南京航空航天大学
Nanjing University of Aeronautics and Astronautics

The BDS/GNSS-Based Quality Control for ITS Applications

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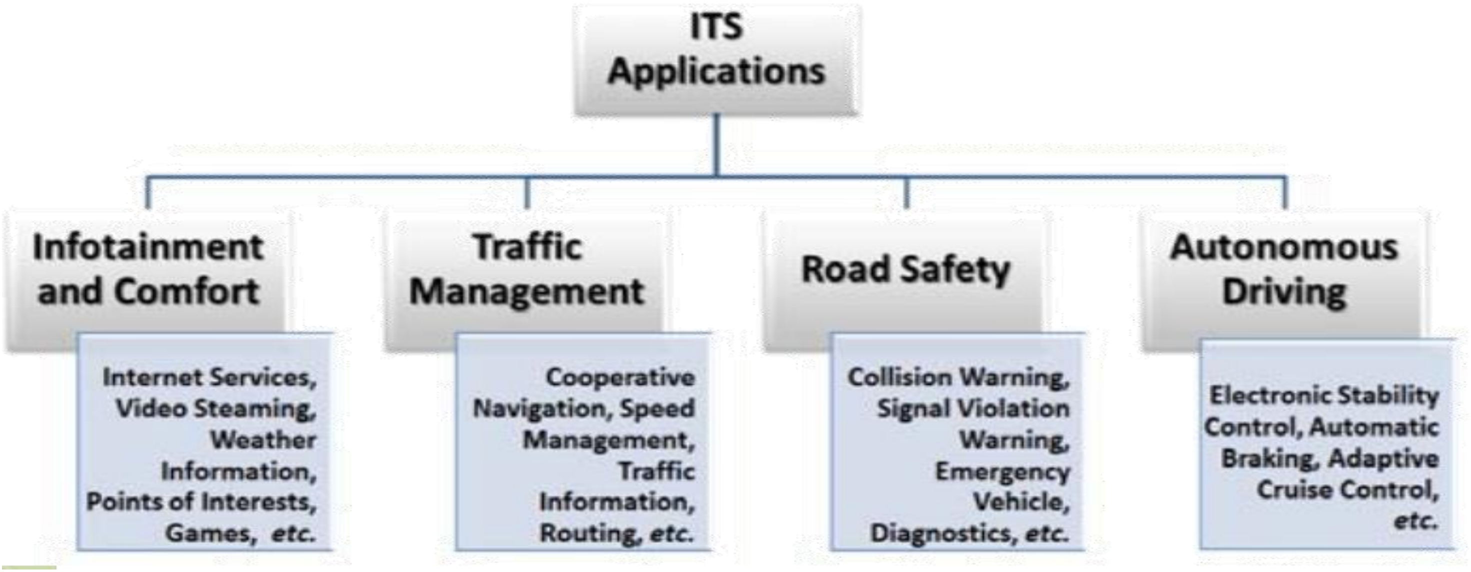
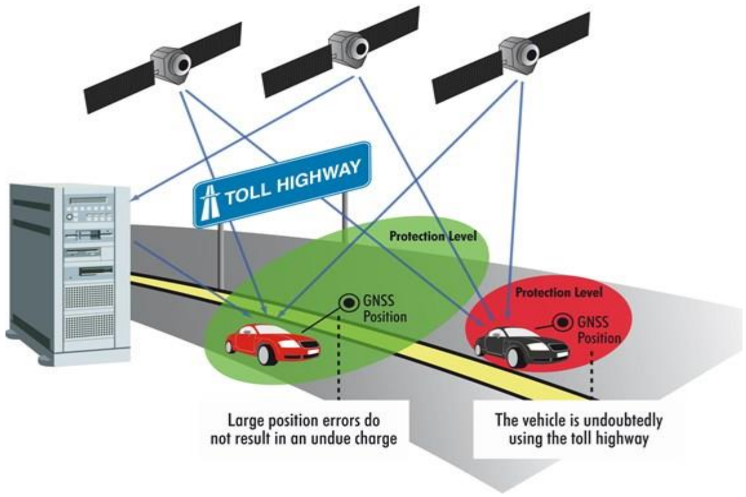
OUTLINE

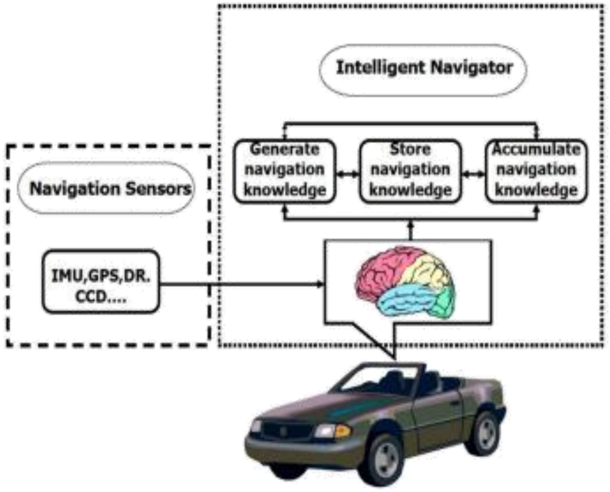
• Intelligent Transport Systems (ITS)

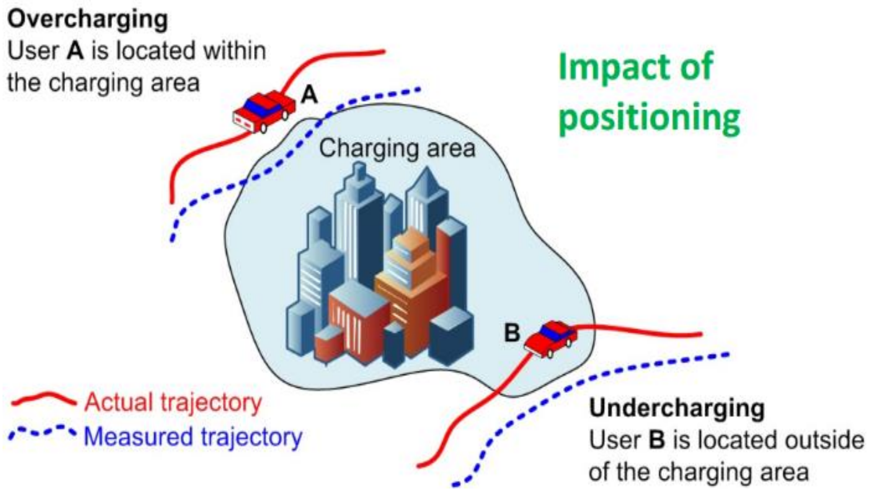
- *ITS is the integration of **information and communications** technology with transport infrastructure, vehicles and users*
- *ITS improves transport safety and mobility and enhances productivity through the use of advanced **information** and **communications** technologies.*

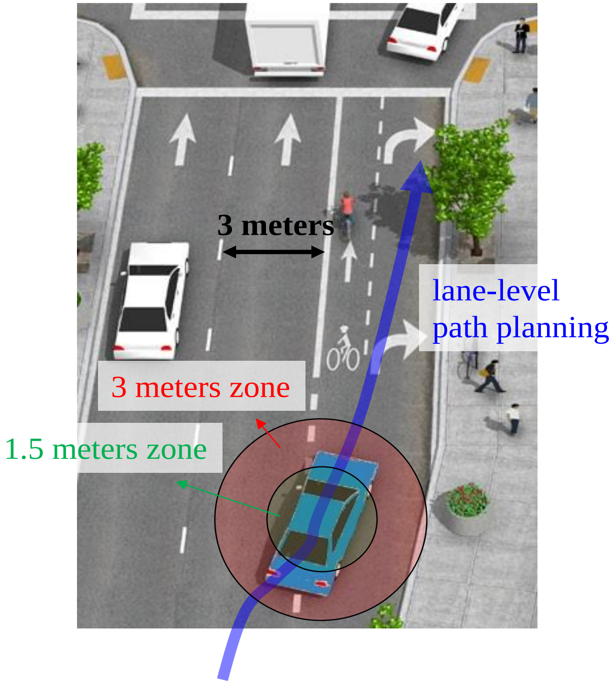


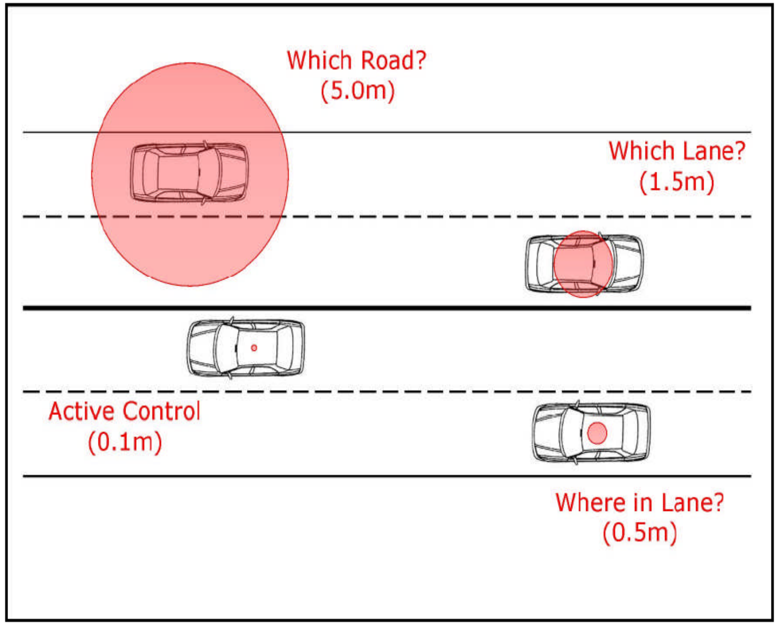
- **Safety-Critical Applications**
  - Autonomous Driving
  - ADAS (such as Intelligent speed adaptation)
  - Hazardous Material Tracking
- **Payment-Critical Applications**
  - Road User Charging (RUC)
  - Pay-per-use services (PAYD, PPUI…)
- **Regulatory-Critical Applications**
  - Emergency services (eCall)
  - Emergency vehicles navigation

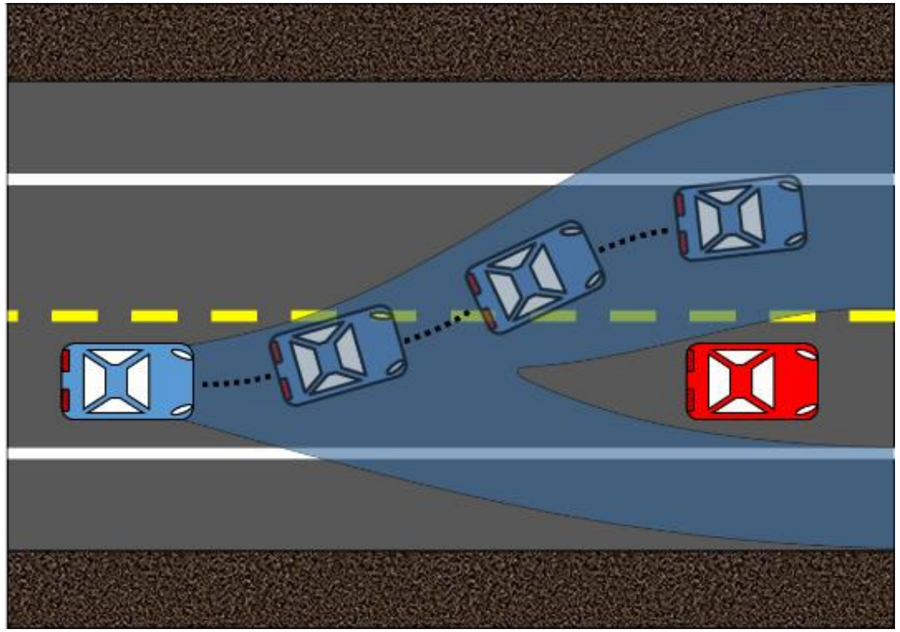

TOLL HIGHWAY
Protection Level
GNSS Position
Protection Level
GNSS Position
Large position errors do not result in an undue charge
The vehicle is undoubtedly using the toll highway


Intelligent Navigator
Generate navigation knowledge
Store navigation knowledge
Accumulate navigation knowledge
Navigation Sensors
IMU,GPS,DR. CCD....


Overcharging
User A is located within the charging area
A
Impact of positioning
Charging area
B
Actual trajectory
Measured trajectory
Undercharging
User B is located outside of the charging area


3 meters
lane-level path planning
3 meters zone
1.5 meters zone


Which Road? (5.0m)
Which Lane? (1.5m)
Active Control (0.1m)
Where in Lane? (0.5m)



• Performance Features

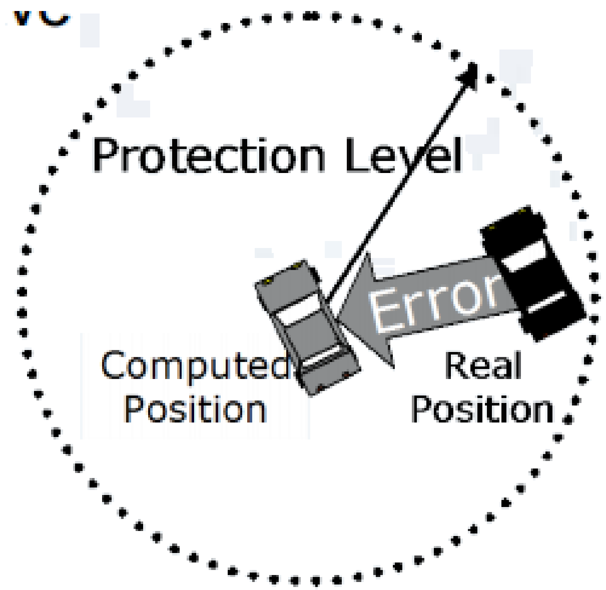
Accuracy: it refers to statistical figures of merit of position error, velocity error or speed error

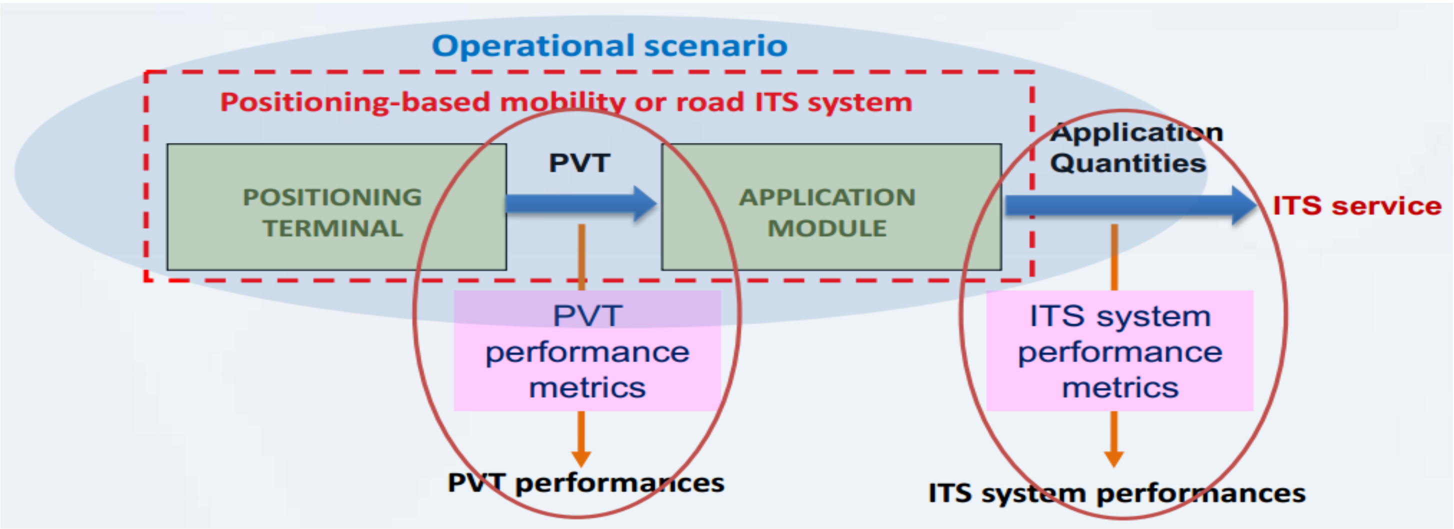
Integrity: it refers to the level of **trust** a user can have in the value of a given component :

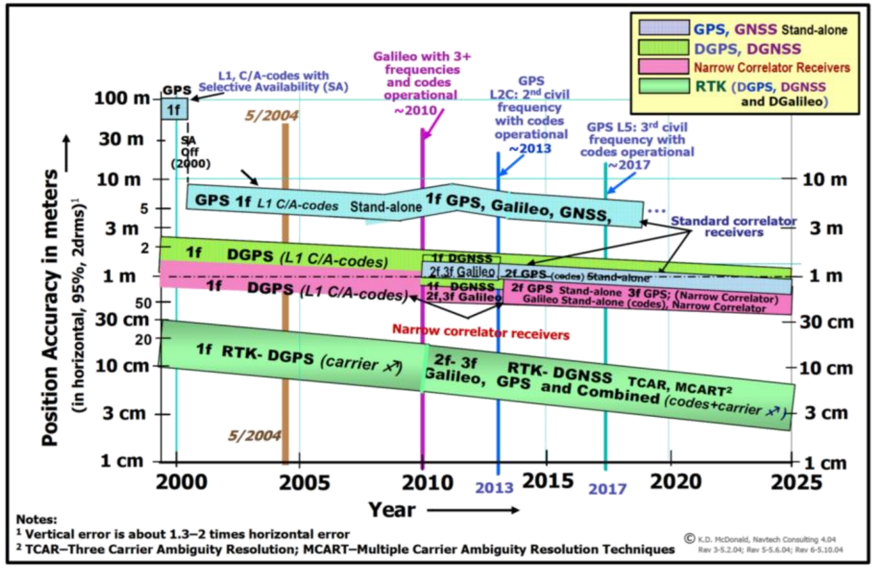
- in terms of reliability (*Integrity risk*)
- efficiency and usability (size of the *Protection level*).

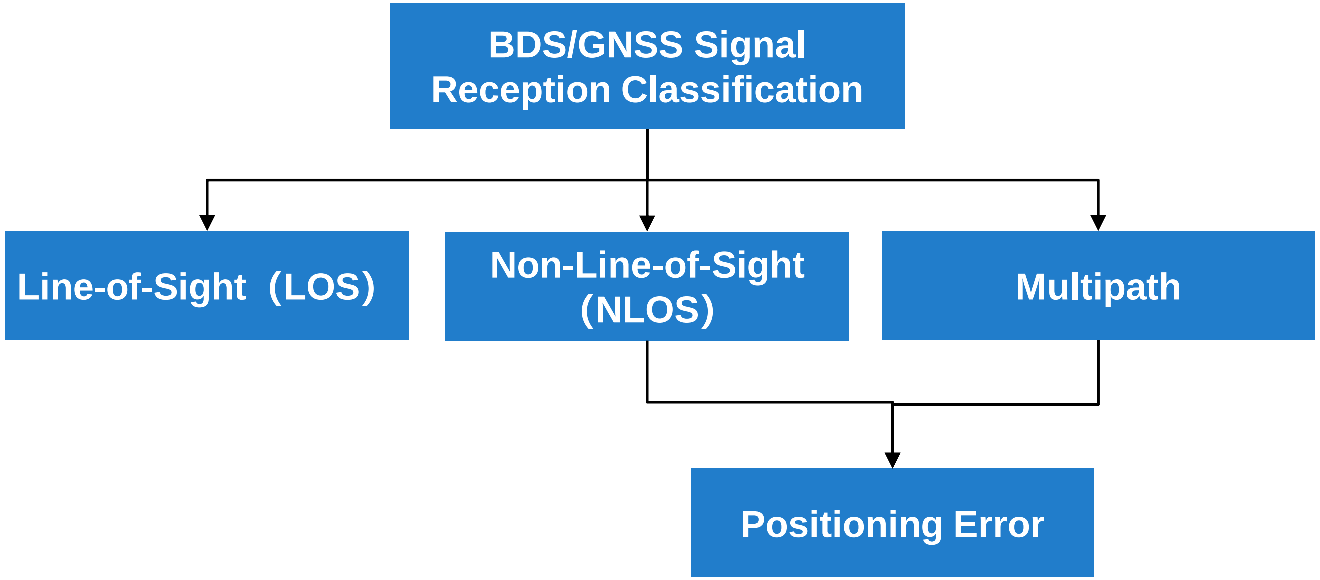
Availability: generally speaking, it refers to the percentage of time during which the output of the positioning terminal is available.

Timing performance: it refers to timestamp resolution, output latency, rate stability and Time To First Fix.

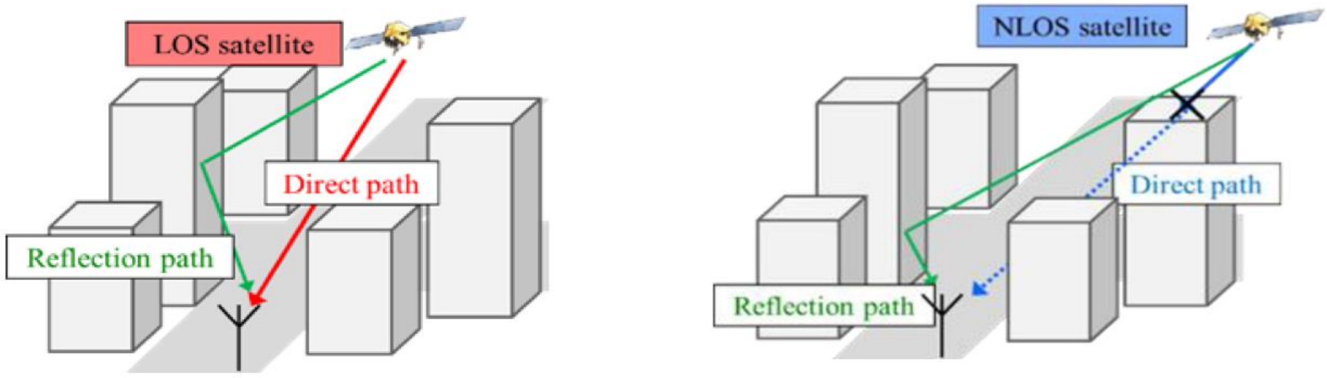




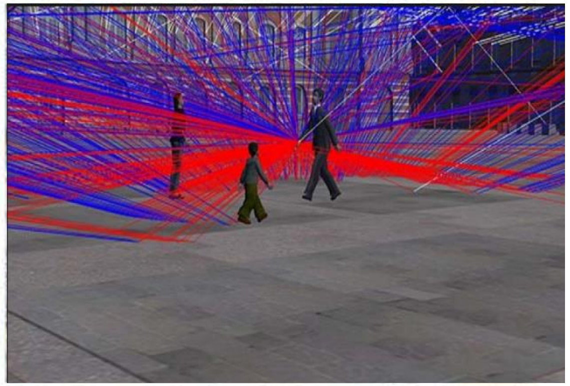




- Cannot be corrected by differential positioning method
- The error caused by NLOS can be tens of meters



(a) Multipath effect (b) NLOS effect



• BDS/GNSS-Based Quality Control Techniques

Measurement weighting based techniques

- satellite elevation angle
- pseudorange rate
- C/N_0
- …

→ Basic variables

- Inertial Measurement Units (IMU)
- camera
- 3D maps
- …

→ Other sources

transferability issues to different environmental scenarios

Fault Detection and Exclusion based Techniques

- range and position comparison methods
- least squares residuals methods
- parity space methods
- maximum slope (MS) methods
- …

→ widely used for RAIM

- consistency checking-based methods

→ for ARAIM

based on the assumption of a single failure at a time

only effective when at least six satellites can be observed

high computational cost

Signal Reception Type Classification

9 Input Variables + PCA + machine learning

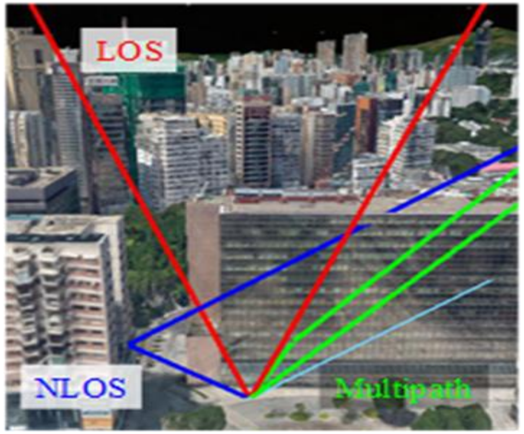
- ✓ Received Signal Strength (C/N_0)
- ✓ Temporal Difference of Received Signal Strength ($\Delta C/N0$)
- ✓ Horizontal Dilution Of Precision (HDOP)
- ✓ Vertical Dilution Of Precision (VDOP)
- ✓ Satellite Elevation Angle (EA)
- ✓ Azimuth Angle (AA)
- ✓ Pseudorange residual (η)
- ✓ Consistency between delta pseudorange and pseudorange rate(ζ)
- ✓ Number of visible Satellites (NS)

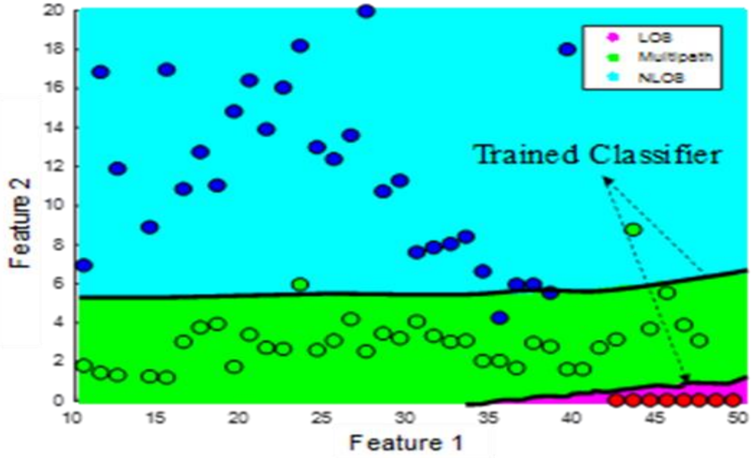
C/N_0 > threshold ? — **Unreliable !**

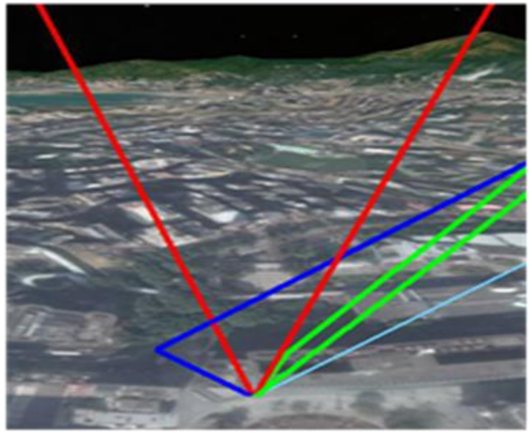
- Yes → **LOS**
- No → **Multipath**

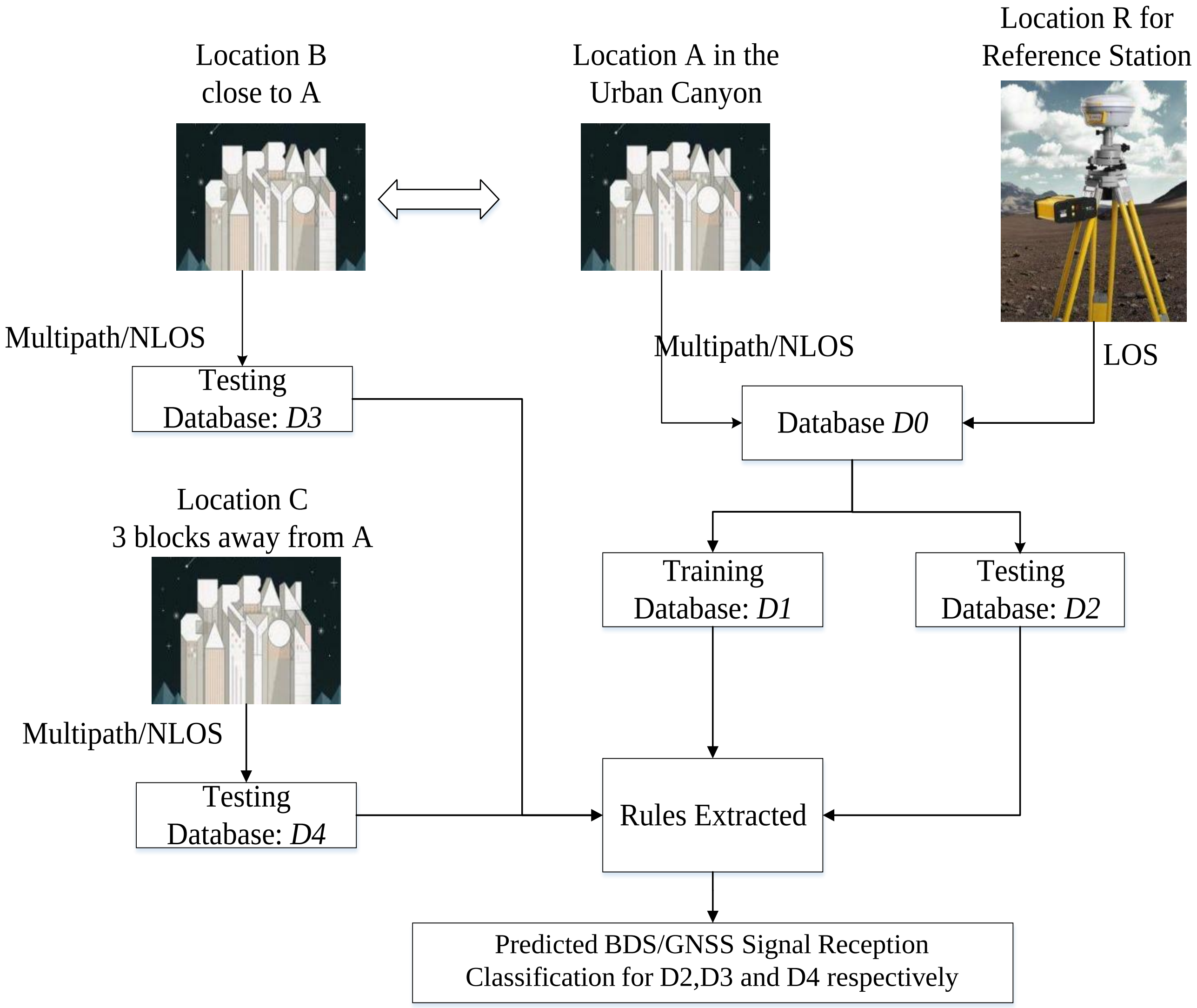
Other Features

- Satellite elevation angle
- Pseudorange residual
- Pseudorange rate
- HDOP
- VDOP

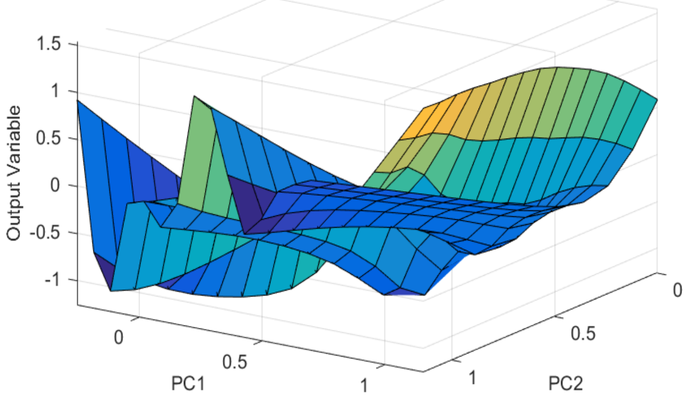


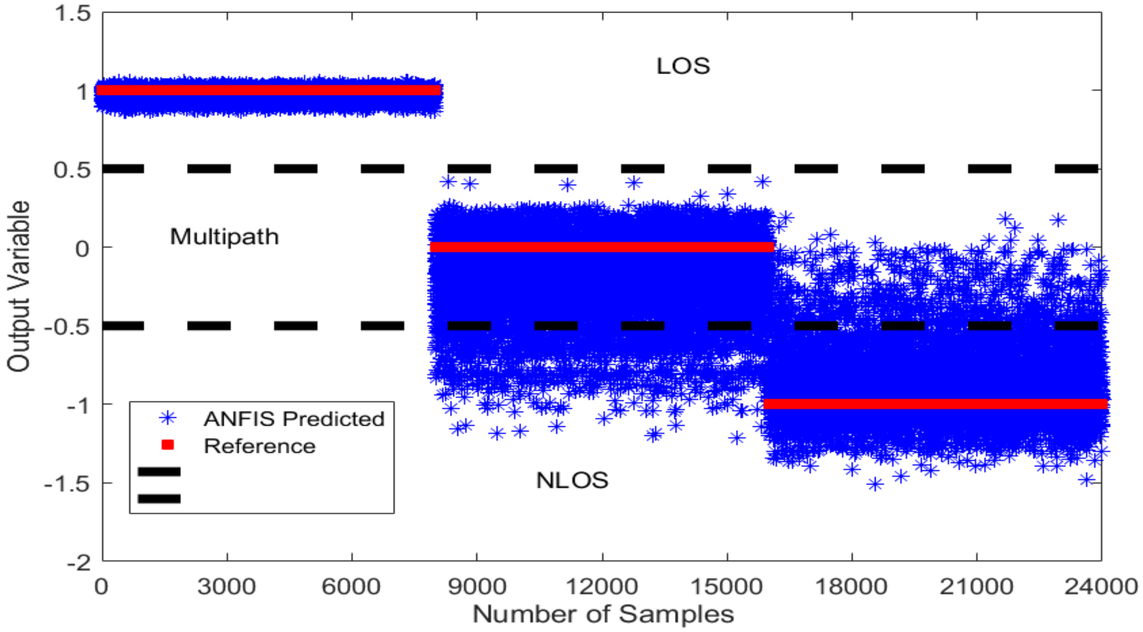





Location B
close to A
Location A in the
Urban Canyon
Location R for
Reference Station
Multipath/NLOS
Multipath/NLOS
LOS
Testing
Database: D3
Database D0
Location C
3 blocks away from A
Training
Database: D1
Testing
Database: D2
Multipath/NLOS
Testing
Database: D4
Rules Extracted
Predicted BDS/GNSS Signal Reception
Classification for D2,D3 and D4 respectively


Patch Antenna


Output Variable
PC1
PC2


LOS
Multipath
NLOS
ANFIS Predicted
Reference
Output Variable
Number of Samples

		Proposed ANFIS			Decision Tree			SVM			C/N_0 based Classification		
		-1	0	1	-1	0	1	-1	0	1	-1	0	1
Label Result	-1	7291	709	0	3963	4036	1	5206	2793	1	13499	6603	708
	0	1269	6731	0	837	7163	0	1995	6005	0	3152	3339	1902
	1	0	0	8000	0	0	8000	0	0	8000	0	779	10018
Accuracy		91.76%			79.69%			80.05%			67.14%		
Accuracy for each class		-1	0	1	-1	0	1	-1	0	1	-1	0	1
		91.14 %	**84.14 %**	**100%**	49.54%	89.54%	100%	65.08%	75.06%	100%	64.87%	40%	93%

		Proposed ANFIS		Decision Tree		SVM		C/N_0 based Classification	
Class Type		-1	0	-1	0	-1	0	-1	0
Dataset D3	Accuracy	**72.98%**		56.24%		75.43%		64.84%	
	Accuracy for each class	76.60%	66.35%	50.82%	66.19%	80.64%	66.19%	100%	0.31%
Dataset D4	Accuracy	**71.51%**		53.17%		71.20%		71.88%	
	Accuracy for each class	64.24%	91.48%	39.27%	91.38%	65.65%	86.46%	96.81%	3.82%

Classification + NLOS Elimination

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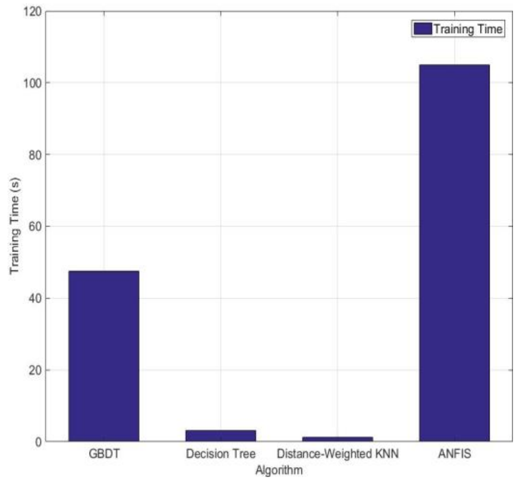
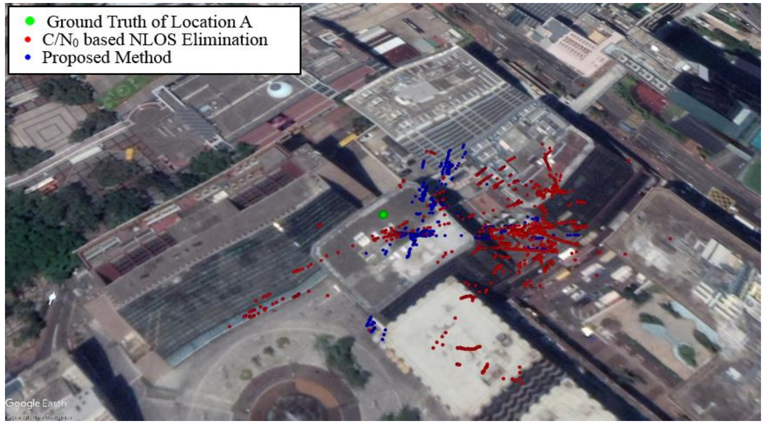
Input:

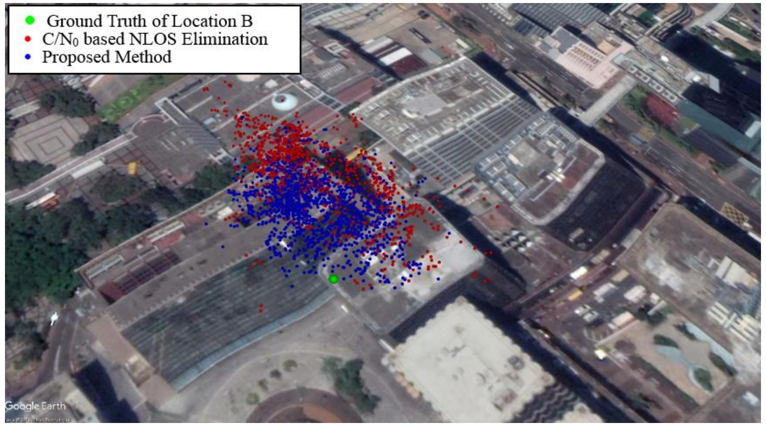
- ✓ C/N_0
- ✓ Pseudorange residuals
- ✓ Satellite elevation angle

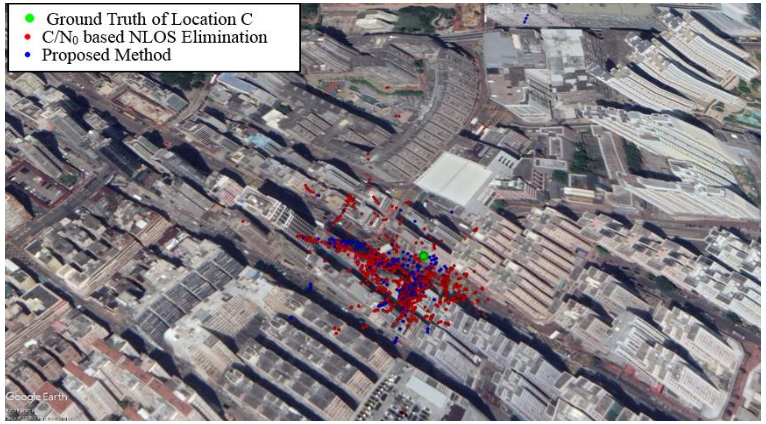


RMSE (m)		E	N	U	3D	horizontal
Location A	C/N_0 Based NLOS Elimination	40.92	17.9	79.01	90.76	44.67
	GBDT with Multi-Feature-Based NLOS Elimination	26.19	17.02	51.02	59.82	31.23
	Improvement (%)	36.0	4.9	35.4	34.1	30.1
Location B	C/N_0 Based NLOS Elimination	20.13	45.41	63.72	80.80	49.67
	GBDT with Multi-Feature-Based NLOS Elimination	18.35	35.61	50.89	64.77	40.06
	Improvement (%)	8.8	21.6	20.1	19.8	19.4
Location C	C/N_0 Based NLOS Elimination	25.4	29.5	127.67	133.37	38.59
	GBDT with Multi-Feature-Based NLOS Elimination	25.07	32.27	123.83	130.39	40.86
	Improvement (%)	1.3	-9.4	3.0	2.2	-5.9

Classification Accuracy: 89%, 77.2% , 55.3%







Using Gradient Boosting Decision Tree (GBDT) to Fit the Pseudorange Error

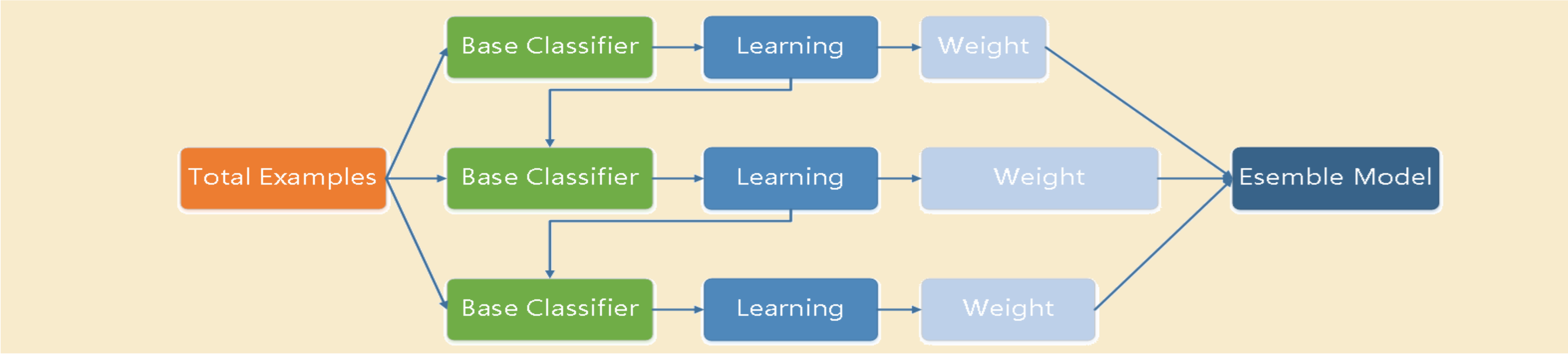
Carrier-to-Noise Ratio: C/N_0(dB-Hz)

Pseudorange residual: The difference between the observed pseudorange measurements and the pseudorange values deduced from the positioning solution.

Satellite Elevation Angle: The angle between the satellite-to-receiver line and the horizon

→ **Pseudorange Error**

- One of the best algorithms for fitting the true distribution
- Data classification is achieved by using an **additive model** to continuously reduce the residuals generated during the training process
- each iteration produces a weak classifier, and each classifier is trained based on the **residual error** of the previous classifiers.



Pseudorange preprocessing

Pseudorange after model correction :

$$\rho^{c} = R + c(\delta t^{r} - \delta t^{sv}) + I + T + \varepsilon - c(\delta t_{c}^{r} - \delta t_{c}^{sv}) - I_{K} - T_{S}$$

$$\rho^{c} = R + c(\Delta\delta t^{r} - \Delta\delta t^{sv}) + \Delta I + \Delta T + \varepsilon$$

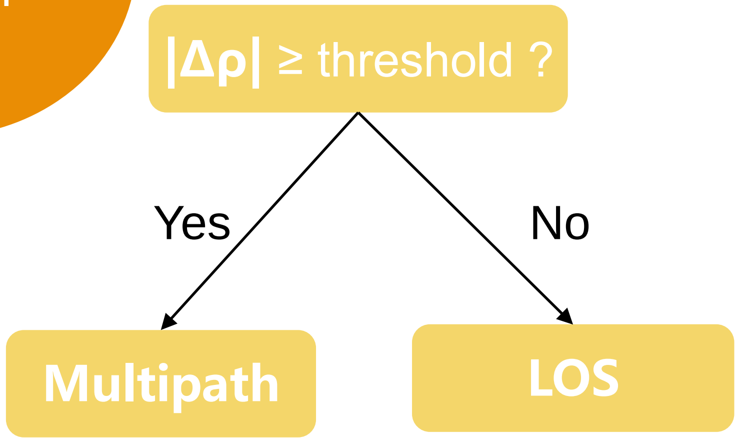
The pseudorange error $\Delta\rho$ is calculated by the following formula:

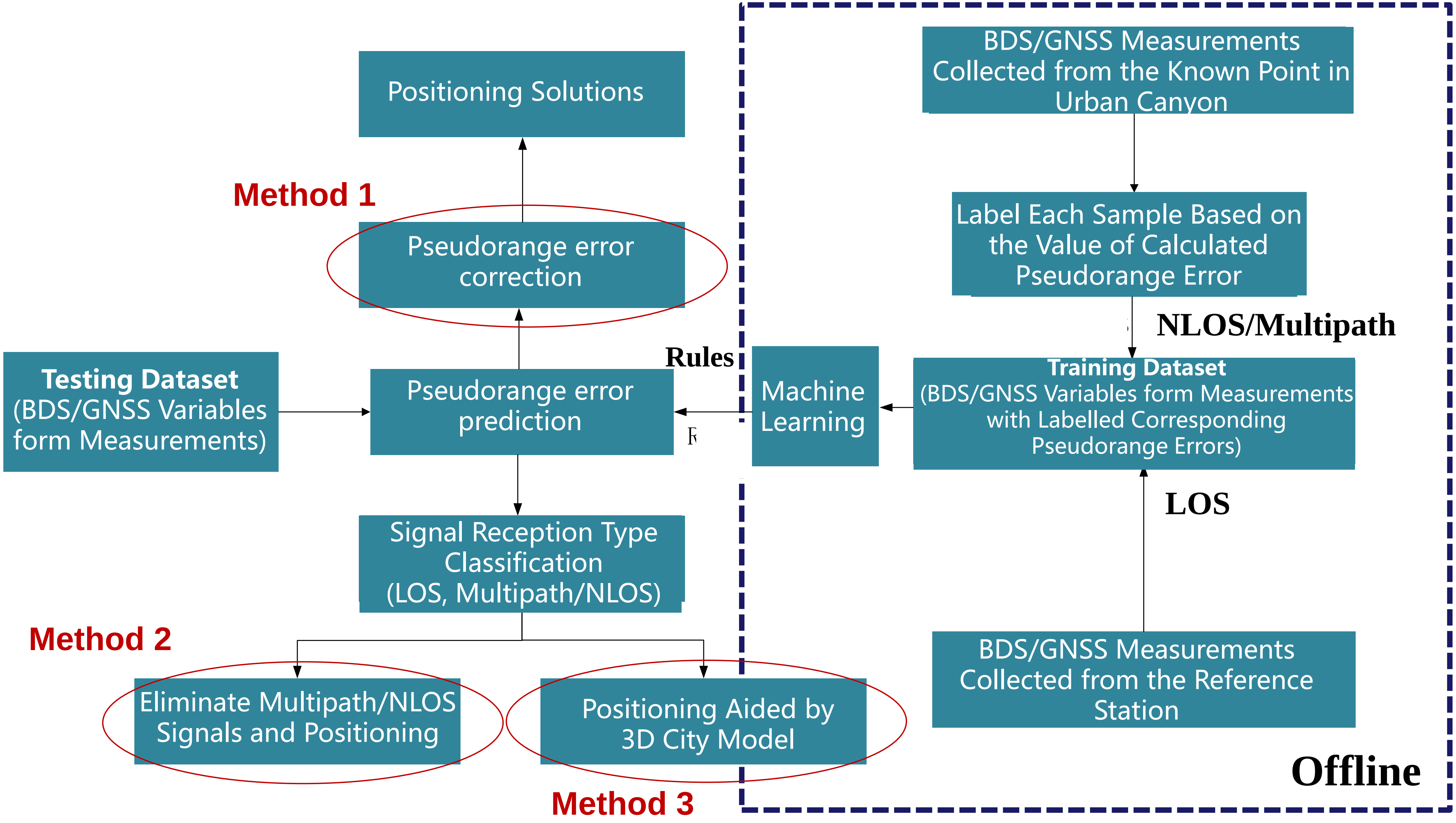
$$\Delta\rho = \rho^{c} - R = c(\Delta\delta t^{r} - \Delta\delta t^{sv}) + \Delta I + \Delta T + \varepsilon$$

The main part is multipath error

Pseudorange error $\Delta\rho$ includes the errors caused by clock errors, ionospheric delay, troposphere delay, and multipath effects that have not been fully corrected (ε).

- NLOS : Positive pseudorange error
- Multipath : Positive or negative pseudorange error




Positioning Solutions
Method 1
Pseudorange error correction
Testing Dataset
(BDS/GNSS Variables form Measurements)
Pseudorange error prediction
Rules
Machine Learning
Training Dataset
(BDS/GNSS Variables form Measurements with Labelled Corresponding Pseudorange Errors)
BDS/GNSS Measurements Collected from the Known Point in Urban Canyon
Label Each Sample Based on the Value of Calculated Pseudorange Error
NLOS/Multipath
LOS
BDS/GNSS Measurements Collected from the Reference Station
Signal Reception Type Classification
(LOS, Multipath/NLOS)
Method 2
Eliminate Multipath/NLOS Signals and Positioning
Positioning Aided by 3D City Model
Method 3
Offline

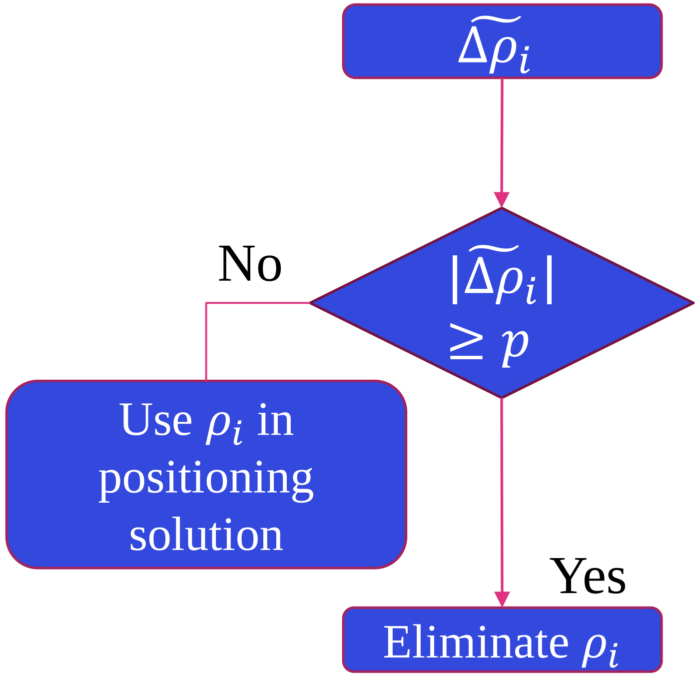
1. Positioning Method Based on Pseudorange Correction

$$\begin{cases} \rho_1^c = \rho_1 - \widetilde{\Delta\rho_1} \\ \rho_2^c = \rho_2 - \widetilde{\Delta\rho_2} \\ \vdots \\ \rho_i^c = \rho_i - \widetilde{\Delta\rho_i} \end{cases}$$

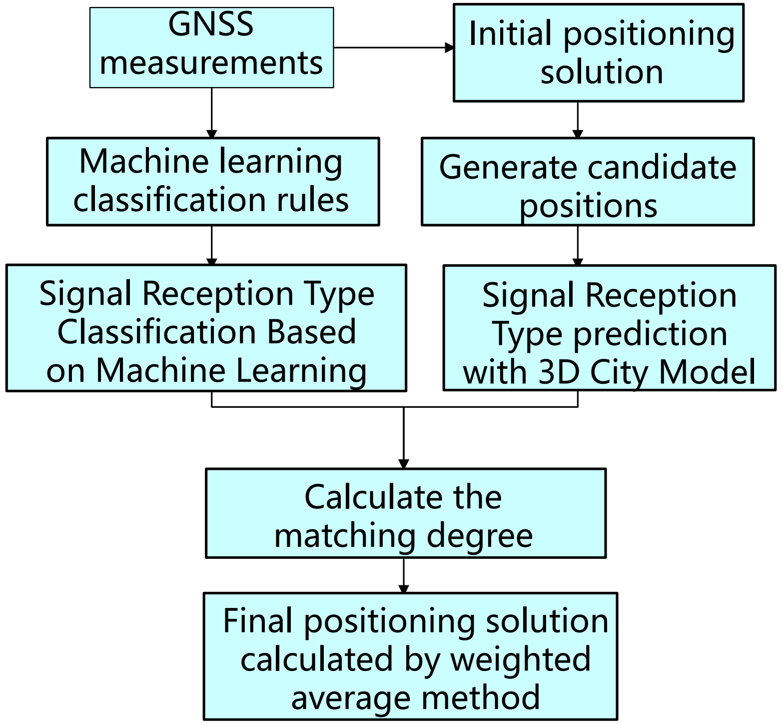
Positioning Solution

(x^r, y^r, z^r)

2. Positioning Method Based on Multipath Signal Elimination

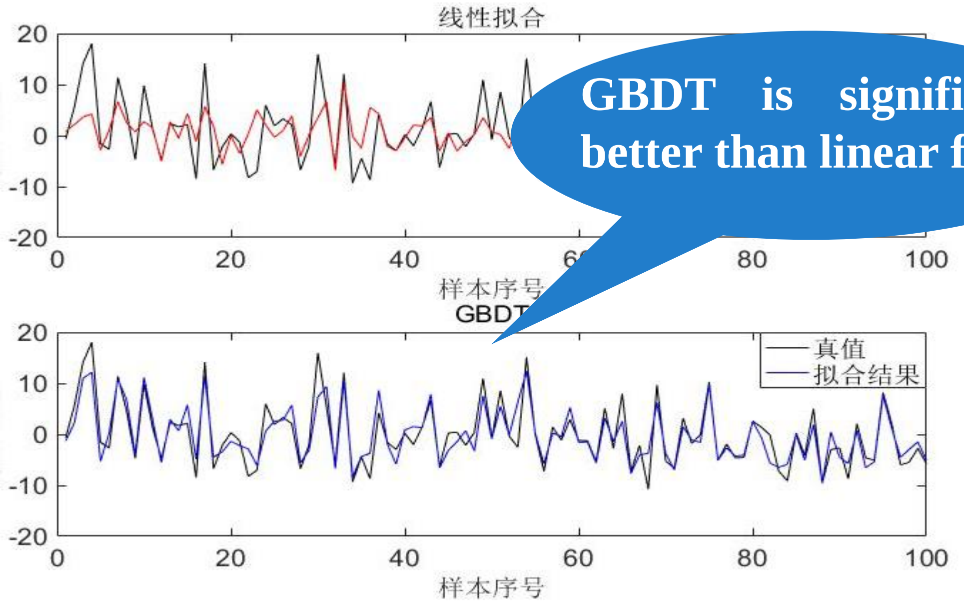


3. Positioning Method Aided by 3D City Model

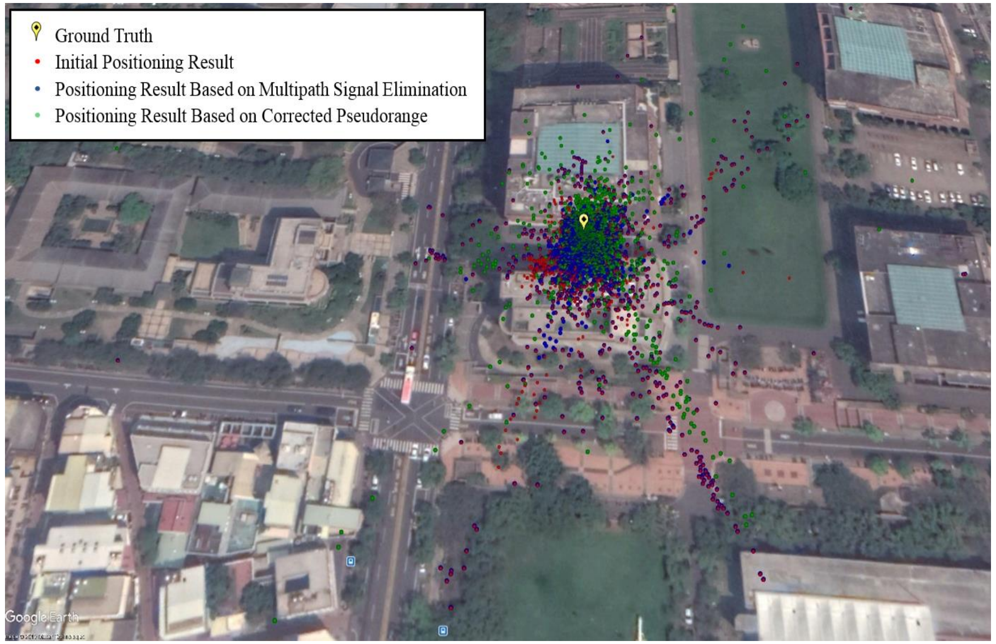


Test Case 1: Narrow road with buildings on both sides

Reference Station: 7 hours of data
Urban Canyon: 1 Hz, NovAtel Propak 7



GBDT is significantly better than linear fitting

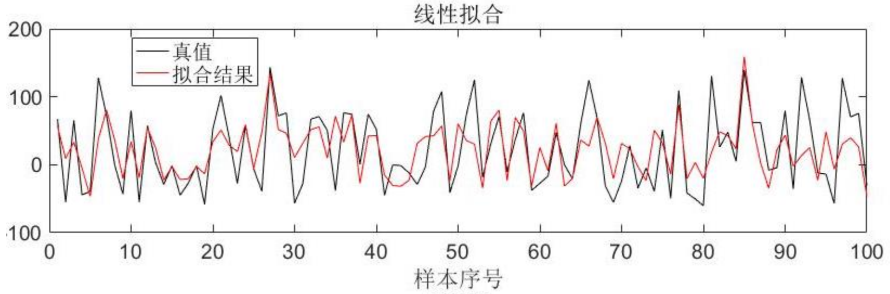


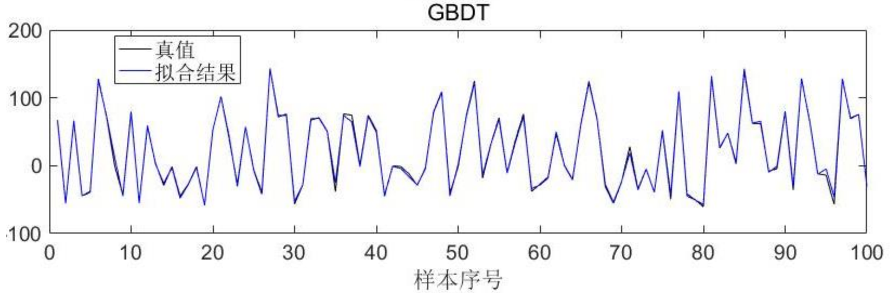
Training Dataset	Urban Canyon		Reference Station
Signal Reception Type	Multipath	LOS	LOS
Number of samples	48000	24000	24000

Testing Dataset	Urban Canyon	
Signal Reception Type	Multipath	LOS
Number of samples	46759	50285

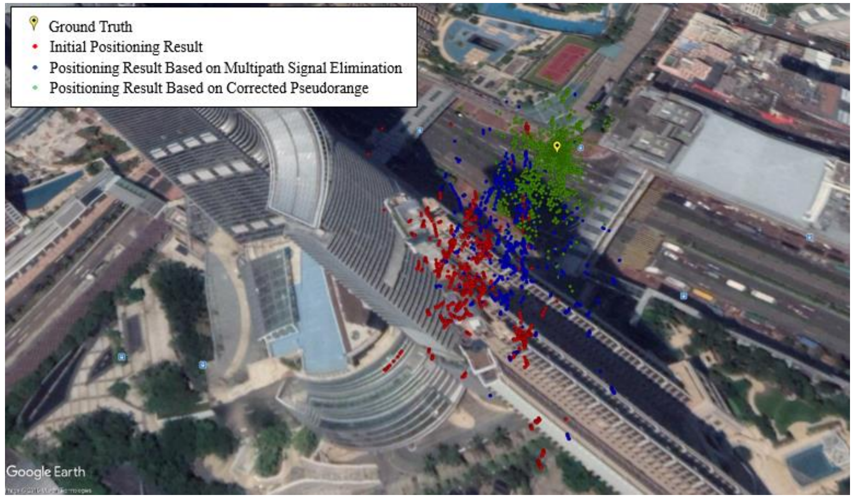
Classification Accuracy	Total	LOS	Multipath
	75.90%	80.29%	71.49%

Positioning Accuracy	E	N	U	3D	2D
Initial Positioning Result (RMSE/m)	18.02	25.85	44.36	54.41	31.51
Positioning Result Based on Multipath Signal Elimination (RMSE/m)	13.74	13.80	32.46	37.86	19.48
Improvement (%)	23.75	46.62	26.83	30.42	38.18
Positioning Result Based on Corrected Pseudorange (RMSE/m)	14.82	21.49	36.27	44.69	26.11
Improvement (%)	17.76	16.87	18.24	17.86	17.14





	linear fitting	GBDT fitting
RMSE/m	38.14	1.24



Test Case 2: High rise building on one side

Reference Station: 4 hours of data with a sampling interval of 5s

Urban Canyon: P1、 P2

Receiver：NovAtel OEM 6

Training Dataset	Urban Canyon				Reference Station
	P1		P2		
Signal Reception Type	Multipath	LOS	Multipath	LOS	LOS
Number of samples	16000	24000	16000	24000	16000

Testing Dataset	Urban Canyon（P1）	
Signal Reception Type	Multipath	LOS
Number of samples	4686	14869

Classification Accuracy	Total	LOS	Multipath
	91.13%	96.42%	74.49%

Positioning Accuracy	E	N	U	3D	2D
Initial Positioning Result (RMSE/m) RMSE/m	36.87	55.16	39.39	77.16	66.34
Positioning Result Based on Multipath Signal Elimination (RMSE/m)	10.30	14.56	16.00	23.96	17.83
Improvement (%)	**72.06**	**73.60**	**59.38**	**68.95**	**73.12**
Positioning Result Based on Corrected Pseudorange (RMSE/m)	24.73	40.21	30.08	61.29	47.21
Improvement (%)	**32.93**	**27.10**	**23.64**	**20.57**	**28.84**

Test Case 3： L-shaped corner + Dense canopy

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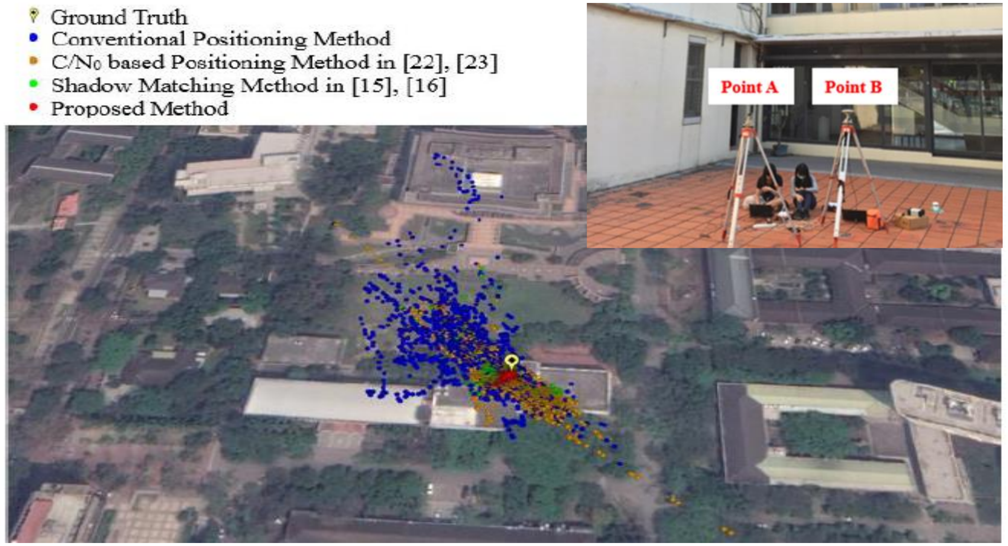
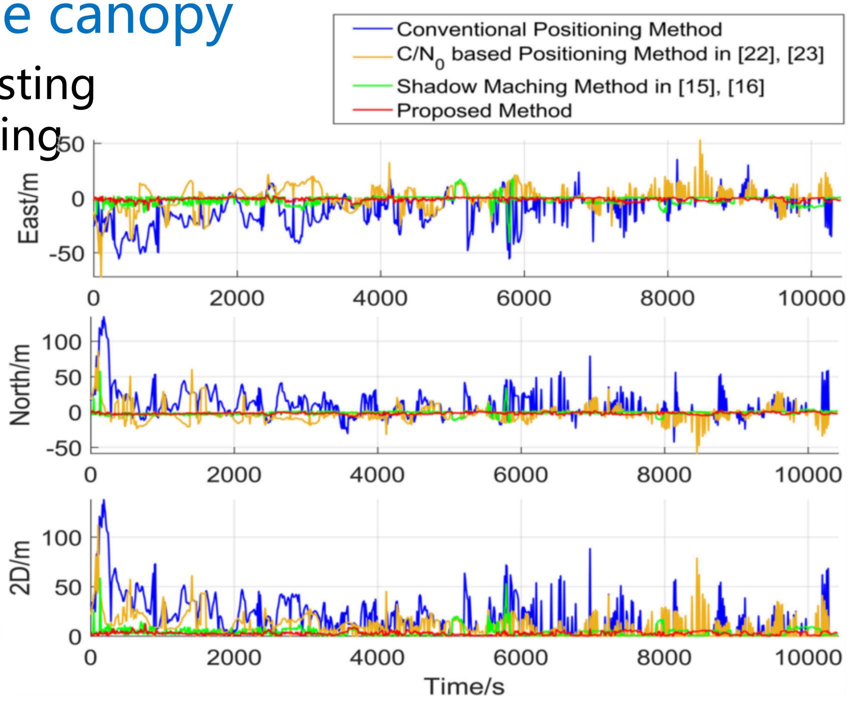
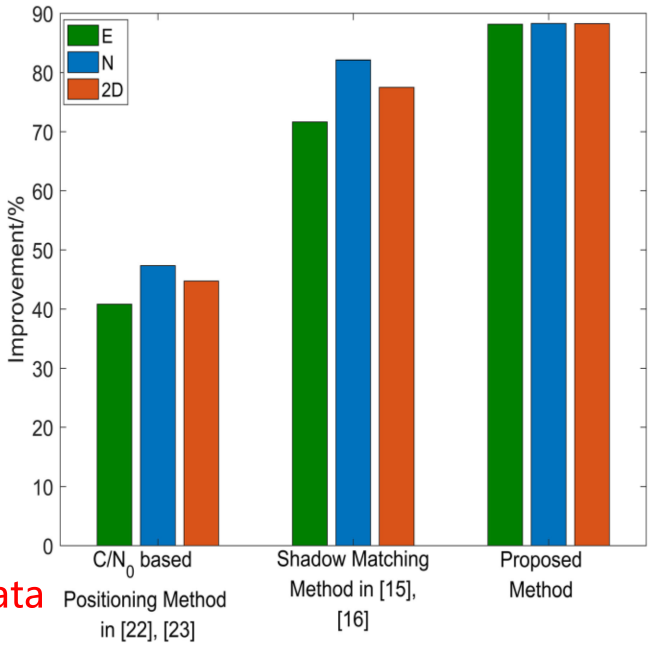
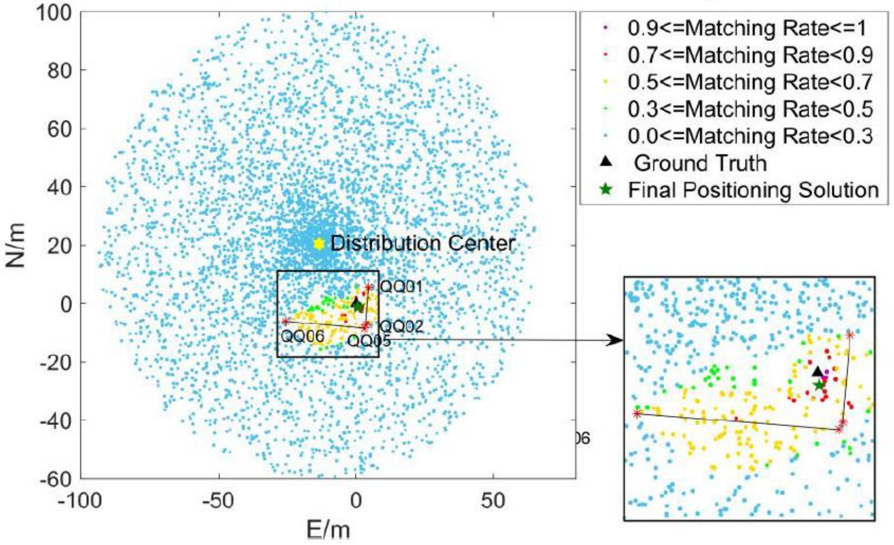
PA: UBLOX M8T, 5 Hz, 30 mins, training and testing
PB: Novatel Propak OEM-6, 1 Hz, 30 mins, testing









Positioning method using raw pseudorange data with a weighted least squares

	Method	E	N	2D
RMSE/m	Conventional Positioning Method	16.87	21.32	27.19
	ML+3D City Model	1.90	2.59	3.21
	Improvement (%)	88.74	87.85	88.19
95th Percentile of Positioning Error/m	Conventional Positioning Method	38.06	40.36	52.44
	ML+3D City Model	4.41	4.15	5.59
	Improvement (%)	88.41%	89.72	89.34

Test Case 3: L-shaped corner + Dense canopy

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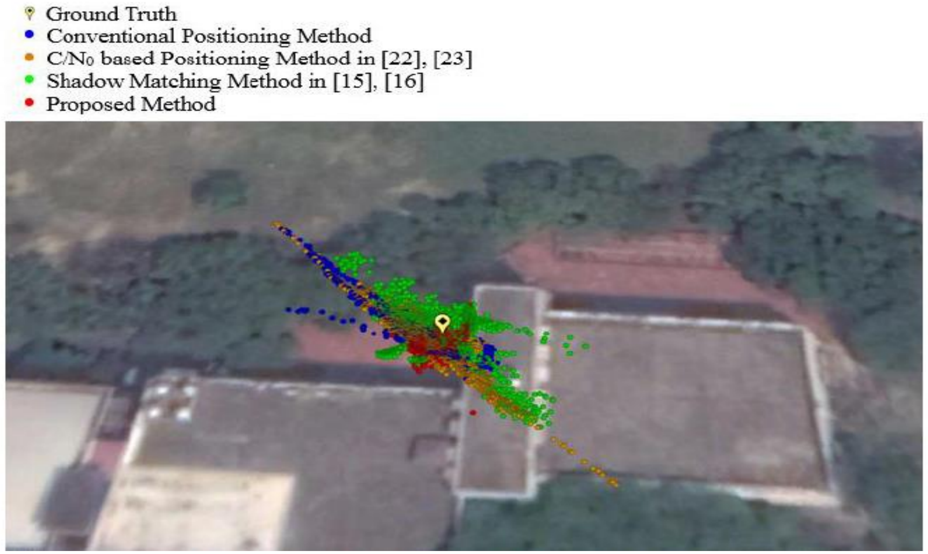

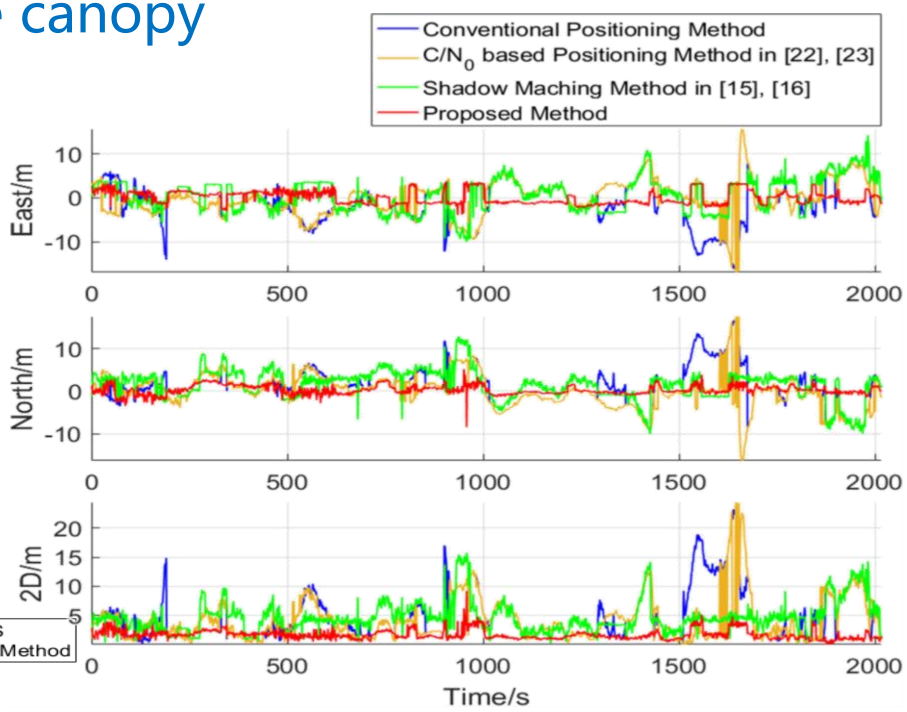

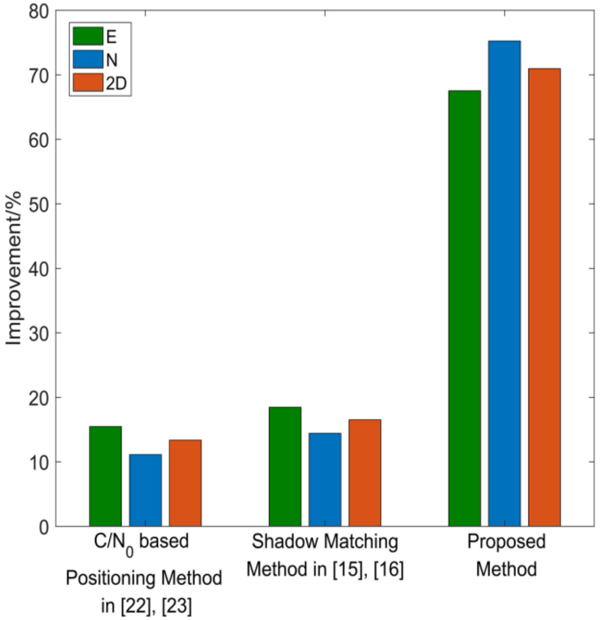

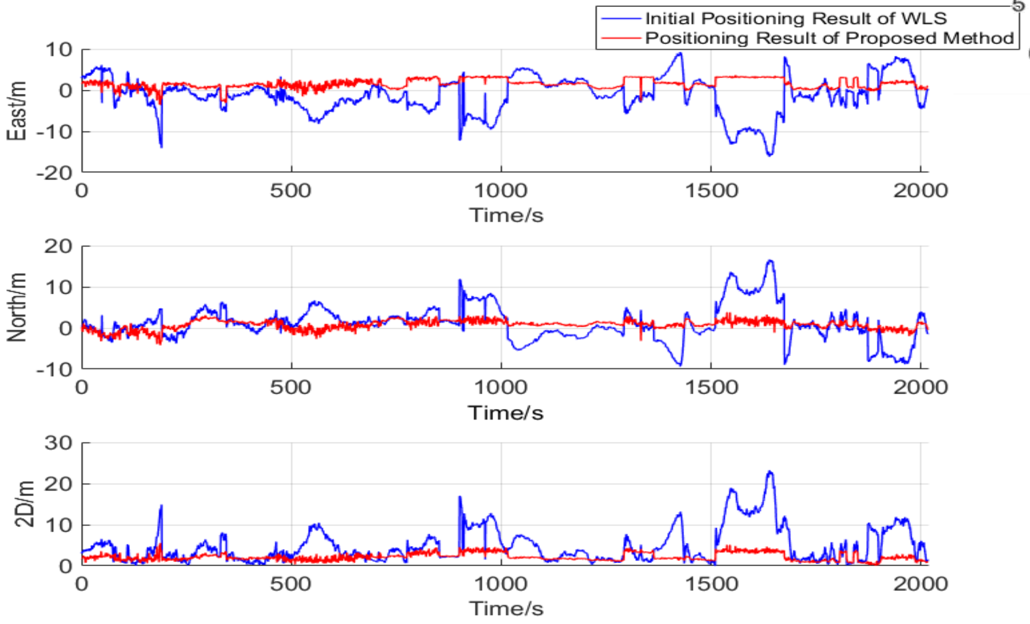

	Method	E	N	2D
RMSE/m	Conventional Positioning Method	4.68	4.48	6.47
	ML+3D City Model	1.90	1.35	2.34
	Improvement (%)	59.40	69.87	63.83
95th Percentile of Positioning Error/m	Conventional Positioning Method	9.78	8.95	13.23
	ML+3D City Model	3.25	2.47	3.84
	Improvement (%)	66.77	72.40	70.98

Dual-Polarization BDS/GNSS Antenna with Optimized Adaptive Neuro-Fuzzy Inference System to Improve Single Point Positioning Accuracy in Urban Canyons

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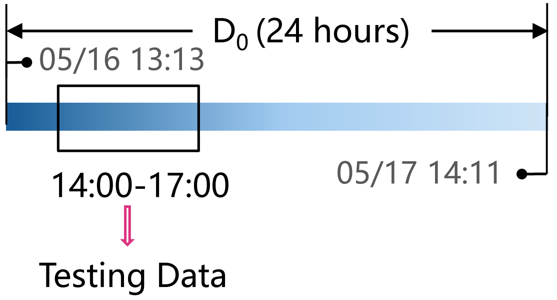
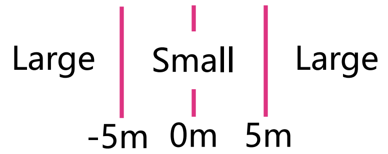
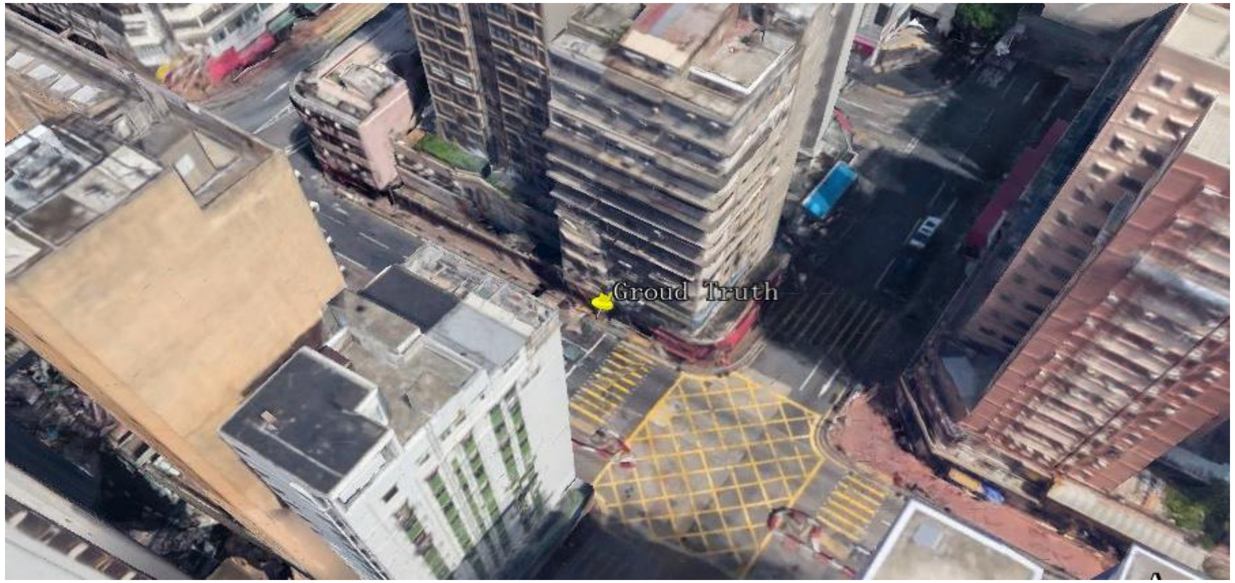
Dataset:

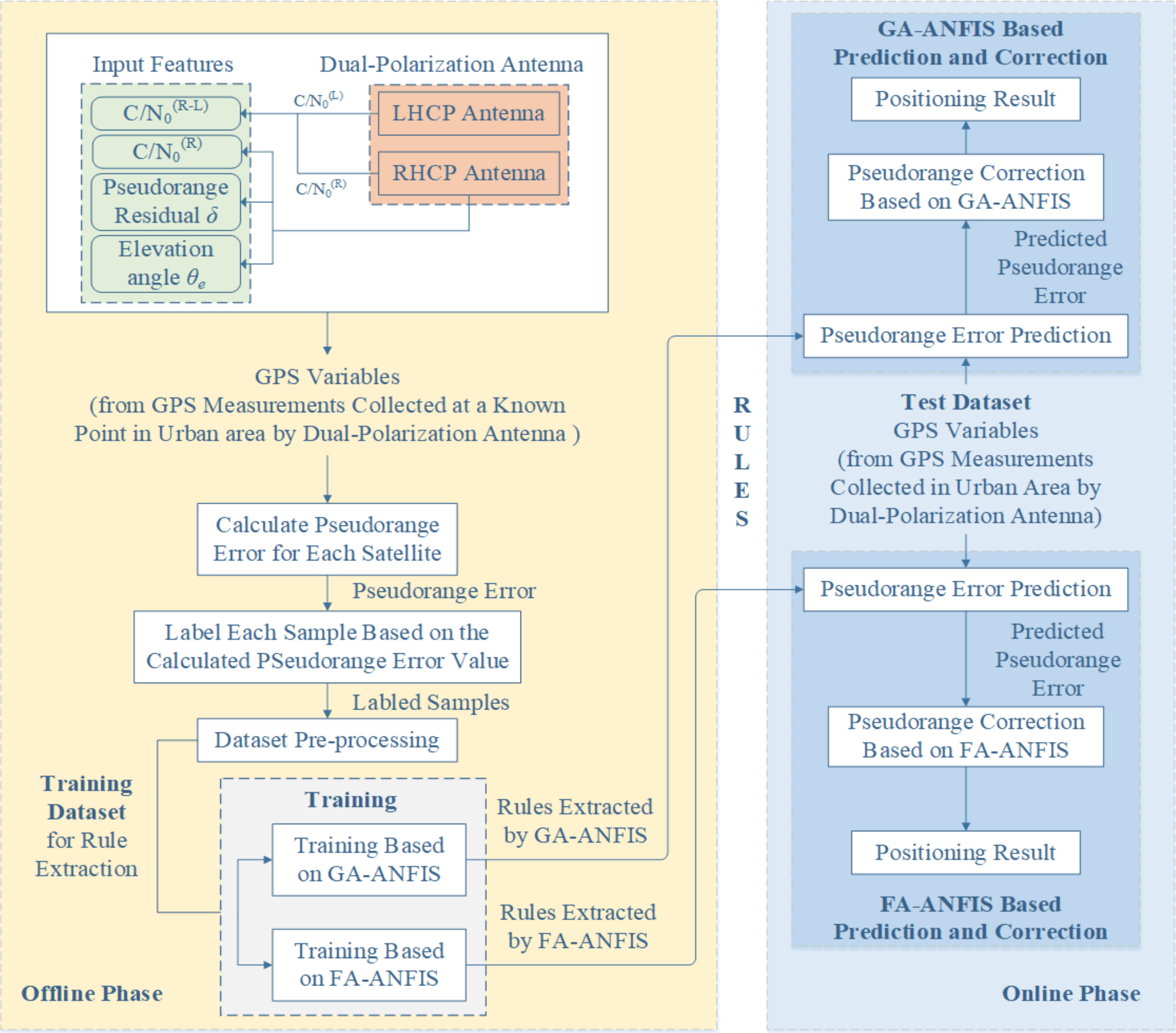


Dataset	Pseudorange Error		
	Large	Small	Total
testing	46,805	8,689	55,494
training	30,000	12,000	42,000
D_0	/	/	388,022

Pseudorange Error Threshold:







Pseudorange Errors

Pseudorange Observation Equation：

$$\tilde{\rho}_{(i)} = r_{(i)} - \left(\tau^R - \tau^S_{(i)}\right)c + D_{trop\,(i)} + D_{iono\,(i)} + D_{orb(i)} + \rho_{sac(i)} + \varepsilon_i$$

- $r_{(i)}$ → geometric rang
- τ^R → receiver clock error → calculated in position solution as the fourth unknown
- $\tau^S_{(i)}$ → satellite clock error → corrections in navigation message
- $D_{trop\,(i)}$ → tropospheric delay → Saastamoinen Model
- $D_{iono\,(i)}$ → Ionospheric delay → Klobuchar Model
- $D_{orb(i)}$ → broadcast ephemeris error → precise ephemeris
- $\rho_{sac(i)}$ → error caused by earth's rotation → Sagnac correction
- ε_i → Other error → Consists of the contribution to the range **error of the effects of Multipath/NLOS**, and observation noise

Given the limitations of the current mitigation methods, the error caused by **Multipath/NLOS** can reach tens of meters particularly in built environments, making it **dominant**.

Geometric Range: $r_{(i)} = \sqrt{\left(X^S_{(i)} - X^R\right)^2 + \left(Y^S_{(i)} - Y^R\right)^2 + \left(Z^S_{(i)} - Z^R\right)^2}$

Satellite Position $(X^S_{(i)}, Y^S_{(i)}, Z^S_{(i)})$ Receiver Position (X^R, Y^R, Z^R)

Pseudorange Error: $\Delta\rho_{(i)} = \rho^c_{(i)} - r_{(i)} = \left(\Delta\tau^R - \Delta\tau^S_{(i)}\right)c + \Delta D^K_{trop} + \Delta D^S_{iono} + \Delta D_{orb} + \varepsilon_i$

Correlation Analysis Between Input Features And Pseudorange Errors

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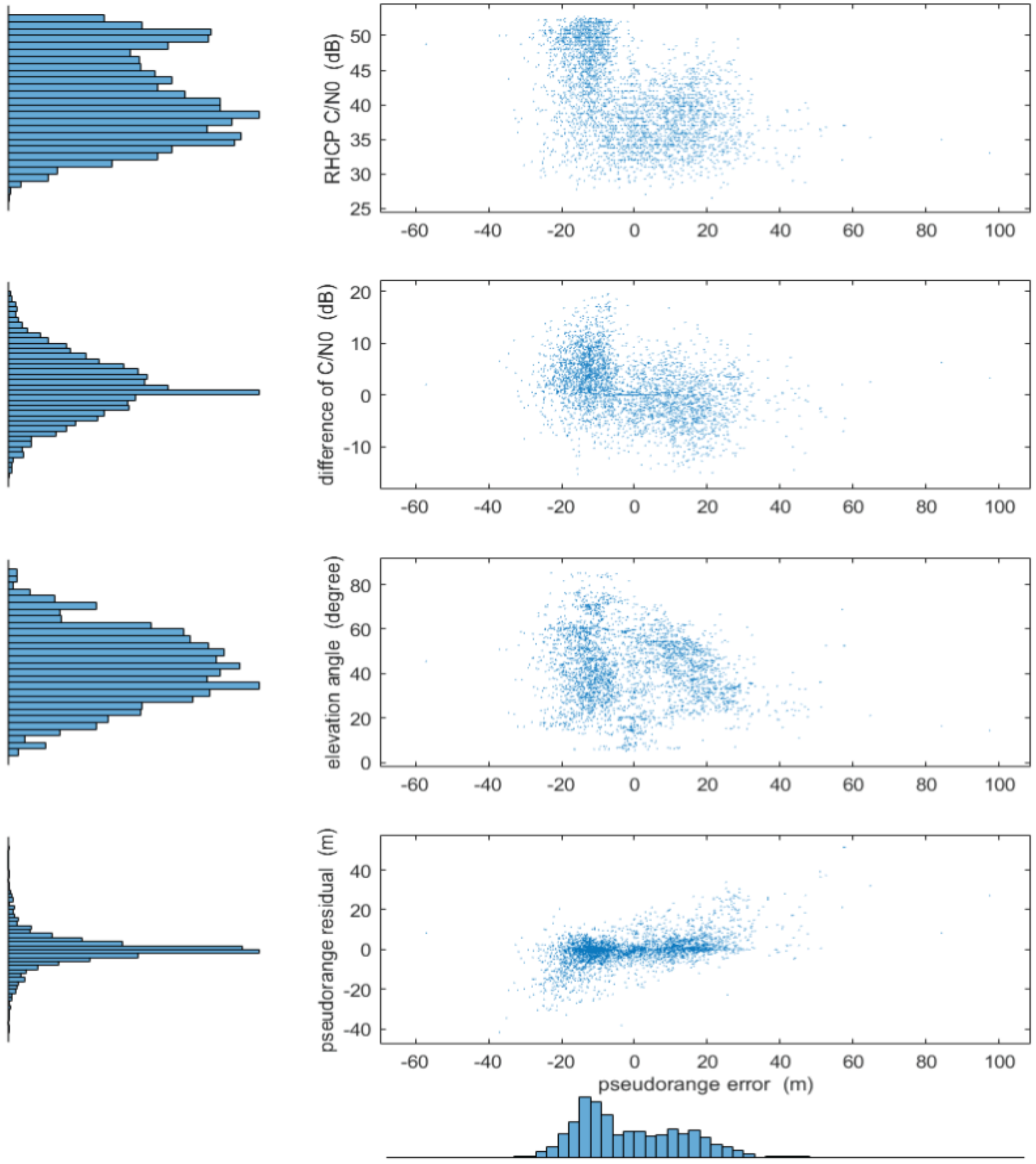


Input Features:

- RHCP signal strength ($C/N_0^{(R)}$)
- Signal strength difference obtained from RHCP and LHCP antenna ($C/N_0^{(R-L)}$)
- Elevation angle (θ_e)
- Pseudorange residual (δ)

Spearman correlation coefficient	Correlation
0.00-0.19	Very week
0.20-0.39	Week
0.40-0.59	Medium
0.60-0.79	Strong
0.80-1.00	Very Strong

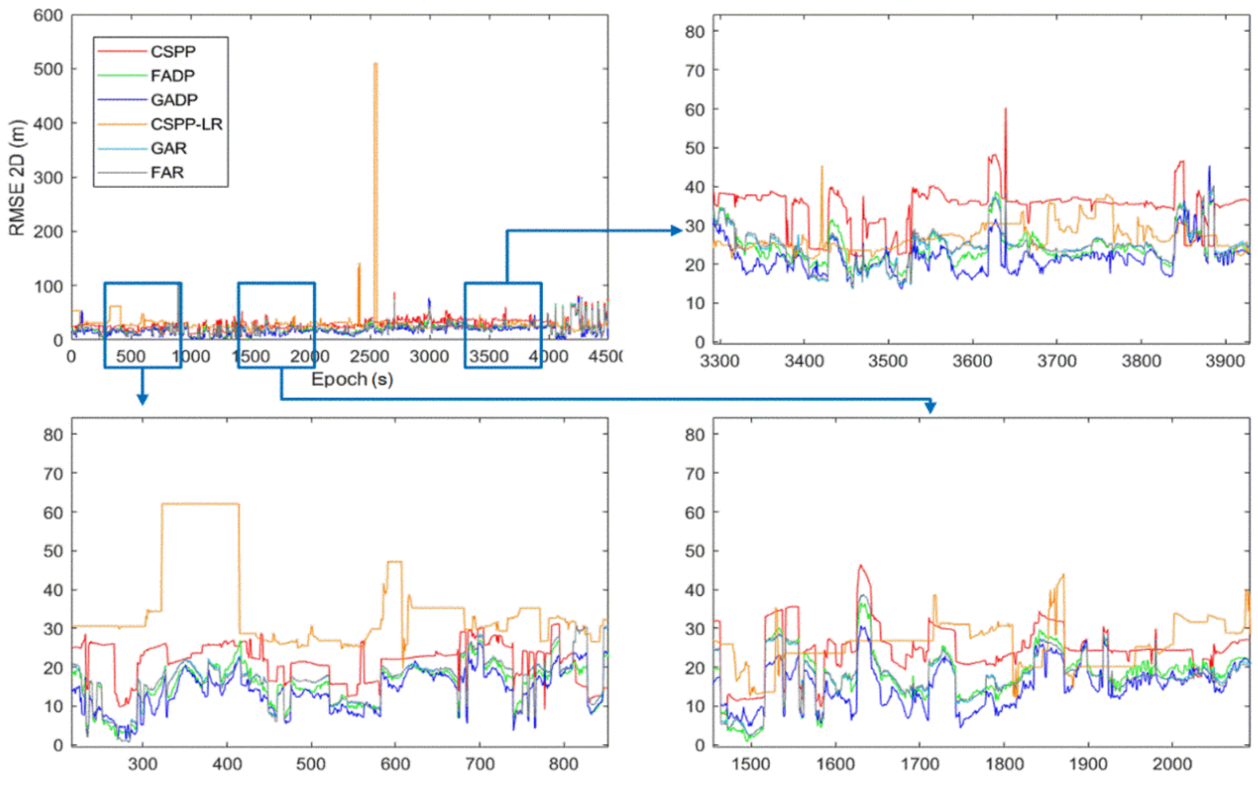
Input Feature	$C/N_0^{(R)}$	$C/N_0^{(R-L)}$	Elevation angle	Pseudorange residual
Spearman correlation coefficient	-0.4934	-0.4318	-0.1523	0.4107
Correlation	**Medium**	**Medium**	**Very week**	**Medium**

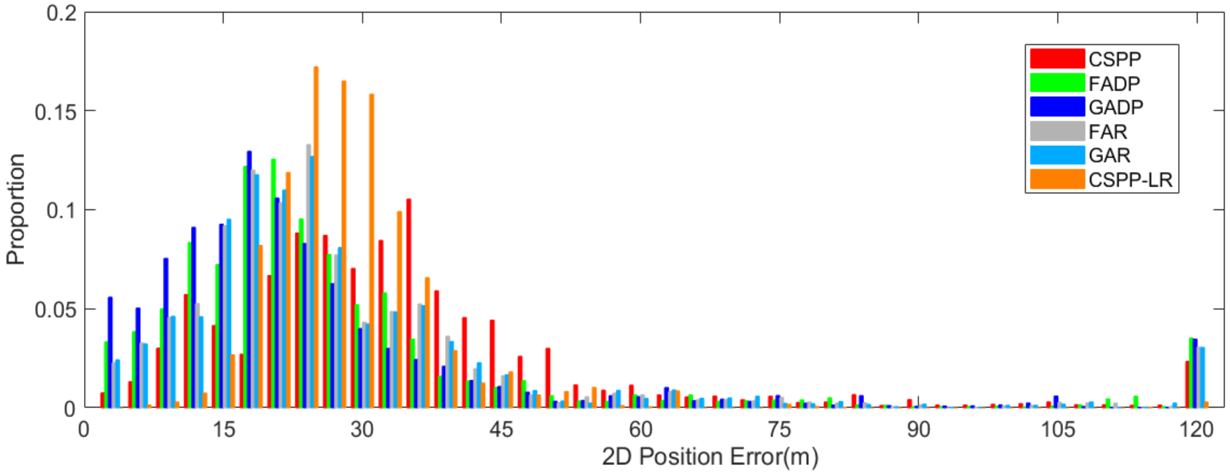
Several Algorithms for Comparison

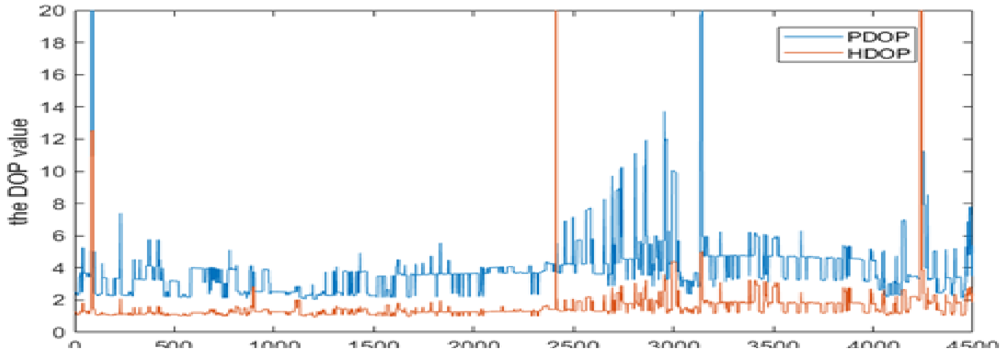
- **Conventional Single Point Positioning (CSPP) method**, i.e. positioning with outlier detection and exclusion, which uses Efficient Leave One Block Out (ELOBO) approach to identify outliers and exclude them from the positioning process.
- Conventional Single Point Positioning using the **LHCP-RHCP C/N_0 difference** and **satellite elevation angle** to select and weight the measurements. **(CSPP-LR)**
- **FA-ANFIS** using **RHCP** measurement data only. **(FAR)**
- **GA-ANFIS** using **RHCP** measurement data only. **(GAR)**
- Pseudorange errors predicted by **GA-ANFIS** and **FA-ANFIS** with **Dual Polarization antenna** (noted as **GADP** and **FADP**)

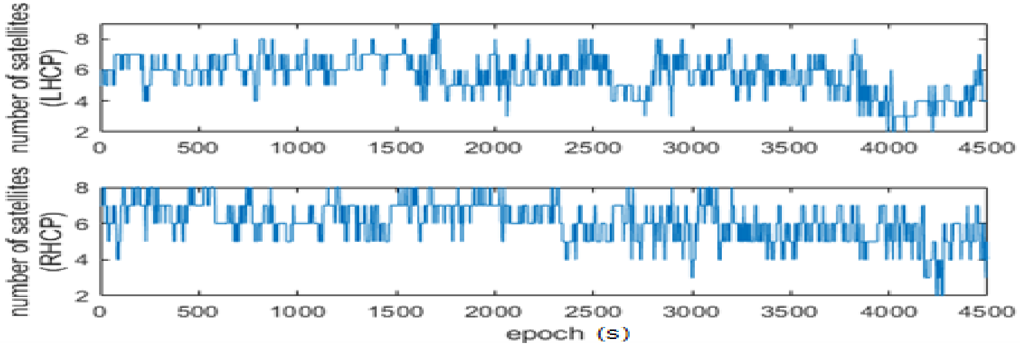
RMSE (m)	E	N	U	2D	3D
CSPP	33.46	28.57	112.14	44.00	120.46
CSPP-LR	27.31	31.54	143.49	41.72	149.44
FAR	29.86	21.61	95.21	36.86	102.10
GAR	29.09	21.90	98.52	36.42	105.03
FADP	**26.90**	**19.22**	**82.92**	**33.06**	**89.27**
GADP	**25.29**	**16.65**	**76.19**	**30.28**	**81.99**

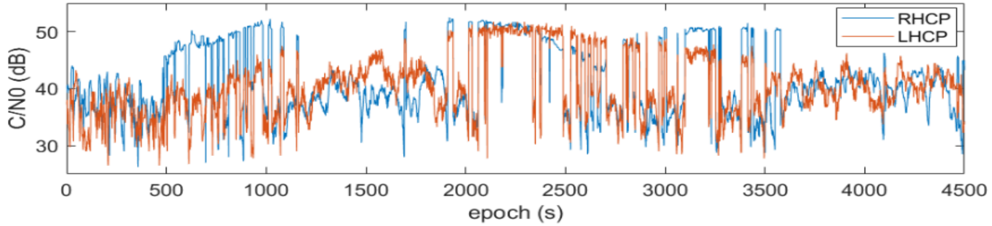
Case 1: Hongkong, deep urban environment

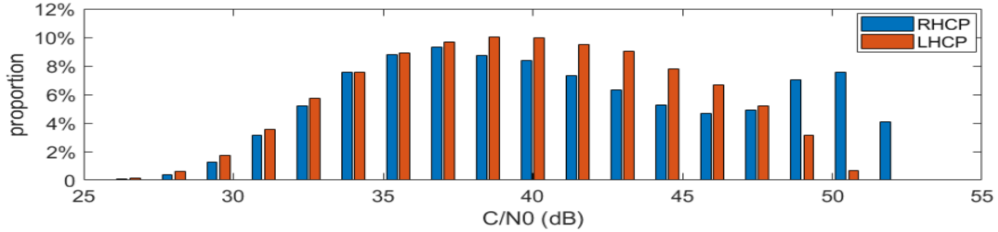

CSPP
FADP
GADP
CSPP-LR
GAR
FAR
RMSE 2D (m)
Epoch (s)


CSPP
FADP
GADP
FAR
GAR
CSPP-LR
Proportion
2D Position Error(m)

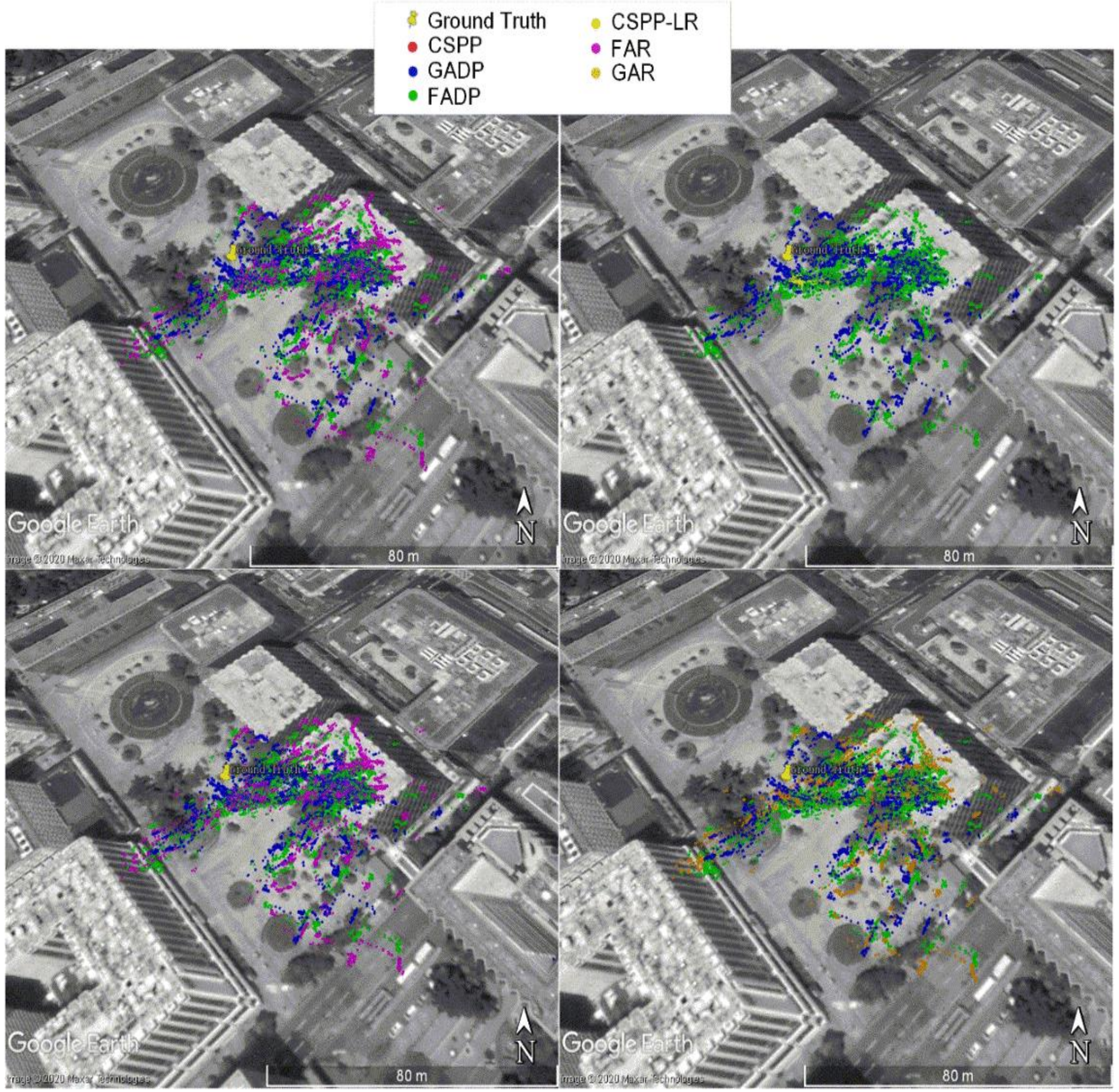

PDOP
HDOP
the DOP value


number of satellites (LHCP)
number of satellites (RHCP)
epoch (s)


RHCP
LHCP
C/N0 (dB)
epoch (s)

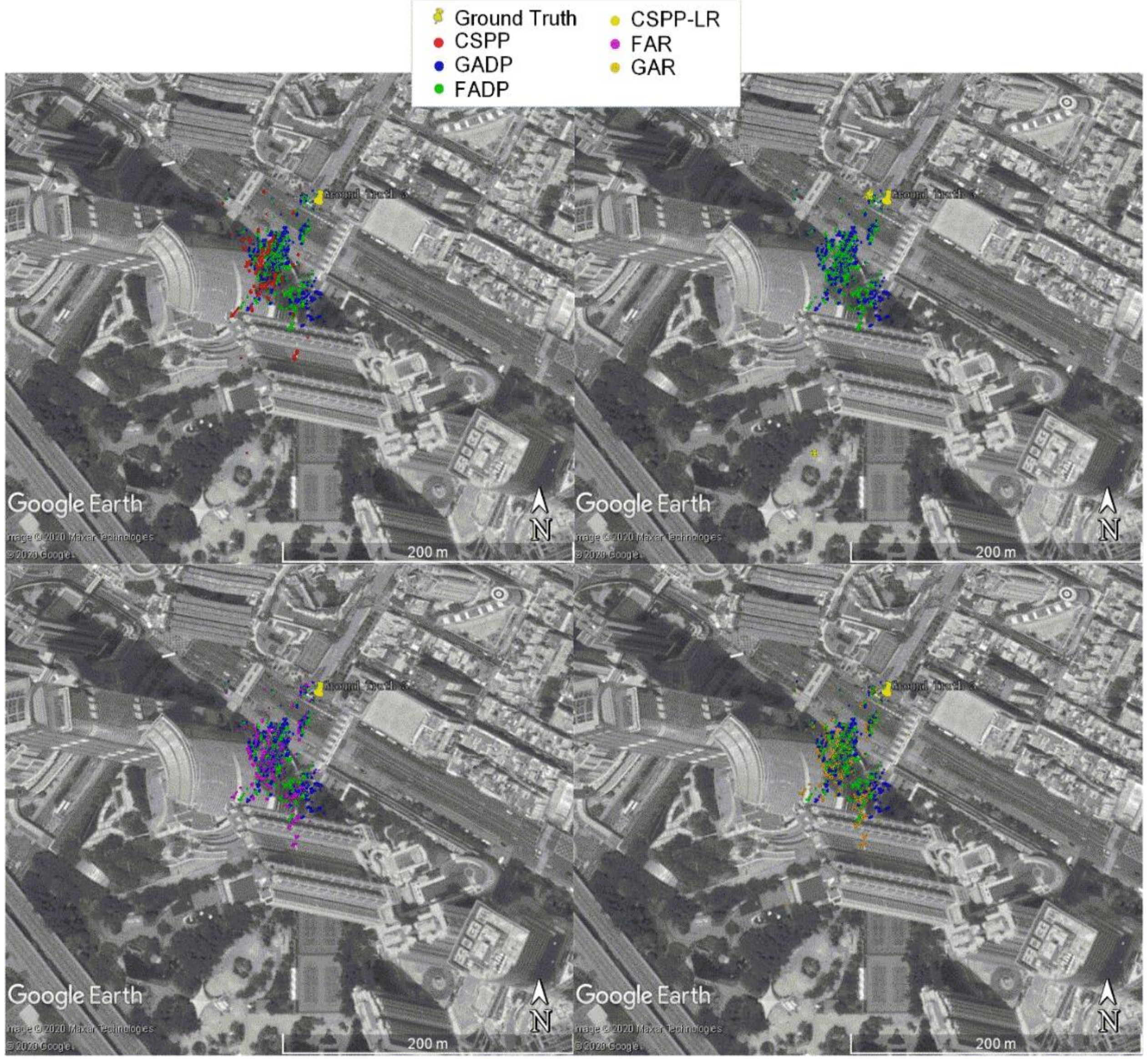

RHCP
LHCP
proportion
C/N0 (dB)

Case 2: Hongkong, mid urban environment

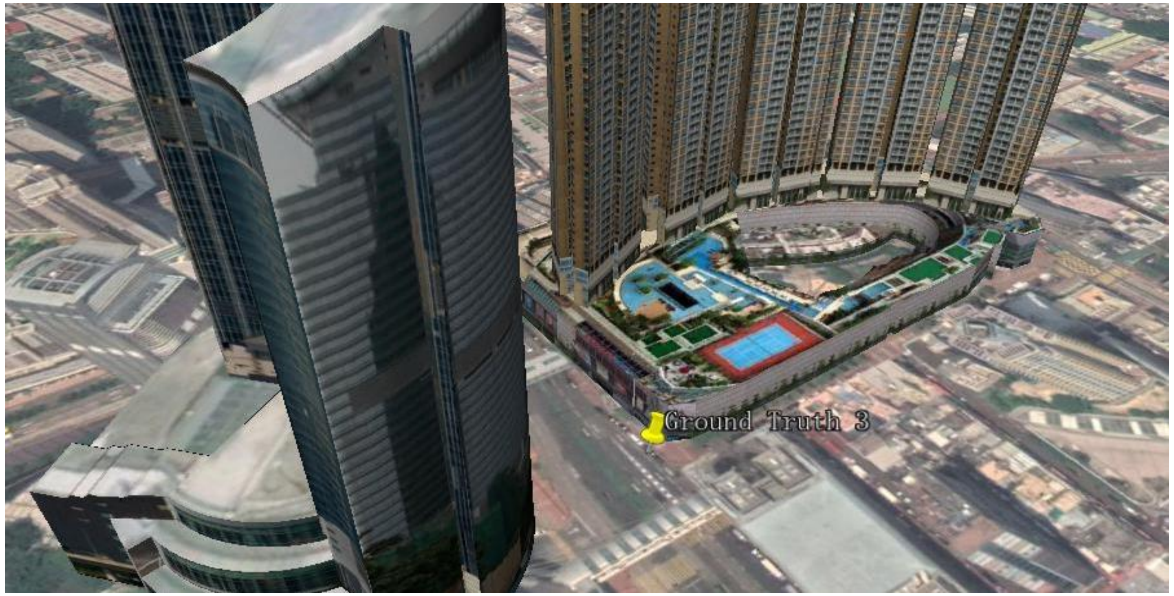


RMSE (m)	E	N	U	2D	3D
CSPP	40.92	17.90	79.01	44.67	90.76
CSPP-LR	27.57	23.92	24.12	36.50	43.75
FAR	38.30	16.21	59.38	41.59	72.50
GAR	36.64	15.89	59.86	39.94	71.96
FADP	**36.27**	**15.11**	**56.98**	**39.30**	**69.21**
GADP	**33.13**	**13.70**	**58.61**	**35.85**	**68.96**

Case 3: Hongkong, tall buildings on both sides

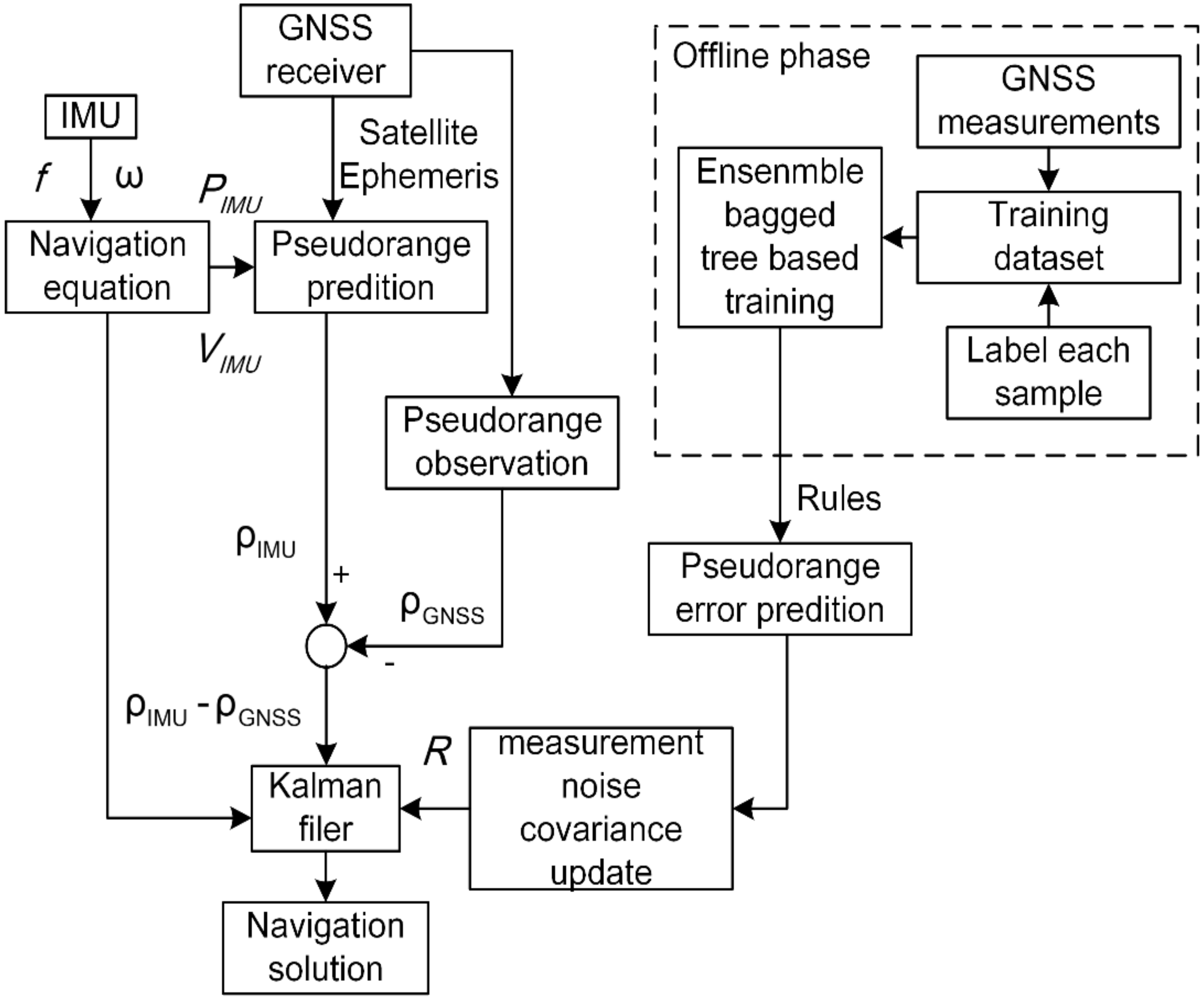


RMSE (m)	E	N	U	2D	3D
CSPP	36.45	55.27	40.52	66.21	77.62
CSPP-LR	20.51	60.92	25.84	64.28	69.28
FAR	34.87	53.06	37.02	63.49	73.49
GAR	34.66	53.43	37.36	63.69	73.84
FADP	**32.65**	**48.89**	**42.03**	**58.79**	**72.27**
GADP	**31.73**	**47.92**	**48.38**	**57.48**	**75.12**



- The proposed algorithm results in a **30%** improvement in Root Mean Square Error (RMSE) in the 2D (horizontal) component for static applications when the training and testing data are collected at the same location. This corresponds to **13 to 20%** when the testing data is from locations away from that of the training dataset

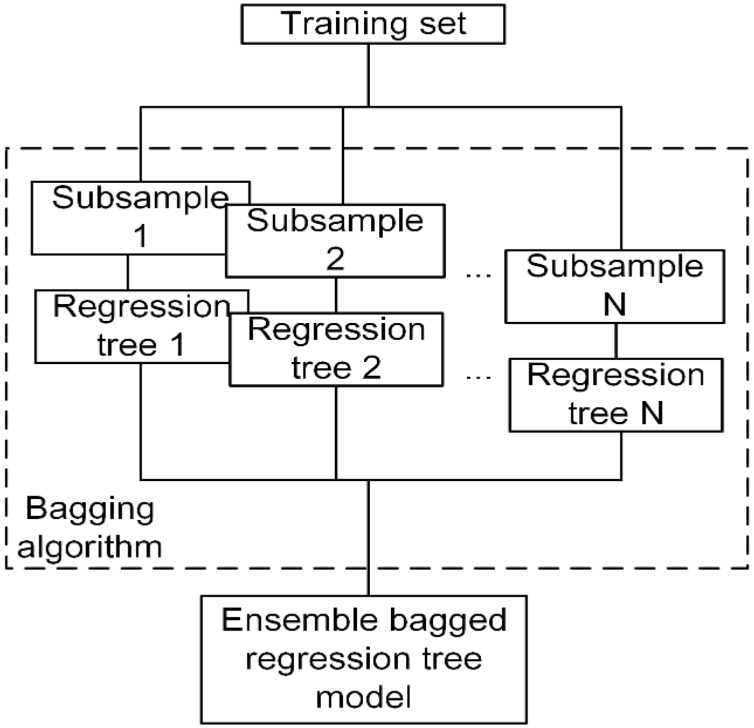
Pseudorange Error Prediction for Adaptive Tightly-Coupled BDS/GNSS/INS Navigation in Urban Areas



➢ In the traditional Kalman filter

The BDS/GNSS measurement noise is fixed **based on factors determined a priori**, **instead of reflecting the impact of the surrounding environment** on the received BDS/GNSS signal.

Degrading the **position accuracy** and **posteriori quality indicators**.



1) Construct the adaptive indicator

$$f(\cdot) = \left(\left|h_{bag}(\cdot)\right| + \eta\right)^2$$

$h_{bag}(\cdot)$: designed ensemble bagged tree model, $\eta = 0.1$

2) Adjust measurement noise covariance matrix

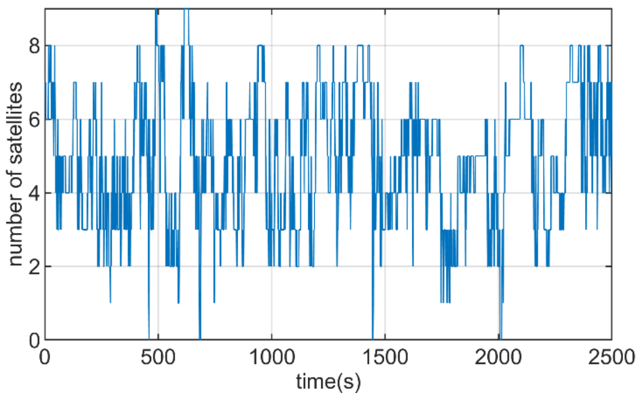
$$\left[R_{(m,m)}\right]_k = f([x_m]_k)$$

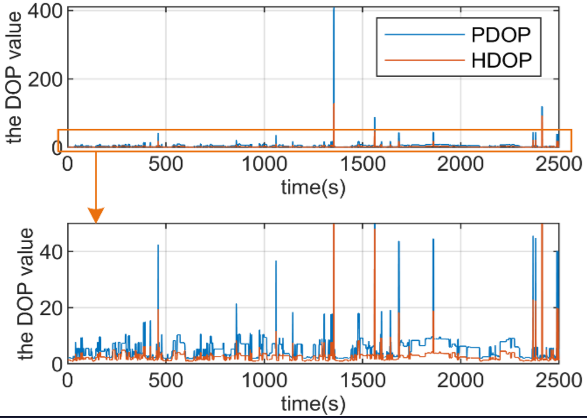
$x = (C/N_0, \theta, L, atLon)$

m means the serial number of the current satellite in the received satellite at the epoch k;

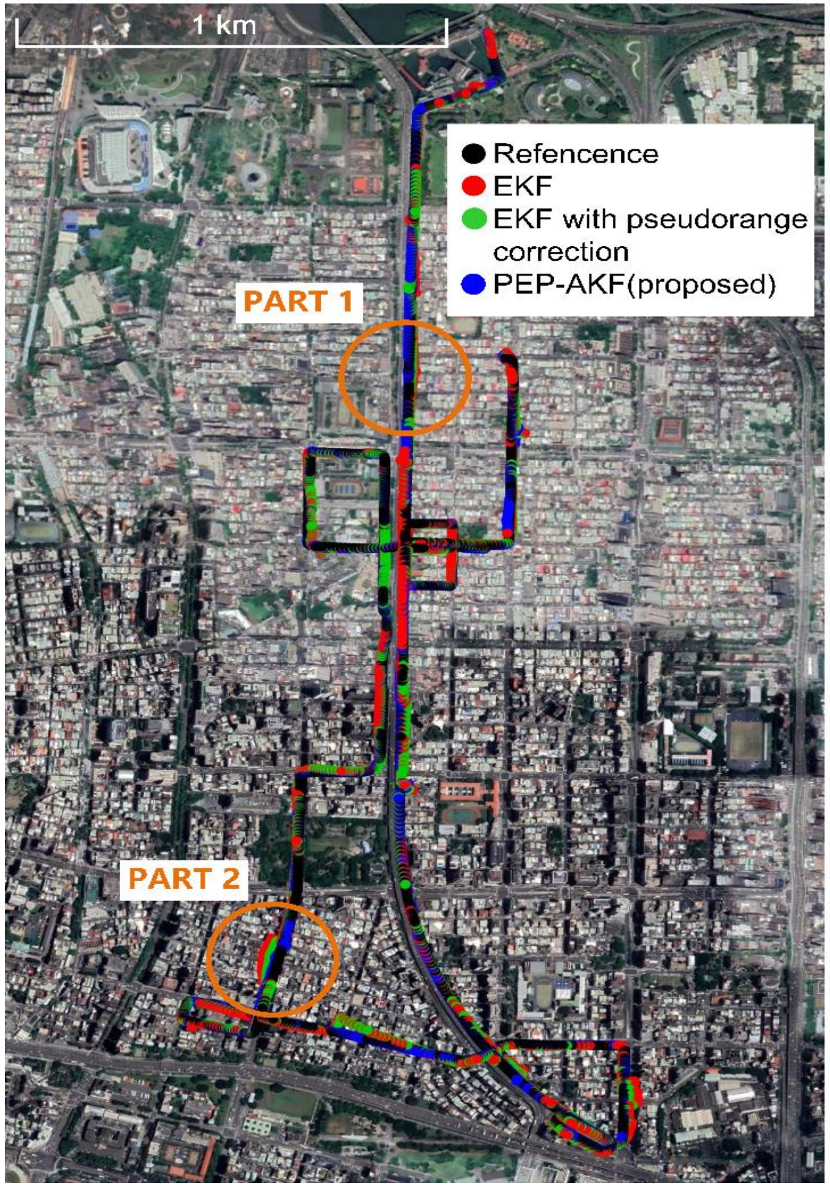
$R_{(m,m)}$ denotes the m row, m column of the measurement noise covariance matrix.

The **closer** the **adaptive indicator estimation** is to **R**, the **closer** the **filter outputs** are **to ideal results**.



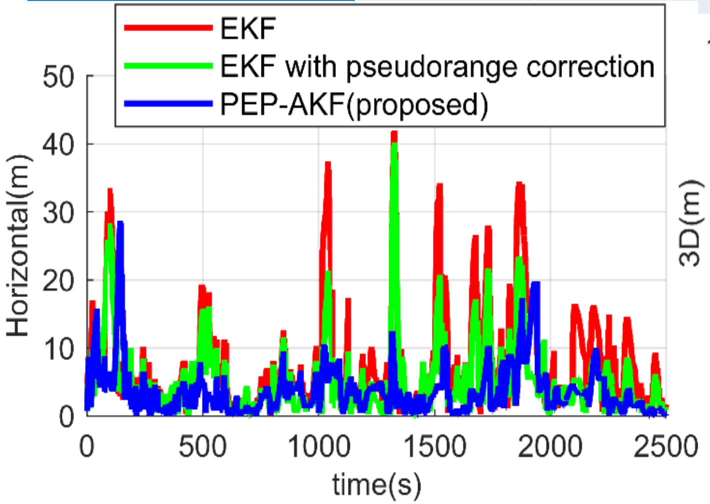


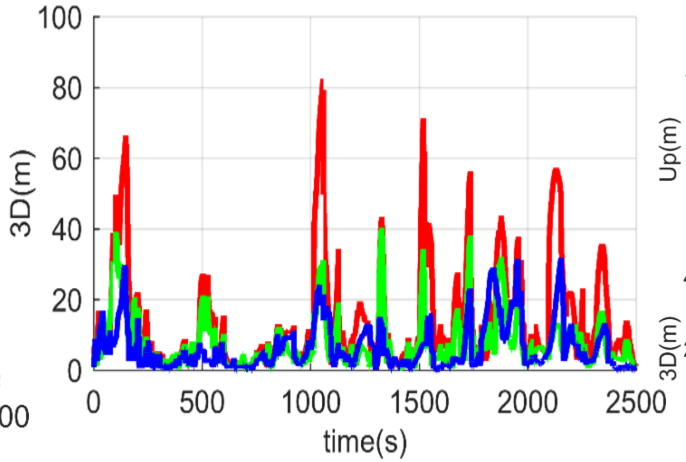
Algorithm	Algorithm Description	Color
EKF	Tightly integration of BDS/GNSS and INS with Extended Kalman filter	Red
EKF with pseudorange correction	Step 1: Using the trained ensemble bagged trees model to predict the pseudorange error and then correct pseudorange. Step 2: Using the corrected pseudorange to form the measurements vector Z in the EKF of the tightly fusion.	Green
PEP-AKF (proposed)	Step 1: Using the trained ensemble bagged trees model to predict the pseudorange error and then construct adaptive indicator. Step 2: Using adaptive indicator to adjust measurement noise covariance matrix in the KF of the tightly fusion.	Blue

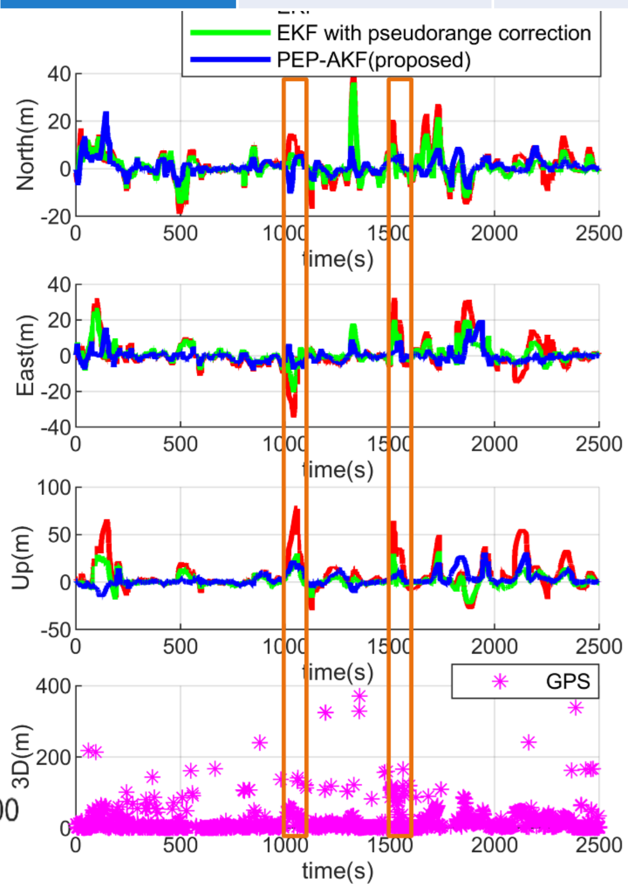


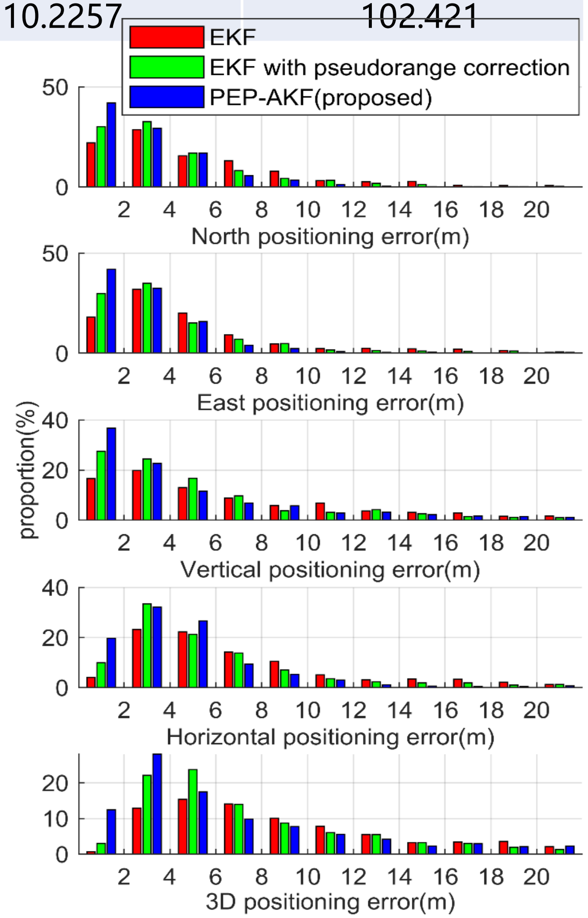
BDS/GNSS/IMU tightly fusion algorithms	RMSE/m				
	North	East	Up	Horizontal	3D
EKF	6.83	8.20	17.80	10.67	20.76
EKF with pseudorange correction	5.27	5.38	7.81	7.53	10.85
Improvement	22.75%	34.46%	56.12%	29.43%	47.72%
PEP-AKF (proposed method)	3.60	3.63	7.66	5.11	9.21
Improvement	47.26%	55.78%	56.98%	52.11%	55.64%

Time(s)	Satellite	Pseudorange error/m	Adaptive indicator
633	30	0.5538	0.296
647	30	0.9201	0.799
1015	30	18.9460	298.856
1071	30	10.2257	102.421

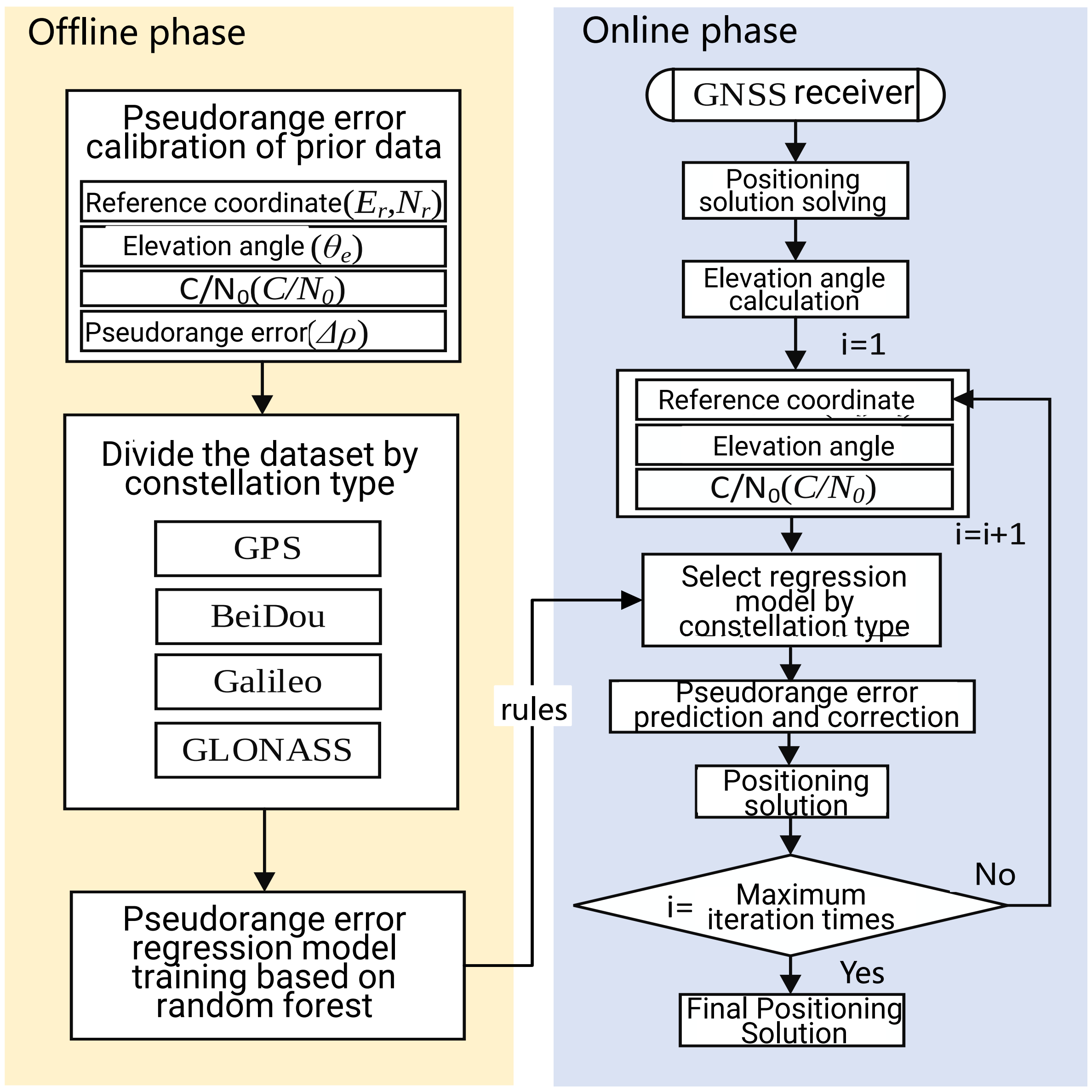


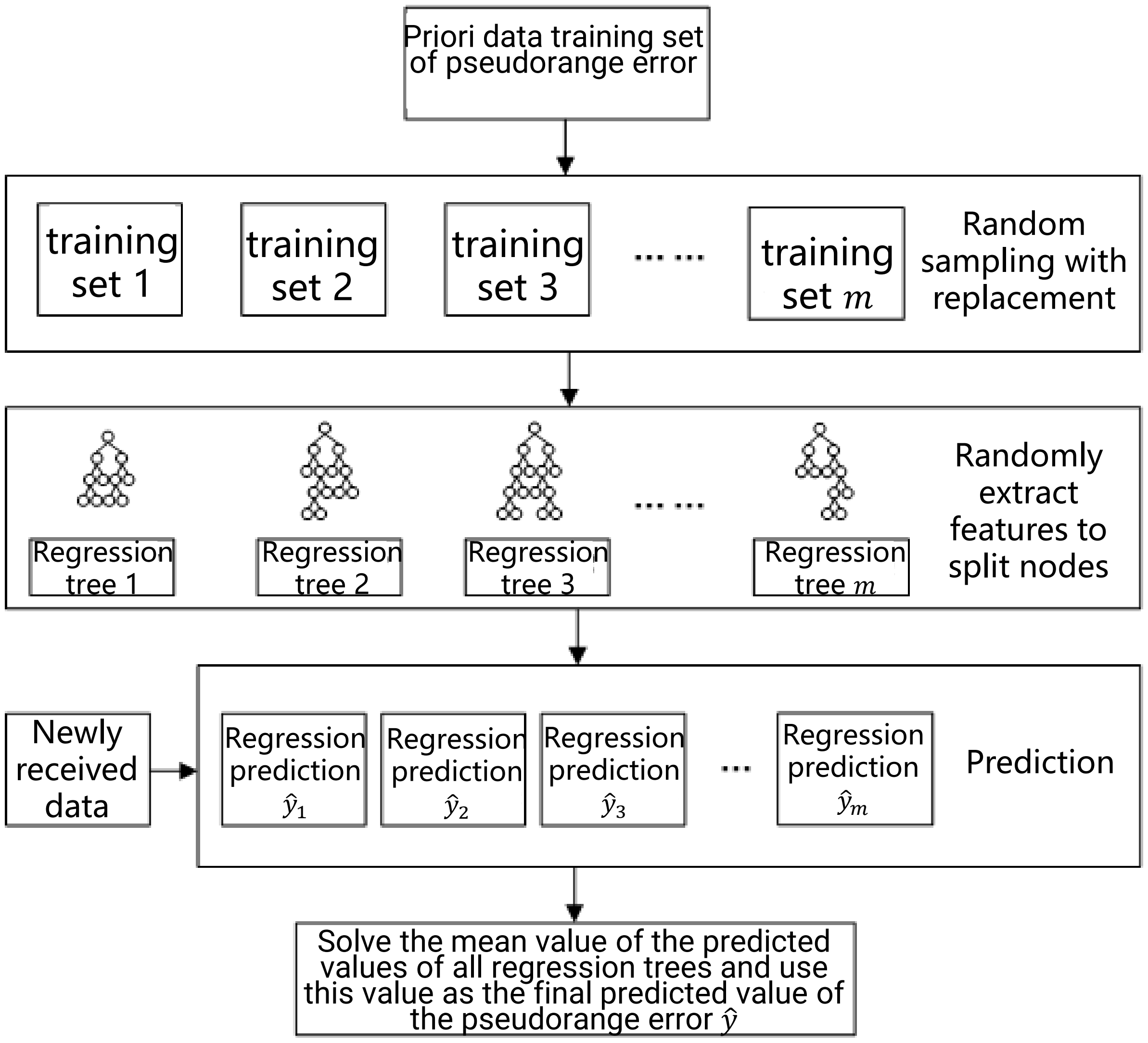






Pseudorange Correction for Vehicle Navigation in Urban Canyon Areas





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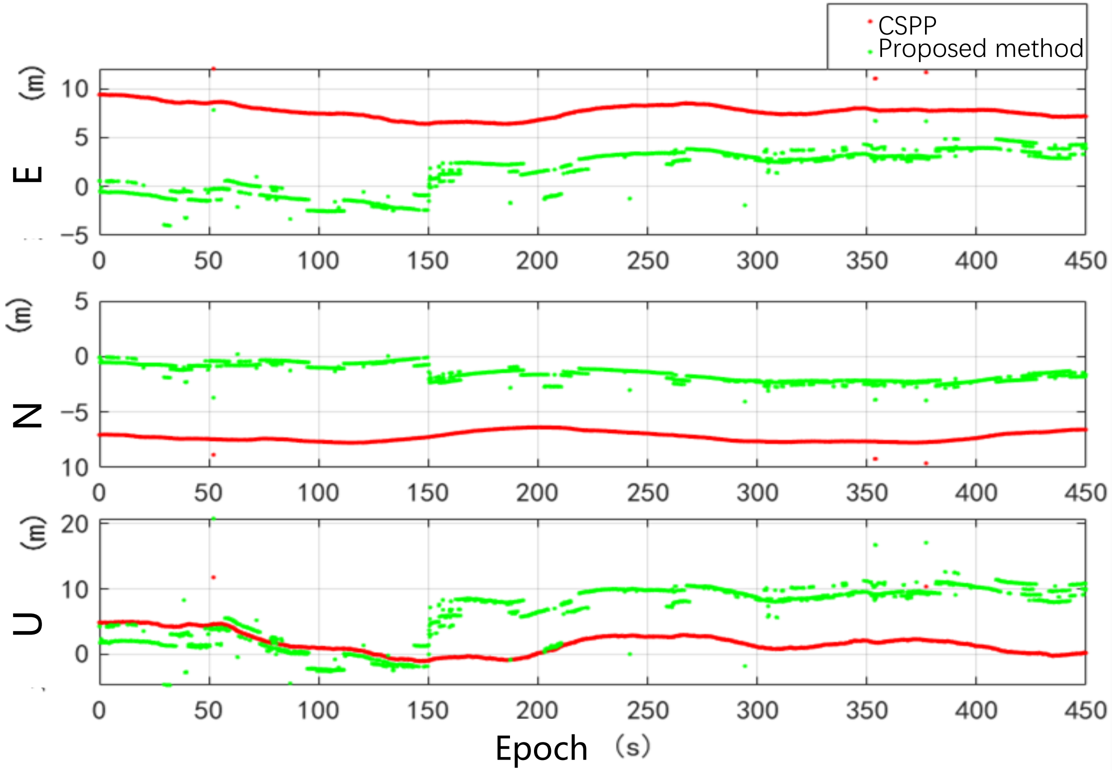
Static Test： Hongkong, mid urban environment

10Hz, 15 mins **BDS/GNSS**
Receiver： NovAtel OEM6; Antenna： ZYACF-L004



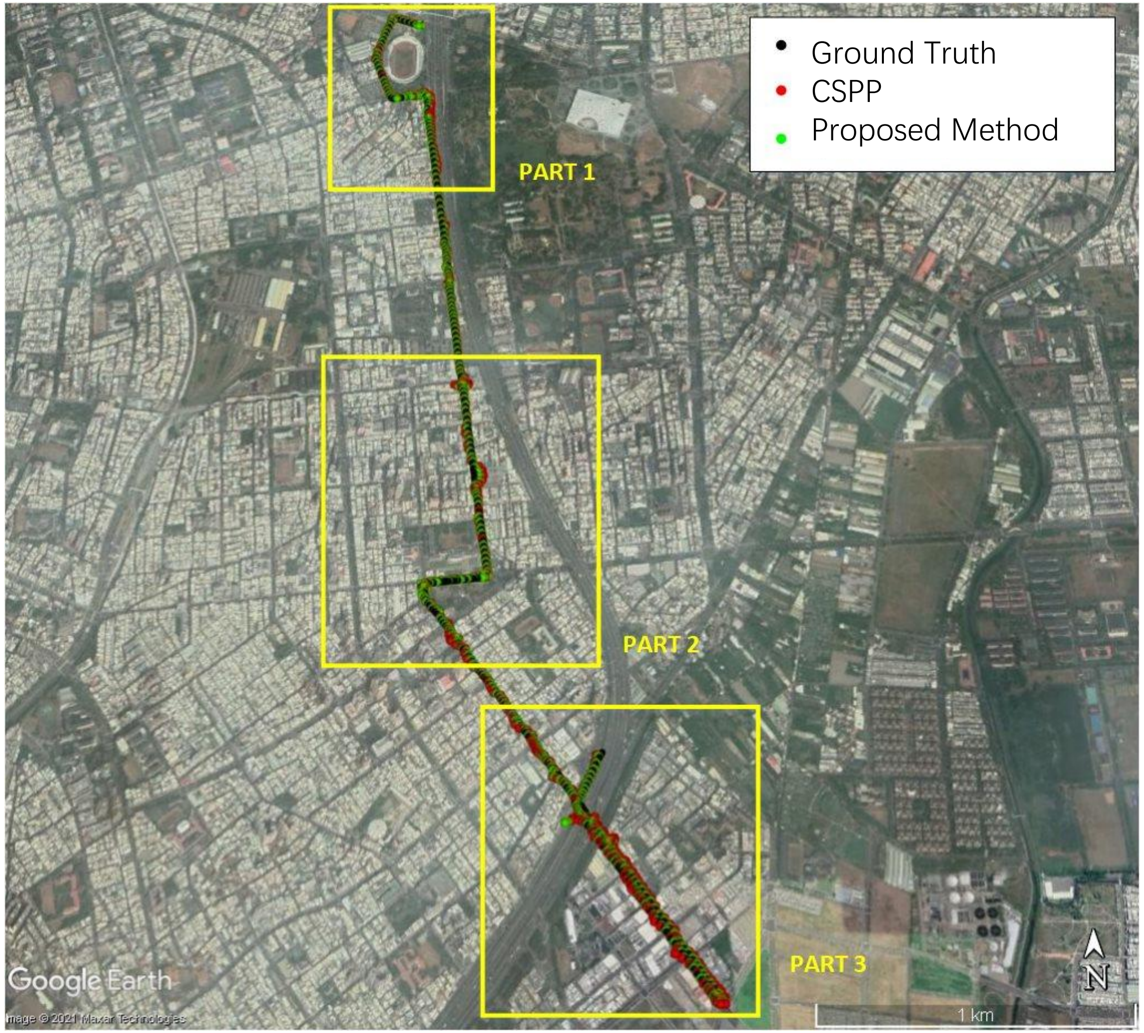
RMSE (m)	1D			2D	3D
	E	N	U	horizontal	
CSPP	7.7334	7.2615	2.3196	10.6083	10.8589
Proposed method	2.6775	1.6737	7.5285	3.1576	8.1639
improvement	65.38%	76.95%	-224.56%	**70.23%**	**24.82%**

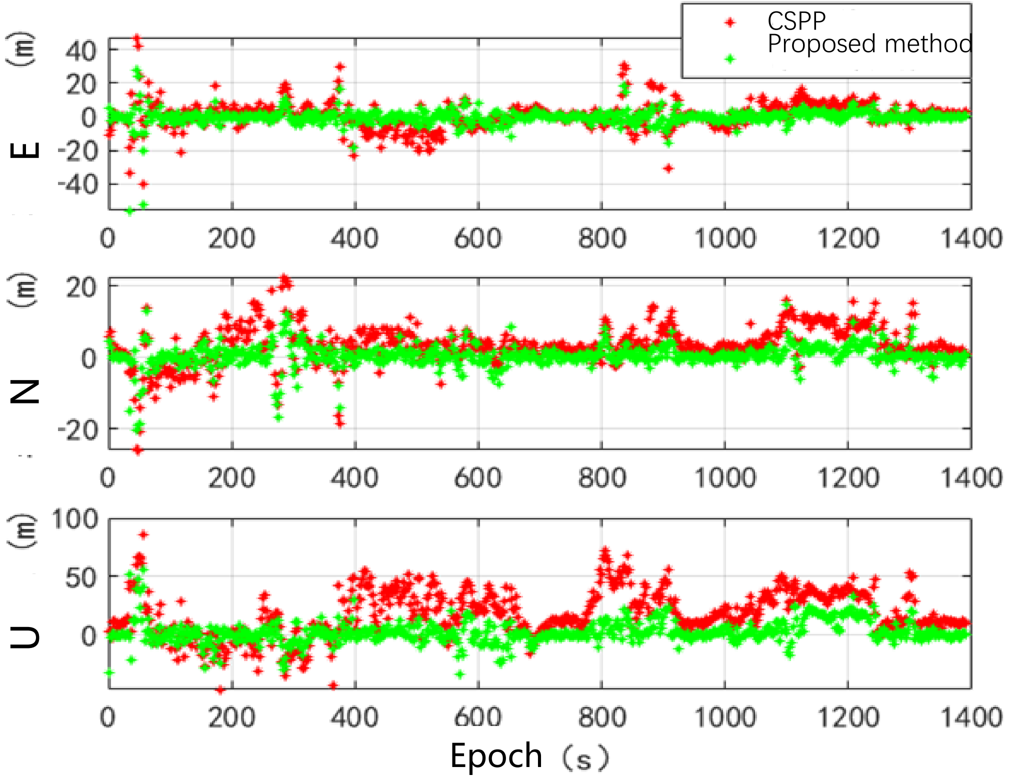
Road Test： deep urban environment

Reference： Receiver: NovAtel SPAN®-LCI; Antenna: NovAtel GPS-GGG-703-HV

Testing Data： Receiver: Allystar EVK-2024 ; Antenna: Allystar AGR 6301

BDS/GNSS,10 Hz, 20 mins, Average speed: 26 km/h **Crowdsourced Data**





RMSE (m)	1D			2D	3D
	E	N	U	horizontal	
CSPP	7.5293	6.3063	26.8642	9.8214	28.6032
Proposed method	4.6455	3.2010	9.8762	5.6415	11.3739
improvement	38.30%	49.24%	63.24%	42.56%	60.24%

IMU-Aided Multiple BDS/GNSS Fault Detection and Exclusion Algorithm for Integrated Navigation in Urban Environments

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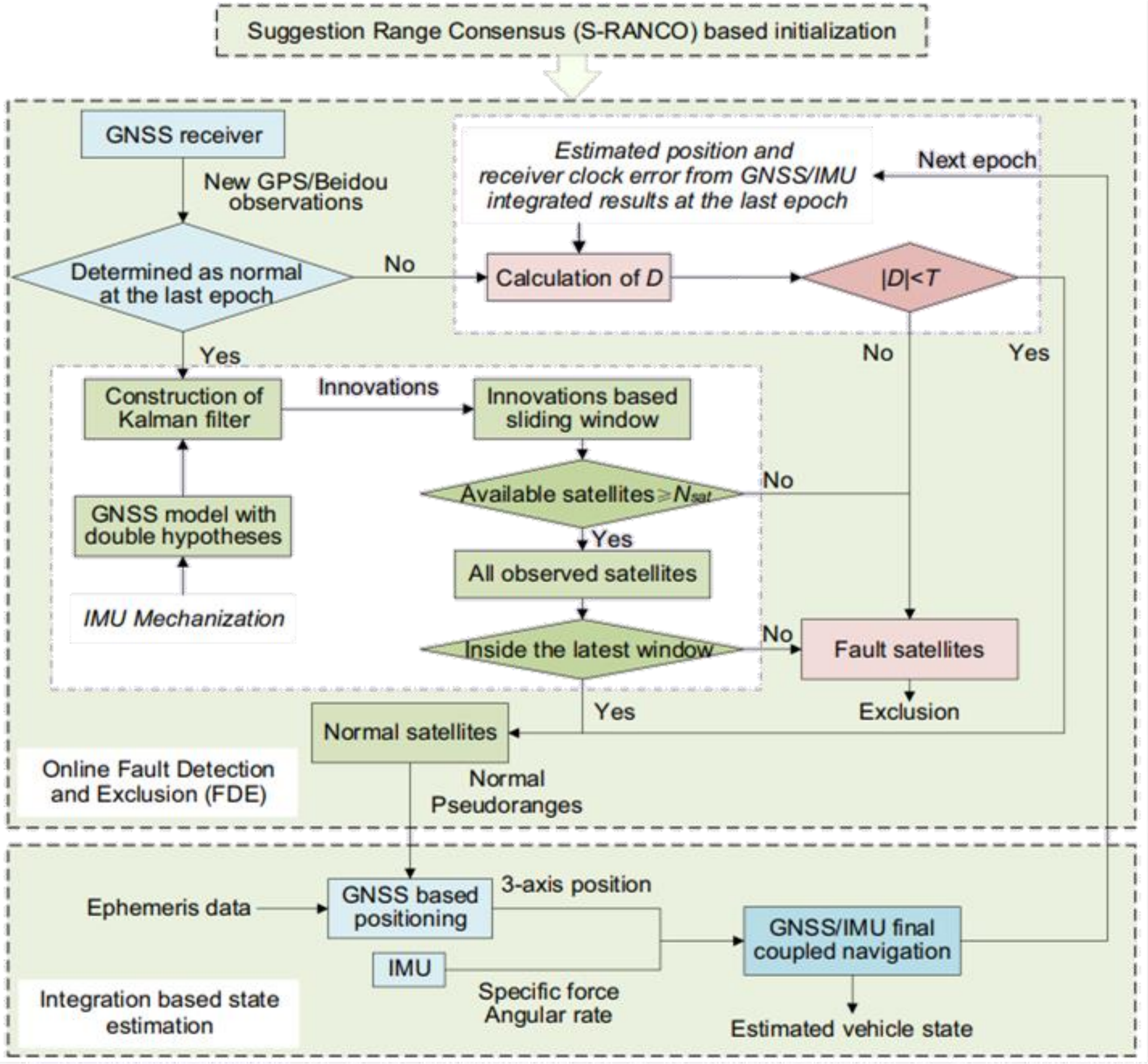
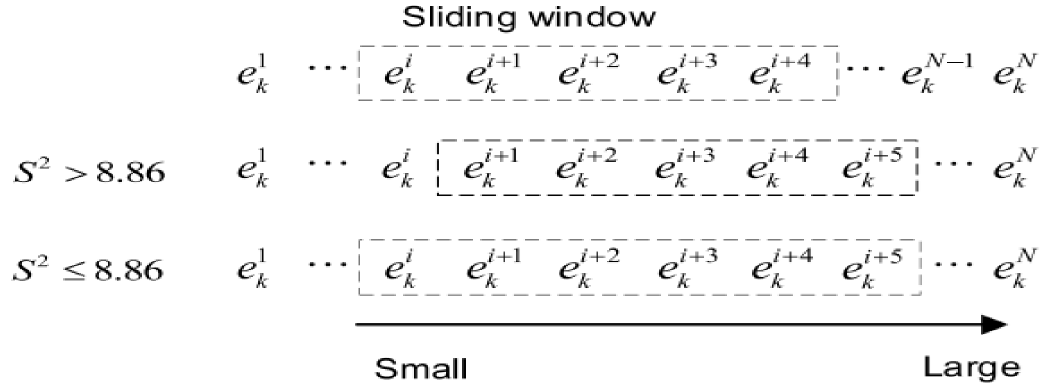
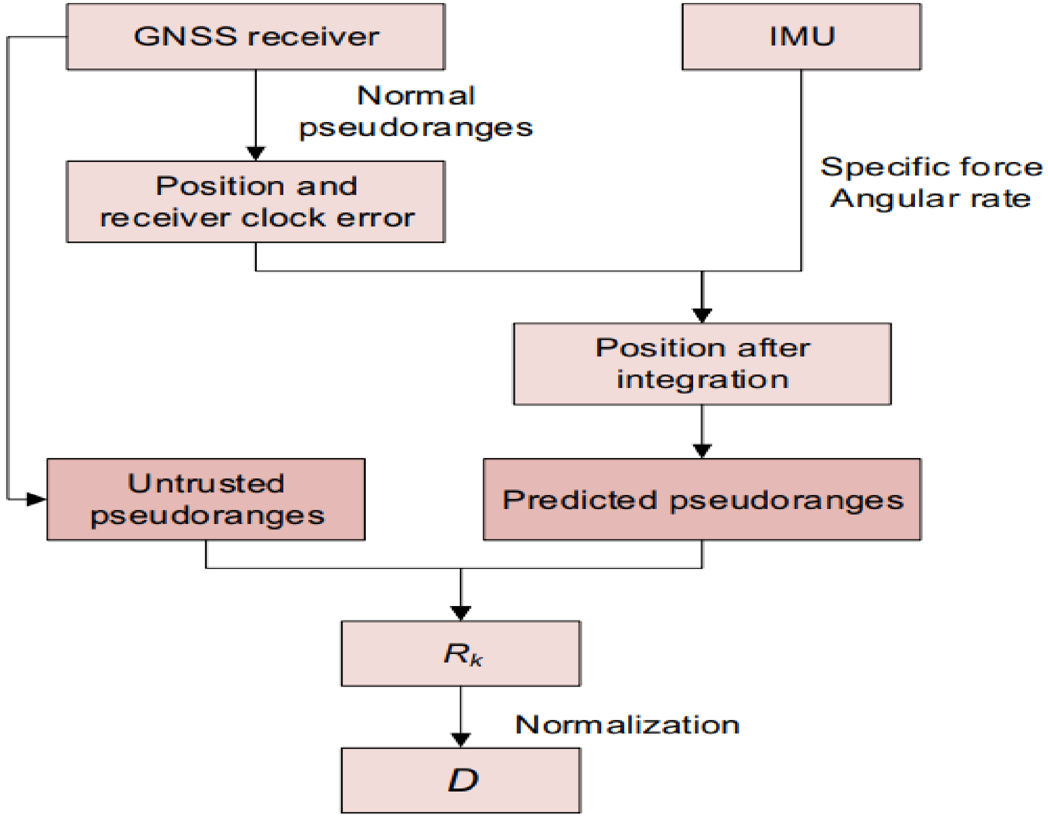
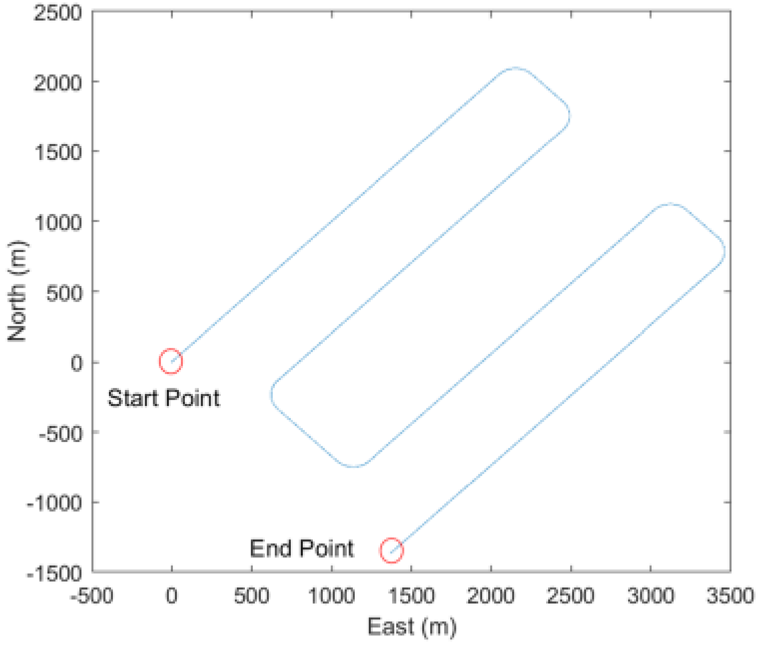


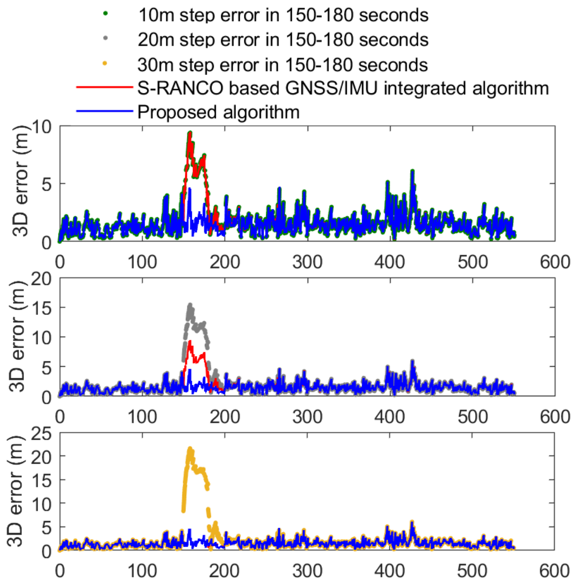


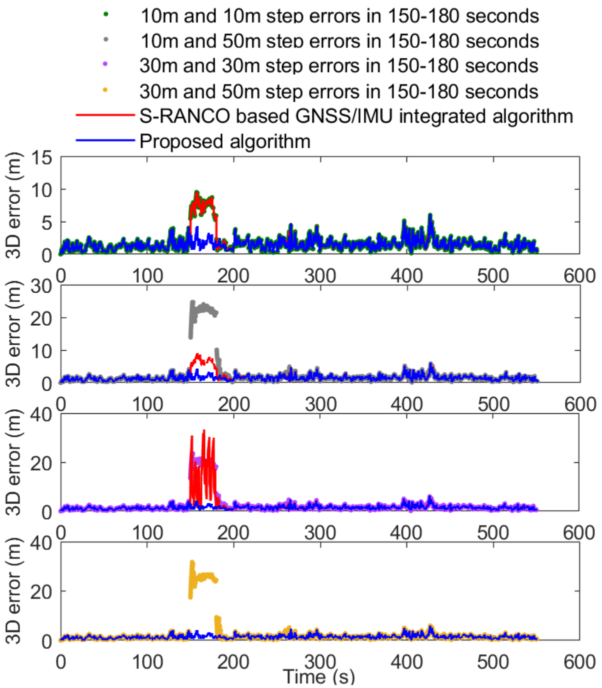


Simulation



Case	Number of fault satellites	Time interval of faults	Error source
1	1	30 s	10 m, 20 m and 30 m step errors added to the pseudorange of one satellite
2	2	30 s	10 m, 30 m and 50 m step errors added to the pseudoranges of two satellites





Step error	Traditional GNSS/IMU integration	S-RANCO based GNSS/IMU integration		Proposed algorithm	
	Positioning accuracy	Correct detection rate	Positioning accuracy	Correct detection rate	Positioning accuracy
10 m	6.41 m	0%	6.41 m	100%	1.91 m
20 m	11.71 m	53.3%	7.63 m	100%	1.91 m
30 m	17.06 m	100%	1.91 m	100%	1.91 m

Step error of PRN 2	Step error of PRN 12	Traditional GNSS/IMU integration	S-RANCO based GNSS/IMU integration		Proposed algorithm	
		Positioning accuracy	Correct detection rate	Positioning accuracy	Correct detection rate	Positioning accuracy
10 m	10 m	7.40	0%	7.40 m	100%	1.95 m
10 m	50 m	22.11	0%	22.11 m	100%	1.95 m
30 m	30 m	19.91	40%	17.12 m	100%	1.95 m
30 m	50 m	25.61	100%	1.95 m	100%	1.95 m

Test Case 1: mid urban environment

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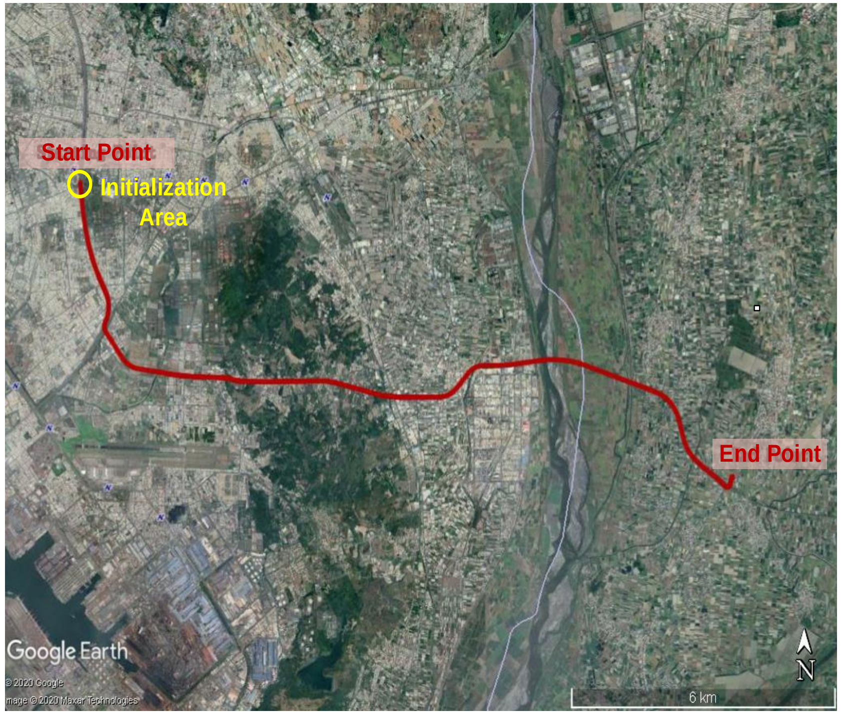
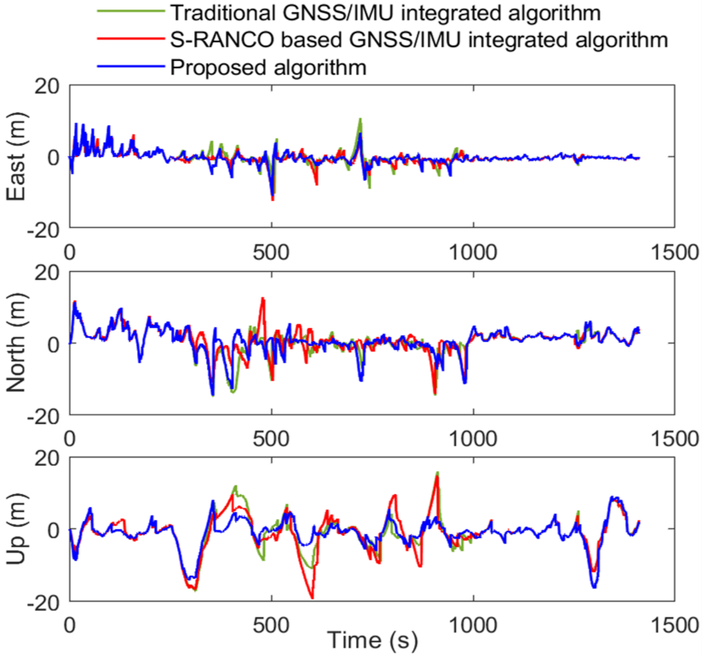
BDS/GNSS, Novatel PwrPak7, 1 Hz
IMU, Bosch BMI055, 50 Hz





Methods	RMSE	Without FDE	S-RANCO based GNSS/IMU integrated algorithm	Proposed algorithm
Velocity (m/s)	East	0.37	0.37	0.35
	North	0.36	0.35	0.34
	Up	0.28	0.29	0.27
	3D	0.58	0.59	0.56
Attitude (degree)	Roll	0.483	0.493	0.452
	Pitch	0.392	0.409	0.604
	Yaw	2.046	2.060	2.043

Methods	Without FDE	S-RANCO based GNSS/IMU integrated algorithm		Proposed algorithm	
Position (m)	RMSE	RMSE	Improvement	RMSE	Improvement
East	1.81	1.69	6.6%	1.70	6.1%
North	3.59	3.35	6.7%	3.34	7.0%
Up	4.88	5.19	-6.4%	3.88	20.5%
Horizontal	4.02	3.75	6.7%	3.75	6.7%
3D	6.32	6.40	-1.3%	5.39	14.7%

Test Case 2: deep urban environment

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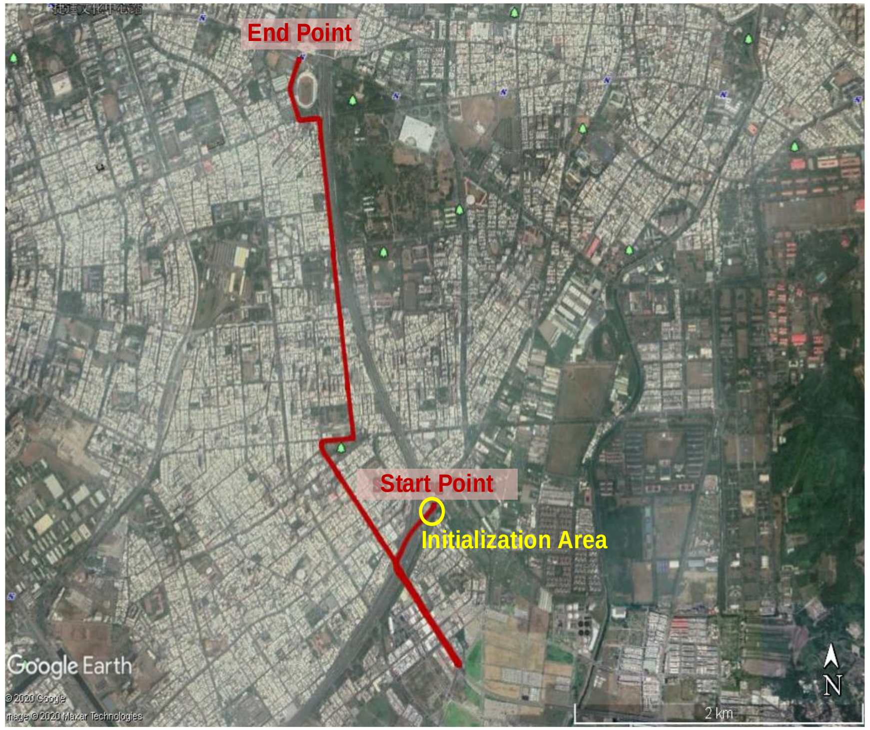
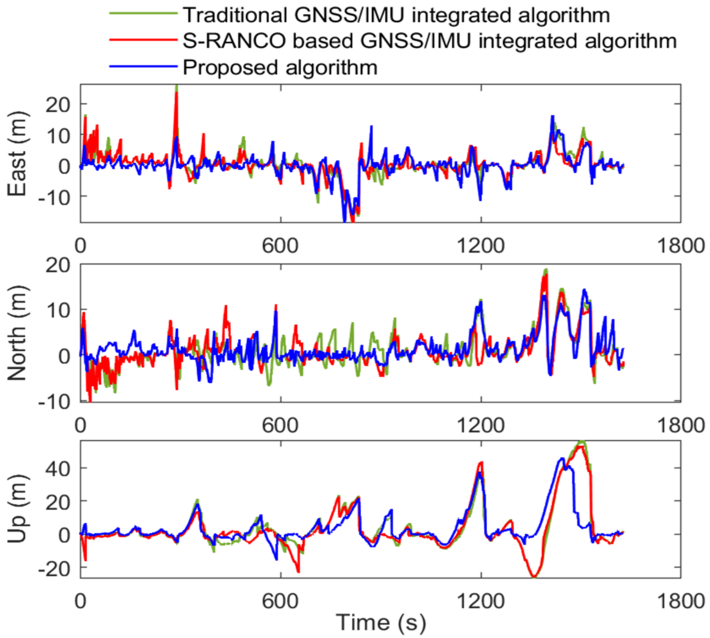
BDS/GNSS, Novatel PwrPak7, 1 Hz
IMU, Bosch BMI055, 50 Hz





Methods	RMSE	Without FDE	S-RANCO based GNSS/IMU integrated algorithm	Proposed algorithm
Velocity (m/s)	East	0.51	0.48	0.51
	North	0.49	0.48	0.49
	Up	0.42	0.40	0.40
	3D	0.82	0.79	0.81
Attitude (degree)	Roll	0.734	0.756	0.766
	Pitch	0.233	0.217	0.228
	Yaw	8.477	9.045	8.949

Methods	Without FDE	S-RANCO based GNSS/IMU integrated algorithm		Proposed algorithm	
Position (m)	RMSE	RMSE	Improvement	RMSE	Improvement
East	4.35	4.25	2.3%	3.73	14.3%
North	4.07	5.47	-34.4%	3.86	5.2%
Up	14.64	12.08	17.5%	10.98	25.0%
Horizontal	5.96	6.93	-16.3%	5.37	9.9%
3D	15.81	13.93	11.9%	12.22	22.7%

Conclusions

- ✓ Improving the BDS/GNSS data quality in urban areas can be benefit for many ITS applications.
- ✓ The proposed **machine learning based BDS/GNSS quality control methods can** effectively improve positioning accuracy.
- ✓ The proposed pseudorange error correction based methods can achieved a **70%** positioning accuracy improvement in static mode and a **60%** improvement in dynamic mode.
- ✓ The IMU-aided multiple BDS/GNSS fault detection and exclusion algorithm can provide an positioning accuracy improvement of **15-23 in urban areas**.

Future Works

- **Adaptive multi-sensor fusion strategy based on BDS/GNSS quality control will be carried to support more ITS applications**