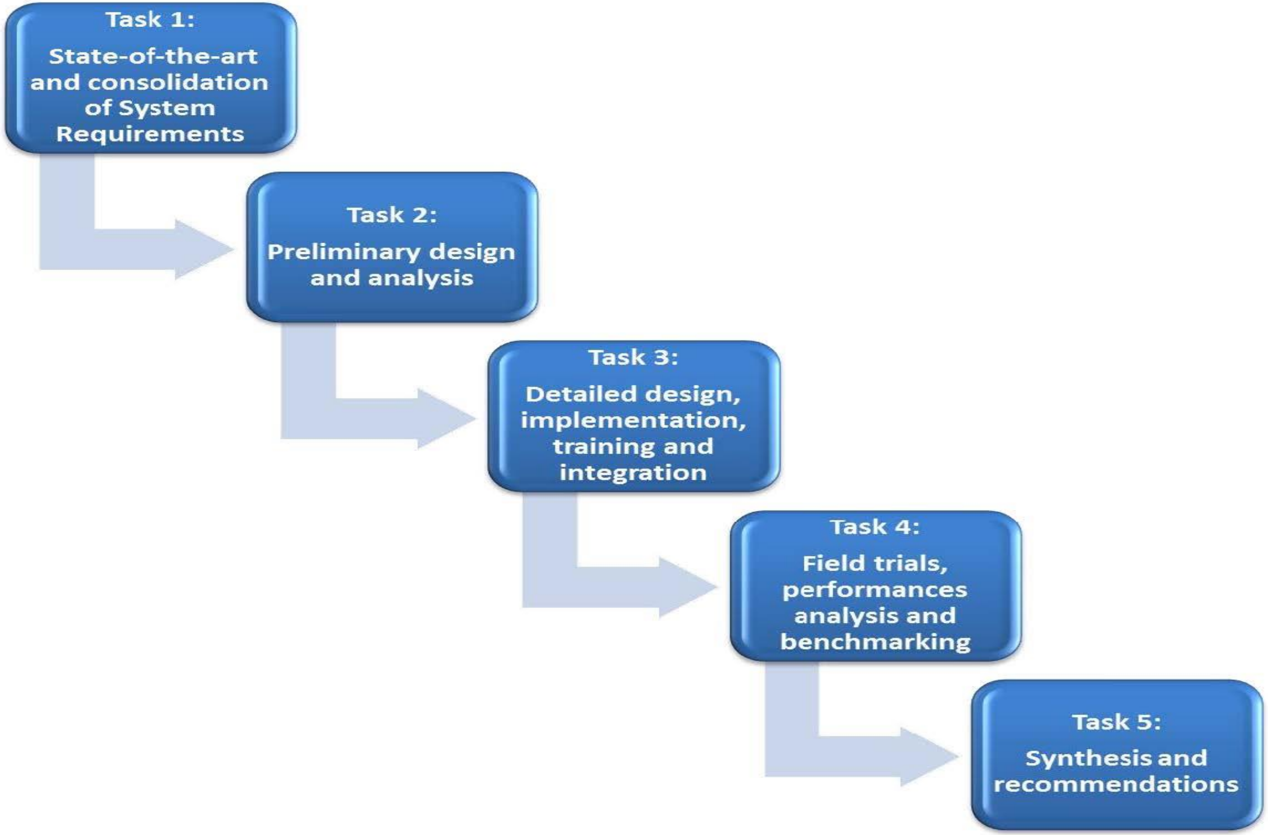
- **AInGNSS project meta data**
- AInGNSS project context, and challenges raised by evolving & stringent user needs
- AInGNSS methodology
- How AI may fill the gap
- Conclusions and perspectives

AINGNSS PROJECT CONSORTIUM

- AI algorithms design,
- AI algorithms training and development,
- GNSS signal processing
- Implementation in TAS SDR SW Rx
- Results Analysis

- State of the art of AI algorithms and use cases
- Real data collection testbed
- Results analysis

AINGNSS PROJECT ACTIVITES



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/// AInGNSS methodology

/// How AI may fill the gap

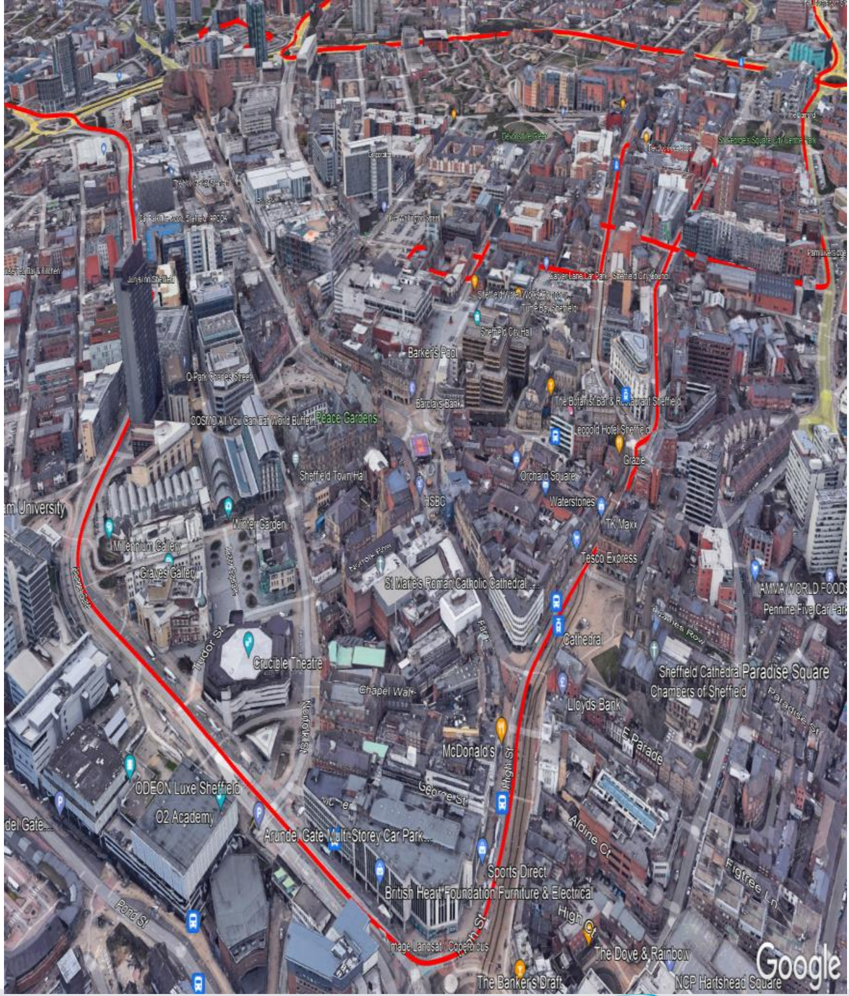
/// Conclusions and perspectives

CONTEXT & CHALLENGES

- Applications requiring more and more stringent requirements in terms of positionning and navigation are booming, especially fastly evolving transport applications

- These applications create several technological gaps that cannot yet be filled with current positioning techniques.

- Current technologies based on numerical models and empirical parameters are not efficient in harsh environment (Urban canyon, low C/N0…). In these specific areas, one solution consists in taking into account a priori knowledge of the environment (such as 3D maps) correlated to the GNSS signal received.



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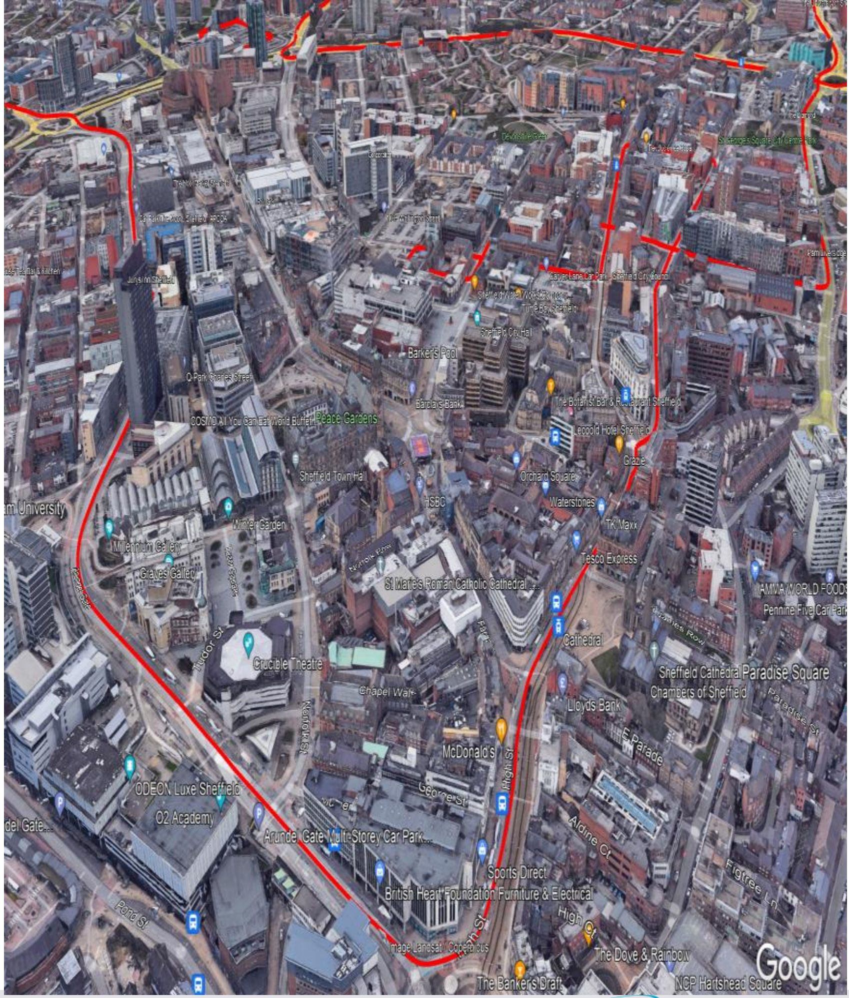
CONTEXT & CHALLENGES

/// In these specific areas, one solution consists in taking into account a priori knowledge of the environment (such as 3D maps) correlated to the GNSS signal received.

/// This raises several challenges:

- A high refresh rate of this a priori knowledge to avoid any fluctuations (new building, tall vehicle blocking the LOS) which make a priori knowledge obsolete,
- High computational and memory resources need,
- Highly adaptive configuration and parameters to cope with the variability of the autonomous vehicle environment.

This is where AI is expected to play a role in filling these Gaps.



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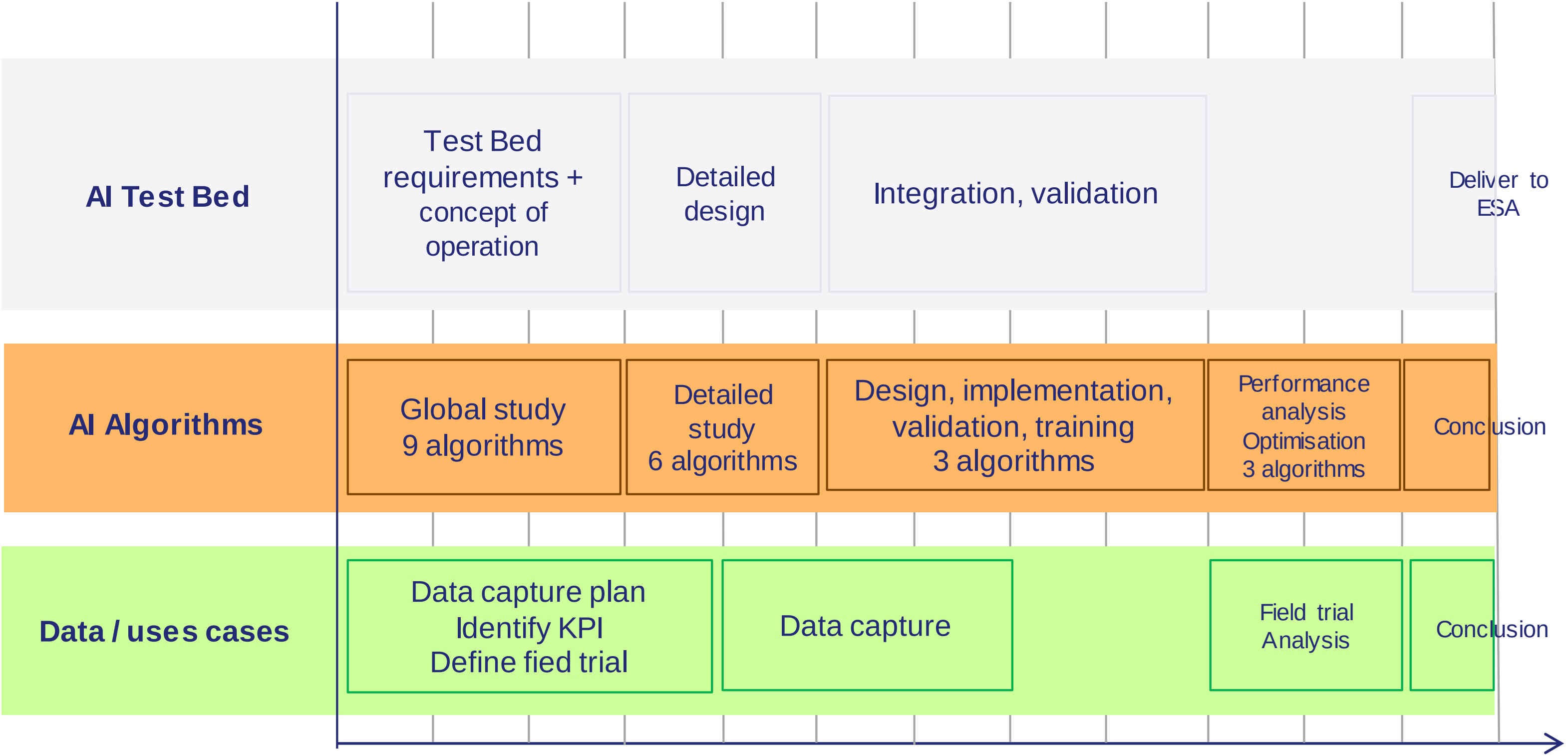
AINGNSS METHODOLOGY



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/// **How AI may fill the gap**

- State of the Art
- Preliminary Design and analysis
- Data collection
- Detailed Design, Implementation & Field trials

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STATE OF THE ART REVIEW ACTIVITY

/// Robust carrier phase measurements

- Tracking loop design
- Multi-correlator methods for multipath detection and mitigation

/// AI-enabled GNSS processing algorithms

- 22 algorithms reviewed, at various stages of the receiver chain
  - pre-correlator
  - post-correlator
  - RINEX-level measurements
  - PVT level (fused with INS measurements)
- Generally classification algorithms to detect multipath (or other errors) in the measurements

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STATE OF THE ART REVIEW ACTIVITY

Input	#	AI Method	Output	SOW REQs	Difficulty / complexity score (1 = easy, 5 = very difficult)			Simulated/ real data coherence	Total (the less the better)
					AI	Labelling	Integration		
Pre-correlator	1	Unsup. Anomaly detection	Anomaly score (→ class)	REQ-090a	2	1	1	1	5
Post-correlator	2	Sup. multipath classification	Class (MP / NLOS / LOS)	REQ-010 REQ-090b	1.5	4	1	2	8.5
	3	Unsup. Anomaly detection	Anomaly score (→ class)	REQ-010 REQ-090b	2	1	1	1	5
	4	Sup. regression	Iono-free pseudorange	REQ-090b REQ-170	3	4	2	2	11
	5	Sup. regression	E1E5 unambiguous wide-lane pseudorange	REQ-090b REQ-180	3	4	3	2	12
RINEX	6	Sup. regression (4 rxs.)	Iono-free pseudorange	REQ-090c REQ-190	2.5	4	1	2	9.5
	7	Sup. MP detection	Class (MP / NLOS / LOS)	REQ-090c	2	4	2	2	10
PVT	8	Sup. PVT regression (with IMU)	PVT estimation and/or PVT increment from last epoch	REQ-010	4	2	2	2	10
	9	Sup. regression	Size of error	-	4	2	3	2	11

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DETAILED STUDY OF 6 ALGORITHMS

/// 6 AI algorithms selected out of SoA

Input	#	Method	Output	SOW REQs	Difficulty / complexity score (1 = easy, 5 = very difficult)			Simulated/ real data coherence
					AI	Labelling	integration	
Pre-correlator	1	Unsup. Anomaly detection	Anomaly score (→ class)	REQ-090a	2	1	1	1
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	3	Unsup. Anomaly detection	Anomaly score (→ class)	REQ-010 REQ-090b	2	1	1	1
	4	Sup. regression	Iono-free pseudorange	REQ-090b REQ-170	3	4	2	2
RINEX	5	Sup. regression (4 rxs.)	Iono-free pseudorange	REQ-090c REQ-190	2.5	4	1	2
PVT	6	Sup. PVT regression (with IMU)	PVT estimation and/or PVT increment from last epoch	REQ-010	4	2	2	2

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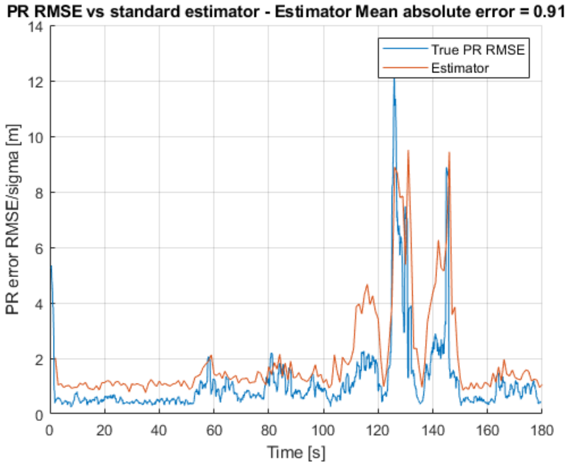
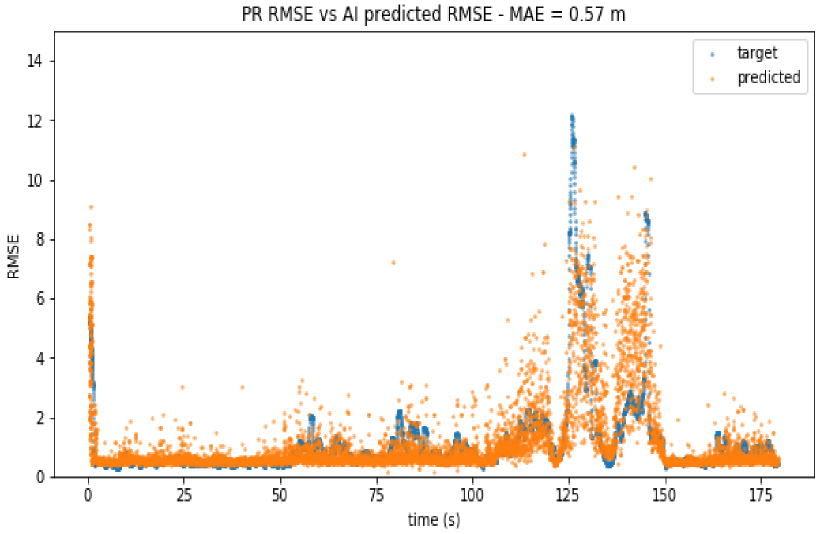
DOWN-SELECTION OF 3 ALGORITHMS

/// Algo 1 Post-correlation - Supervised MP error regression (3/3)

- The initial algorithm was modified to output real values (confidence, weights) instead of a discrete class (LOS, MP, NLOS). The input data (ACF functions) was not modified
- Label : moving average of PR error (PR RMSE)





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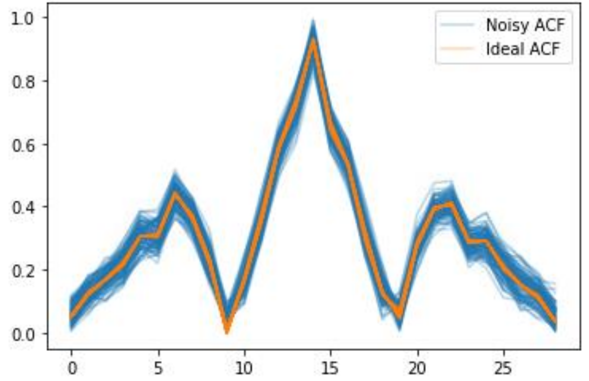
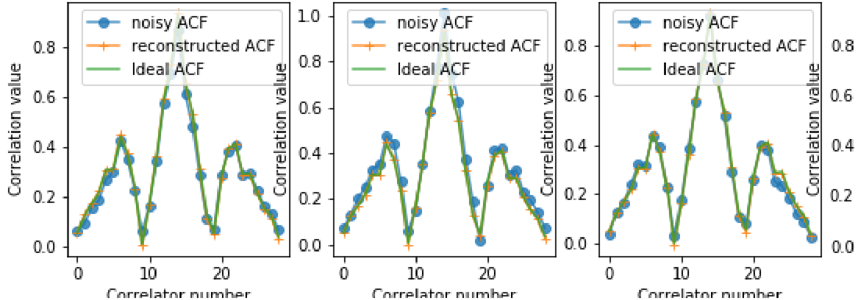
DOWN-SELECTION OF 3 ALGORITHMS

/// Algo 2 : Post-correlation - ACF Denoising

- Available data:
  - 180 seconds of simulated data
  - SCHUN+RxMacro (Urban channel model and Correlator level GNSS Rx Simulator)
- Algorithm:
  - Input: 29 point (noisy) ACF
  - Output: Ideal ACF
- Methodology:
  - Modern sequence to sequence neural network (LSTM) trained to infer the ideal ACF from the noisy one
- Results :
  - absolute reconstruction error of normalized ACF below 0.01 – RMSE
  - Suspicion of over fitting
- Conclusion : Kept for next phase, with modification (introduction of randomness on labels to prevent overfitting)



Example of reconstructed ACF



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DOWN-SELECTION OF 3 ALGORITHMS

/// Algo 3 : RINEX supervised pseudo-range regression on 4 Rx (1/2)

Available data:

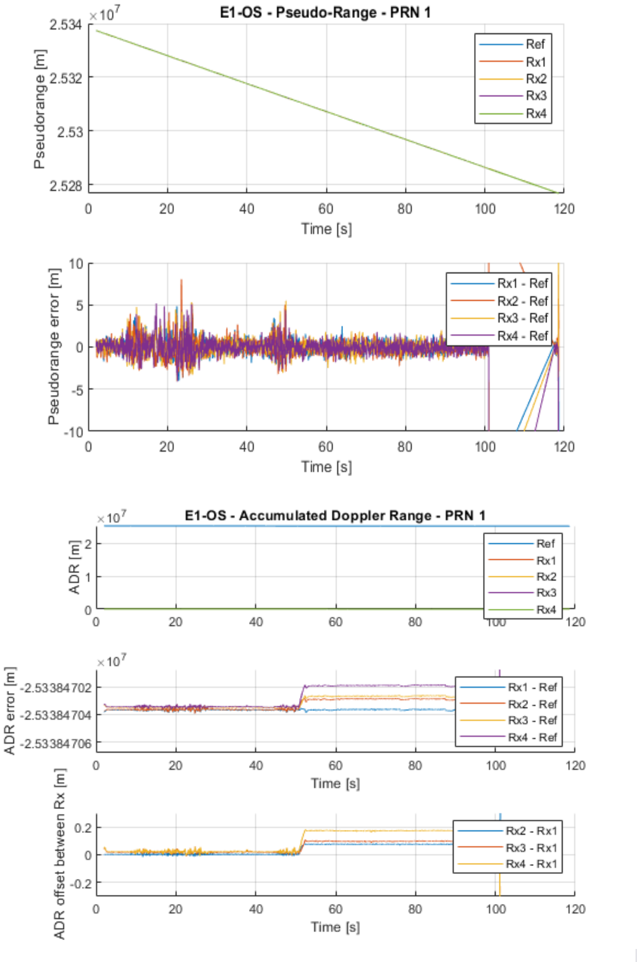
- 180 seconds of simulated data
- SCHUN+RxMacro (Urban channel model and Correlator level GNSS Rx Simulator)

Algorithm:

- Input : Pseudorange, ADR of 4 independent Rx
- Output : Pseudorange

Methodology:

- Test a simple neural network (MLP) on this regression problem



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DOWN-SELECTION OF 3 ALGORITHMS

/// Algo 3 : RINEX supervised pseudo-range regression on 4 Rx (2/2)

- Results : AI regression compared to simple average of PR over the 4 Rx receivers

Algorithm	Max error	Mean absolute error	Mean Squared Error	Median absolute error
Baseline	2.967	0.297	0.757	0.152
AI algorithm	25.681	0.837	7.767	0.343

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OVERVIEW OF THE 3 DOWN-SELECTED ALGORITHMS

#	Input(s)	Output	AI	Description
1	• 29 point ACF	Estimate of pseudorange σ	CNN	Post-correlation; supervised MP regression
2	• 29 point (noisy) ACF	Ideal ACF	CNN	Post-correlation; supervised regression
3	• Difference between PR of all Rx with that of a reference Rx • Mean of C/N0 on all Rxs • Difference between Doppler of all Rx with that of a reference Rx • DOA of LOS	Estimated pseudorange error with respect to pseudorange on the reference Rx 1	Gradient Boosted Trees	RINEX; supervised pseudorange regression on 4 receivers

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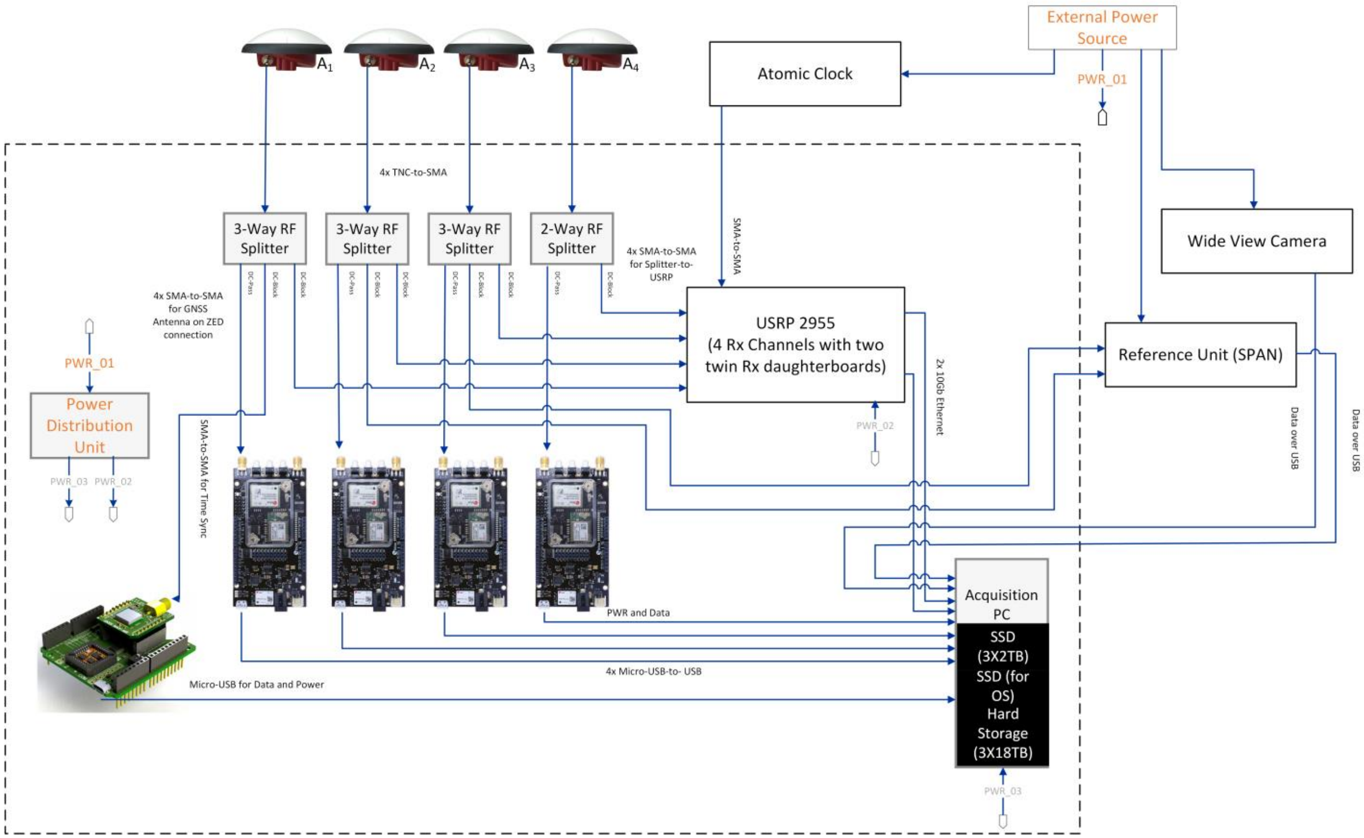
DATA ACQUISITION TESTBED



DATA ACQUISITION TESTBED

X310 USRP

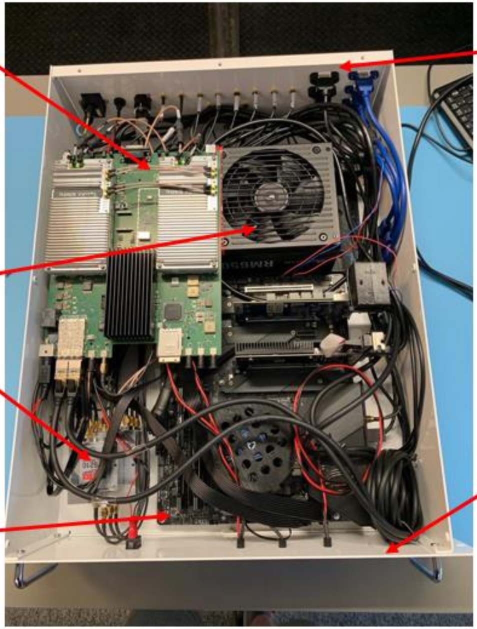
4 u-blox C099 F9P application boards (under X310)

Power supply

Splitters

Cables

MSI MEG Z490 Motherboard (3x M.2 2TB SSD)

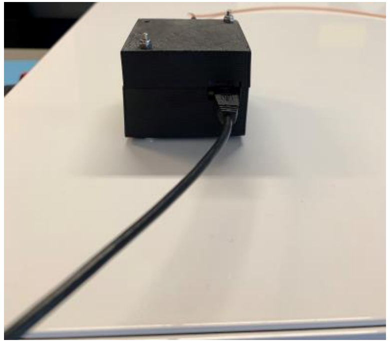


Rear panel interfaces

- 5 USB
- 4 SMA for RF Antennas
- 2 SMA for SPAN
- 1 SMA for external CSAC
- 2 RP-SMA for Wi-Fi antenna
- 1 HDMI
- 1 Reset switch
- 1 Power cable

Front panel

- On/Off switch
- Power LED
- SSD LED
- Sys Ops LED



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DATA COLLECTIONS

///Requirements for routes

- Minimal repetition (to avoid overfitting while training)
- Challenging GNSS environments – deep urban, high multipath, signal blockages
- 14 hours vehicle, 2 hours pedestrian – split across 5 days, 2 days respectively
- Full testbed utilised (USRPs – 4 channels, IMU etc.)

DATA COLLECTIONS

/// Routes

Date	Type	Duration (approx.)	'Waypoints' on routes – all UK	Description of route conditions
4 Mar 2022	Vehicle	2h30	Nottingham, Mansfield, Chesterfield, Sheffield	City centre driving in all 4 towns/cities. Drove along roads connecting them – so mix of suburban, urban, deep urban and rural.
9 Mar 2022	Vehicle	3h30	Nottingham, Loughborough, Leicester	Nottingham city centre, Loughborough town centre and university campus, Leicester city centre and residential areas.
10 Mar 2022	Vehicle	3h10	Birmingham, Coventry	Very built up: Birmingham city centre, University of Birmingham, Coventry city centre.
11 Mar 2022	Vehicle	2h35	Nottingham, Derby, Derbyshire	Derby city centre and residential areas – mainly densely packed terraced housing
25 May 2022	Vehicle	3h30	Nottingham, Nottinghamshire	Focussed mainly on residential areas of Nottingham, including areas with densely packed terraced housing, and streets with thick tree cover.
12 Jul 2022	Pedestrian	0h45	University of Nottingham, Jubilee campus (GMV Nottingham premises)	Contains numerous tall buildings, urban canyons, walls and trees.
20 Jul 2022	Pedestrian	1h25	Nottingham residential areas	Terraced housing, suburban areas

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DATA COLLECTIONS

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DATA LABELLING ACTIVITY

- ///Goal: construct a pseudorange, but without modelling any multipath
  - Real pseudoranges can then be subtracted from the constructed label -> remainder should be the multipath
- ///Method: computed pseudoranges constructed using
  - High accuracy position data from SPAN
  - High accuracy satellite orbit & clock data (CODE SP3 file)
  - Ionospheric delay (IONEX)
  - Tropospheric model (RTCAMOPS)
- ///Output: one csv file per signal containing above pseudoranges for every epoch and SV
- ///Receiver clock: estimated using a clock only state KF with RAIM using PR corrected from reference pseudorange.

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DESIGN, IMPLEMENTATION, VALIDATION, TRAINING OF 3 ALGORITHMS

- Algorithms 1 and 3 were analysed in their PVT level performance – output of AI was injected into KF PVT engine
- Algorithm 2 exhibited strange behaviour on test dataset; open loop injection of AI output not working as expected
  - Decided AI-level results were too poor to warrant exploring the PVT performance

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DESIGN, IMPLEMENTATION, VALIDATION, TRAINING OF 3 ALGORITHMS

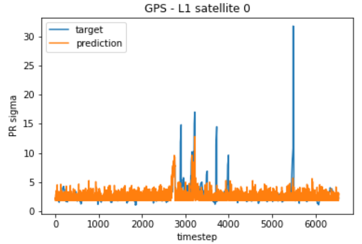
/// Performance of algorithm 1 : Post-correlation - Supervised MP error regression Results

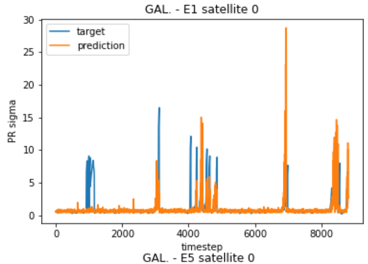
- At IA output :

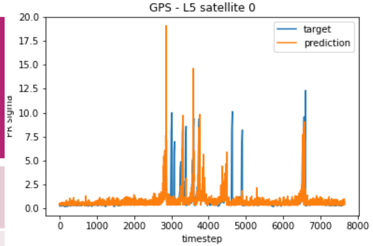
	RMSE (m)	MAE (m)	Medi. AE (m)	Max Error (m)	MAPE (m)
Mean	2.407	0.899	0.299	23.686	0.440

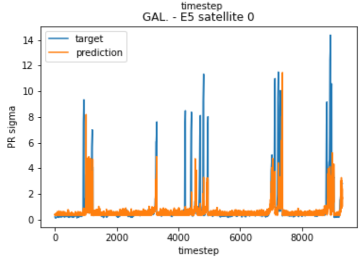
- At PVT level
  - AI output used to weight measurement – KF with KFMI Raim

	Horizontal position error at 50% (m)	Horizontal position error at 95% (m)	Horizontal protection level at 50% (m)	Horizontal protection level at 95%(m)
Legacy PR Sigma	0.94	1.94	5.80	28.25
AI modified PR Sigma	0.67	1.82	6.00	30.40
AI modified PR Sigma – All ACF	0.78	1.59	5.86	35.03
Label PR Sigma	0.49	0.98	5.93	23.12









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DESIGN, IMPLEMENTATION, VALIDATION, TRAINING OF 3 ALGORITHMS

/// Performance of Algo 3 - RINEX supervised pseudo-range regression on 4 Rx Results at PVT level

- PVT with AI modified PR outperforms legacy (mono-Rx) receiver
- Aggressive C/N0 filtering provides the best results

Algo 3	Horizontal position error at 50% (m)	Horizontal position error at 95% (m)	Horizontal protection level at 50% (m)	Horizontal protection level at 95% (m)
Legacy (mono Rx)	0.94	1.94	5.80	28.25
AI - 20 dBHz filtering	0.66	3.58	5.75	28.38
AI – 41 dBHz filtering	0.53	1.44	5.75	24.33
AI – Label filtering	0.72	2.94	5.75	27.98
AI – PR Projected on DoA	0.69	1.78	5.75	26.64
With label (for reference)	0.26	0.72	5.73	39.01

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PERFORMANCE WITH REAL SIGNALS

/// PVT level vs. that of Novatel SPAN

/// For both algorithms 1 and 3, the **use of AI did not offer significant improvement** over an equivalent classical GNSS PVT algorithm.

- But there were some data sets (e.g. 25 May algorithm 3) where the inclusion of AI → up to **21% improvement in ENU RMSE**

/// Algorithm 3 generally performed better than algorithm 1.

/// In the u-blox data, position errors of tens of metres were observed, which is consistent with the performance of algorithms at the 50% and 95% level.

- Algorithm 3 gives a similar level of performance to a COTS receiver.
- For all days (except 10 March), both L1E1 KF algorithm 3 solutions (with/without AI) outperform the u-blox solution by several metres in every ENU component at the 95% level.

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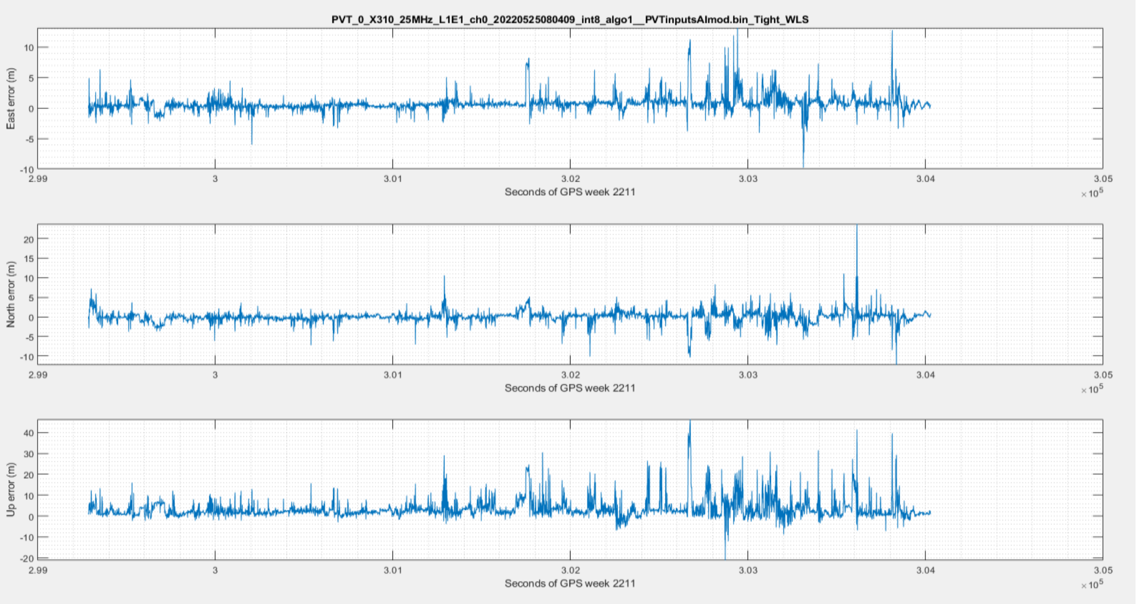
ALGORITHM 1 PERFORMANCE ON REAL DATA



Date	Signal	PVT	AI	Algo	50% Horz. err (m)	95% Horz. err (m)	50% HPL (m)	95% HPL (m)	95% East err (m)	95% North err (m)	95% Up err (m)
25-May-22	L1E1	WLS	0	1	0.971	4.281	27.935	36.674	2.794	3.174	11.828
25-May-22	L1E1	WLS	1	1	0.97	4.304	26.586	37.422	2.763	3.206	12.184
25-May-22	L1E1	KF	0	u-blox; RTKlib	1.913	7.834	-	-	5.503	5.28	24.368

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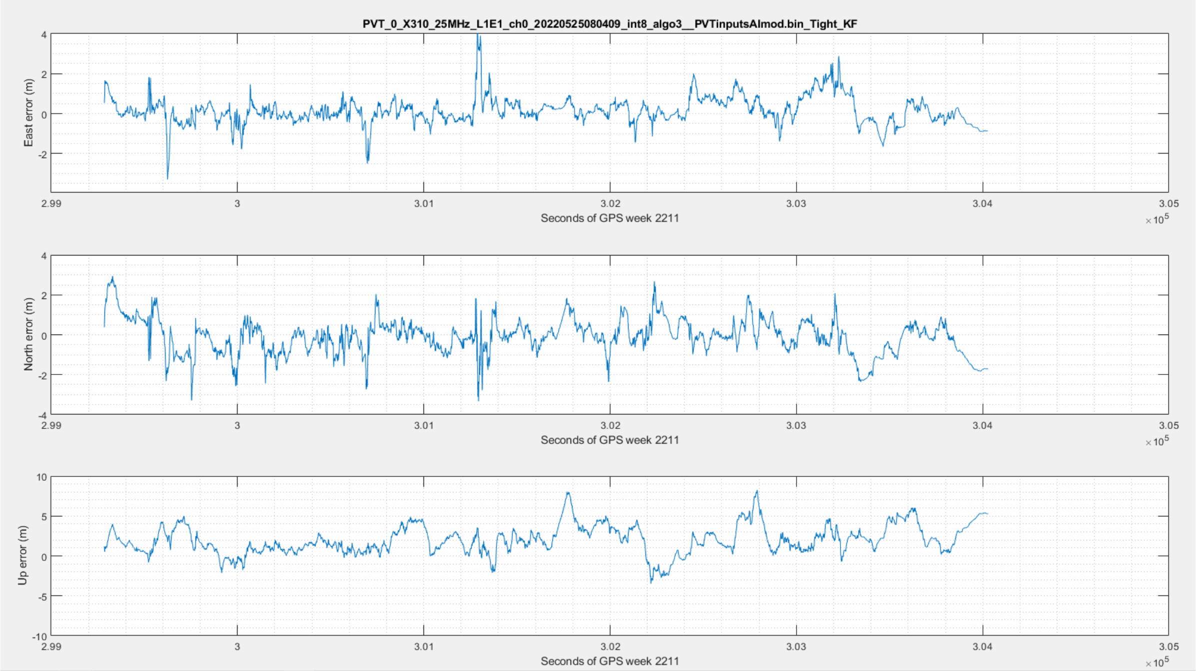
ALGORITHM 2 PERFORMANCE ON REAL DATA



Date	Signal	PVT	AI	Algo.	95% Horz. err (m)	RMSE		
						East (m)	North (m)	Up (m)
25-May-22	L1E1	KF	0	3	2.36	0.75	1.00	3.45
25-May-22	L1E1	KF	1	3	2.13	0.69	0.88	2.72

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CONCLUSIONS AND RECOMMENDATIONS

/// Innovation – AInGNSS went beyond state-of-the-art in 5 main areas

1. Adaptation of different AI algorithms for GNSS raw measurements enhancement
2. Scope of data collections (16+ hours)
3. Dynamic and challenging GNSS environments
4. Number of algorithms considered (9 → 6 → 3)
5. Number of signals considered; use of wider-band signals (E1, E5a, L5)
6. Use of multi-antenna system

/// Also characteristic of the project was a strong focus on IQ data (#6)

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CONCLUSIONS AND RECOMMENDATIONS

/// AInGNSS went beyond SoA in 6 main areas

1. Scope of data collections
2. Dynamic and challenging GNSS environments
3. *Regression, not classification*
4. Number of algorithms considered
5. Number of signals considered
6. Use of multi-antenna system

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CONCLUSIONS AND RECOMMENDATIONS

/// Benefits

- PVT performance improvement noted – occasionally significant (21%)
- At present, impact higher in more controlled environments – SoA review showed classification success rates of ~90%
- Knowledge benefit: successful algorithm development, successful development and deployment of multi-purpose, multi-device testbed (acquisition and processing)
- Innovative

/// Challenges

- Equipment cost high: mainly driven by requirements for (a) IQ data, (b) multiple wideband signals. These also proved challenging from a SW perspective

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Thank you

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ANNEX

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