3D Mapping Aided GNSS-Base Cooperative Positioning Using Factor Graph Optimization

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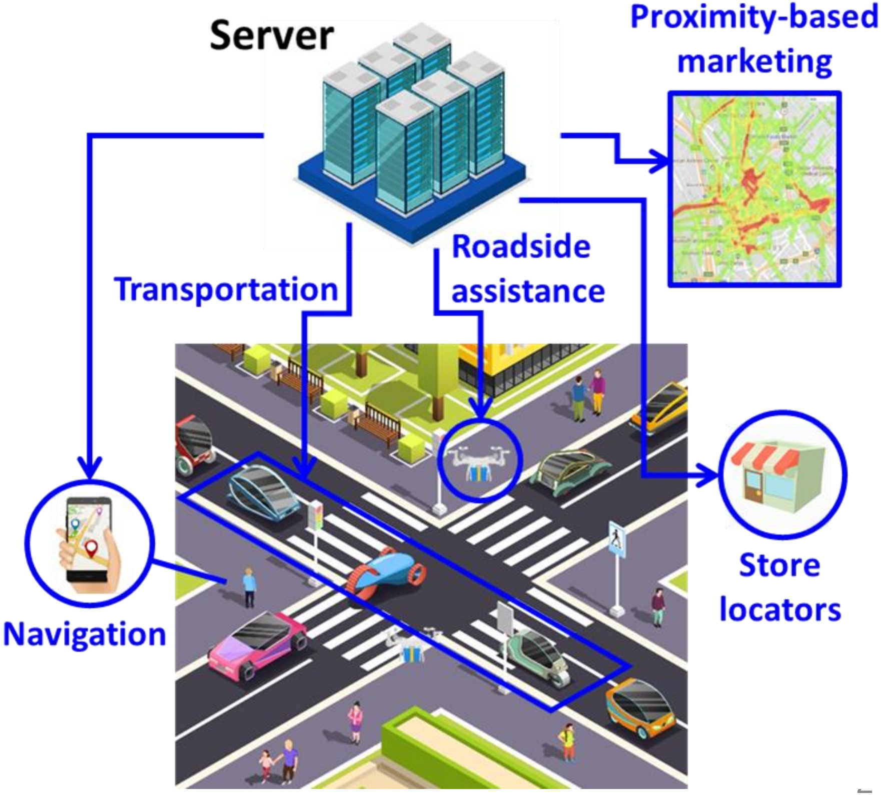
GNSS Data for Location-Based Service (LBS)

The big data can be used to improve the effectiveness of various LBS applications.

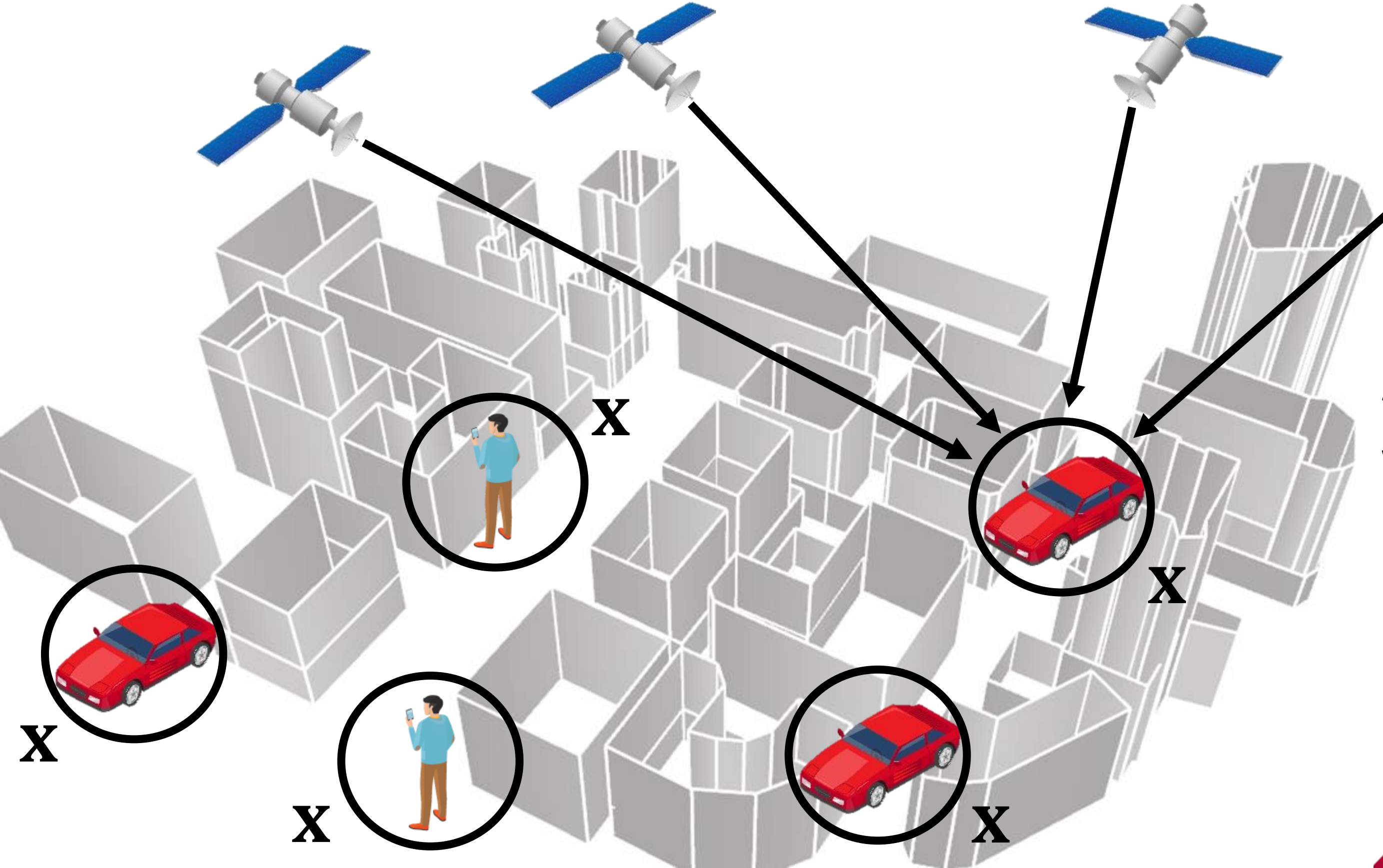
Not accurate in dense urban

Solution:

3D Mapping Aided (3DMA) GNSS-Based Cooperative Positioning



GNSS-Based Cooperative Positioning



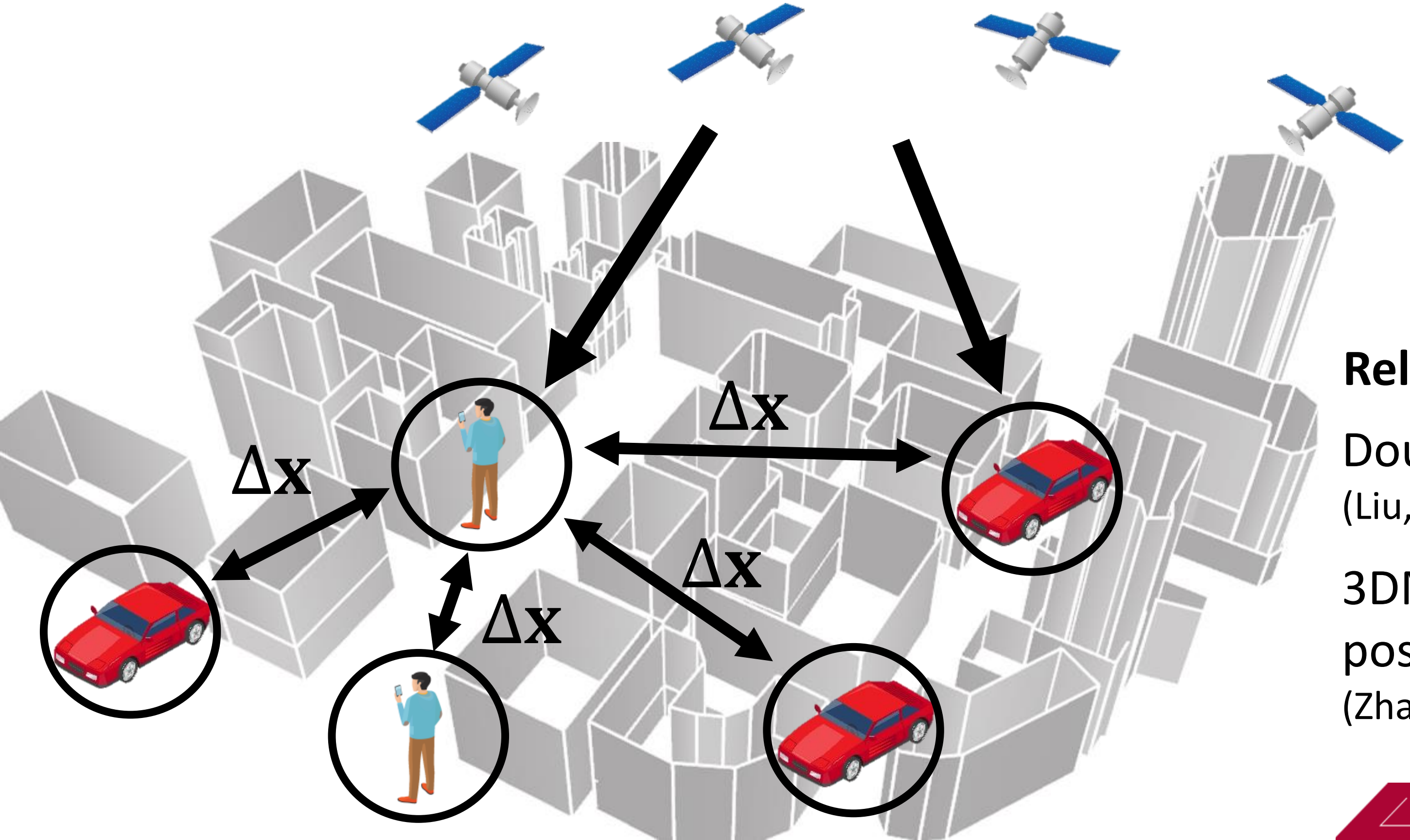
Absolute position

Weighted least squares

3DMA GNSS

(Wang, Groves et al. 2015, Hsu, Gu et al. 2016)

GNSS-Based Cooperative Positioning



Relative position:

Double difference (DD)
(Liu, Lim et al. 2014)

3DMA cooperative positioning
(Zhang, Wen et al. 2018)

GNSS-Based Relative Positioning

Pseudorange:

$$\tilde{\rho}_a^i = R_a^i + \boxed{\delta\rho_a} + \boxed{\delta\rho^i} + \epsilon_a^i$$

Receiver clock offset

Atmospheric delay
Satellite clock/orbit bias

Double difference (DD):

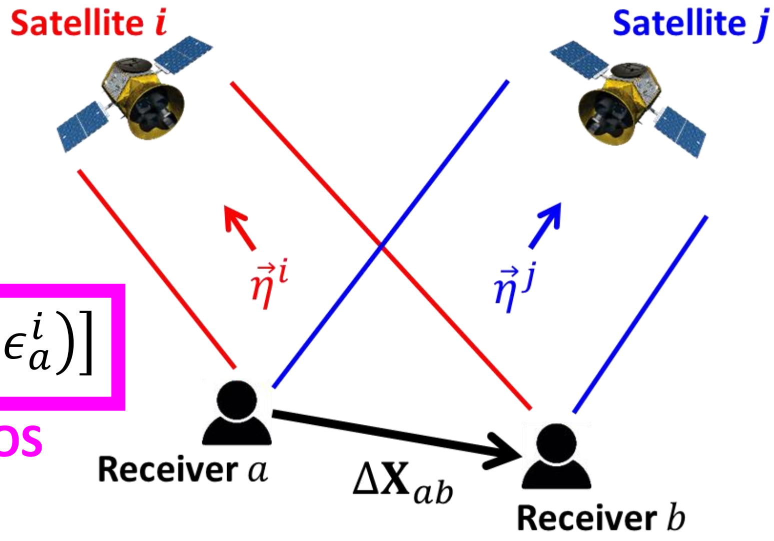
$$D_{ab}^{ij} = (\tilde{\rho}_b^j - \tilde{\rho}_b^i) - (\tilde{\rho}_a^j - \tilde{\rho}_a^i)$$

$$D_{ab}^{ij} = (\vec{\eta}^j - \vec{\eta}^i) \cdot \Delta\mathbf{x}_{ab} + \boxed{[(\epsilon_b^j - \epsilon_b^i) - (\epsilon_a^j - \epsilon_a^i)]}$$

Multipath and NLOS

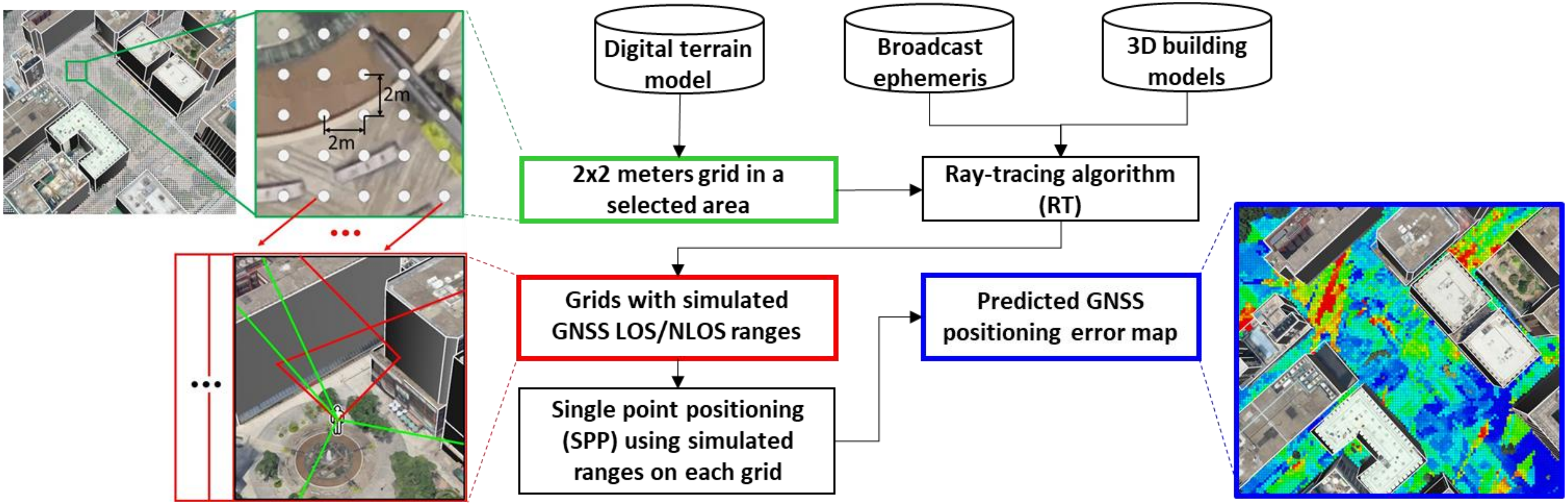
Least square solution:

$$\Delta\mathbf{x}_{ab} = (\mathbf{G}^{\mathrm{T}}\mathbf{G})^{-1}\mathbf{G}^{\mathrm{T}}\mathbf{D}_{ab}$$



3DMA Cooperative Positioning (ION GNSS+ 2018)

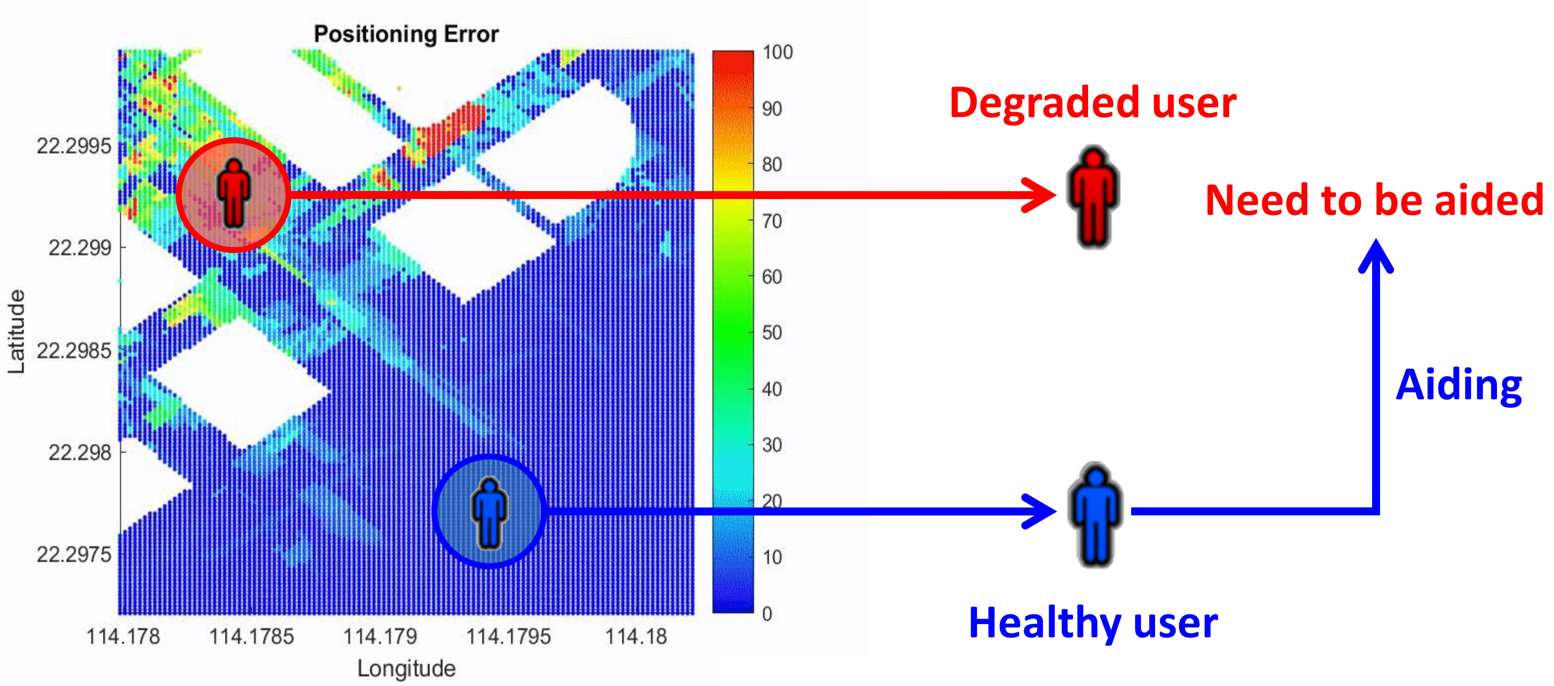
User status evaluation (healthy/NLOS degraded)



Zhang, G., et al. (2018). Collaborative GNSS Positioning with the Aids of 3D City Models. Proceedings of the 31st International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2018), Miami, Florida.

3DMA Cooperative Positioning (ION GNSS+ 2018)

User status evaluation (healthy/degraded) for NLOS-mitigation



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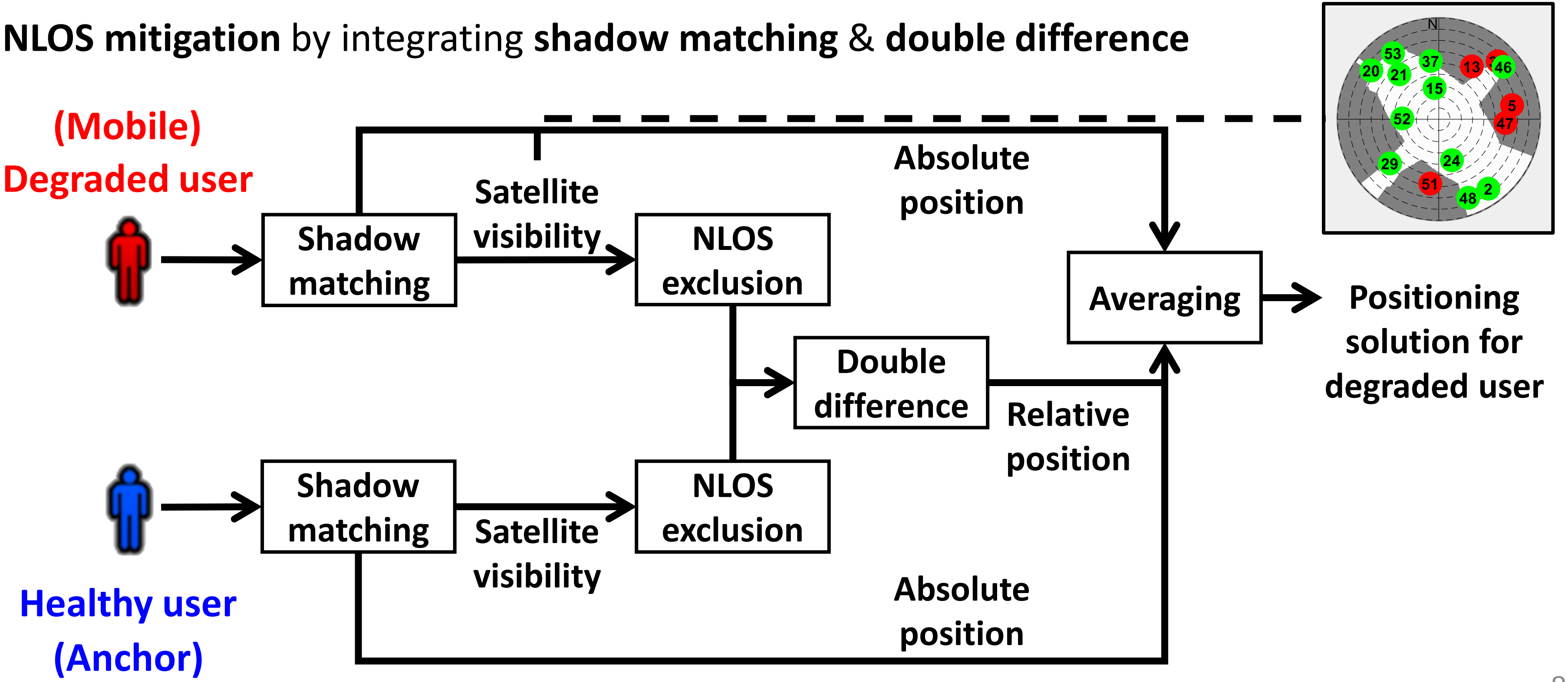
3DMA Cooperative Positioning (ION GNSS+ 2018)

NLOS mitigation by integrating **shadow matching** & **double difference**



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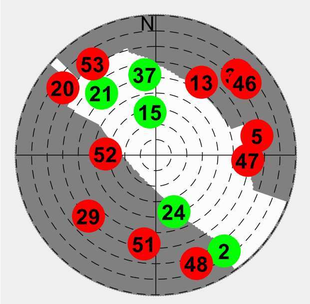
3DMA Cooperative Positioning Performance

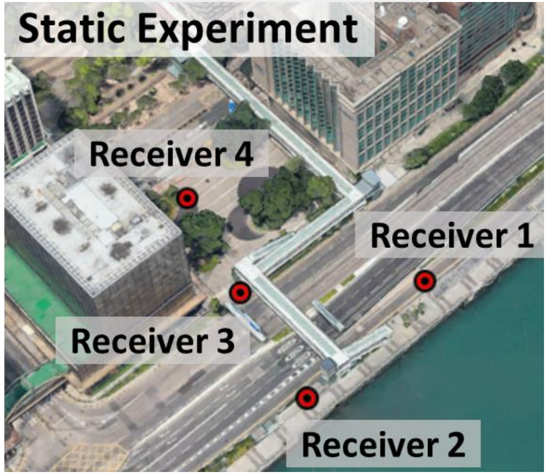
Relative positioning error between Receiver 1 and Receiver 4

Method	LS	DD	SDM-DD
RMSE (m)	33.3	84.6	20.3
Availability	100%	100%	**70%**

LS: Least square positioning
DD: Double difference positioning
SDM-DD: Shadow matching NLOS-excluded DD



LOS
NLOS



3DMA NLOS-excluded cooperative positioning RMSE (m)

Receiver	1	2	3	4
LS	3.7	5.0	14.7	30.9
SDM-CP	4.2	4.7	**14.2**	**16.2**

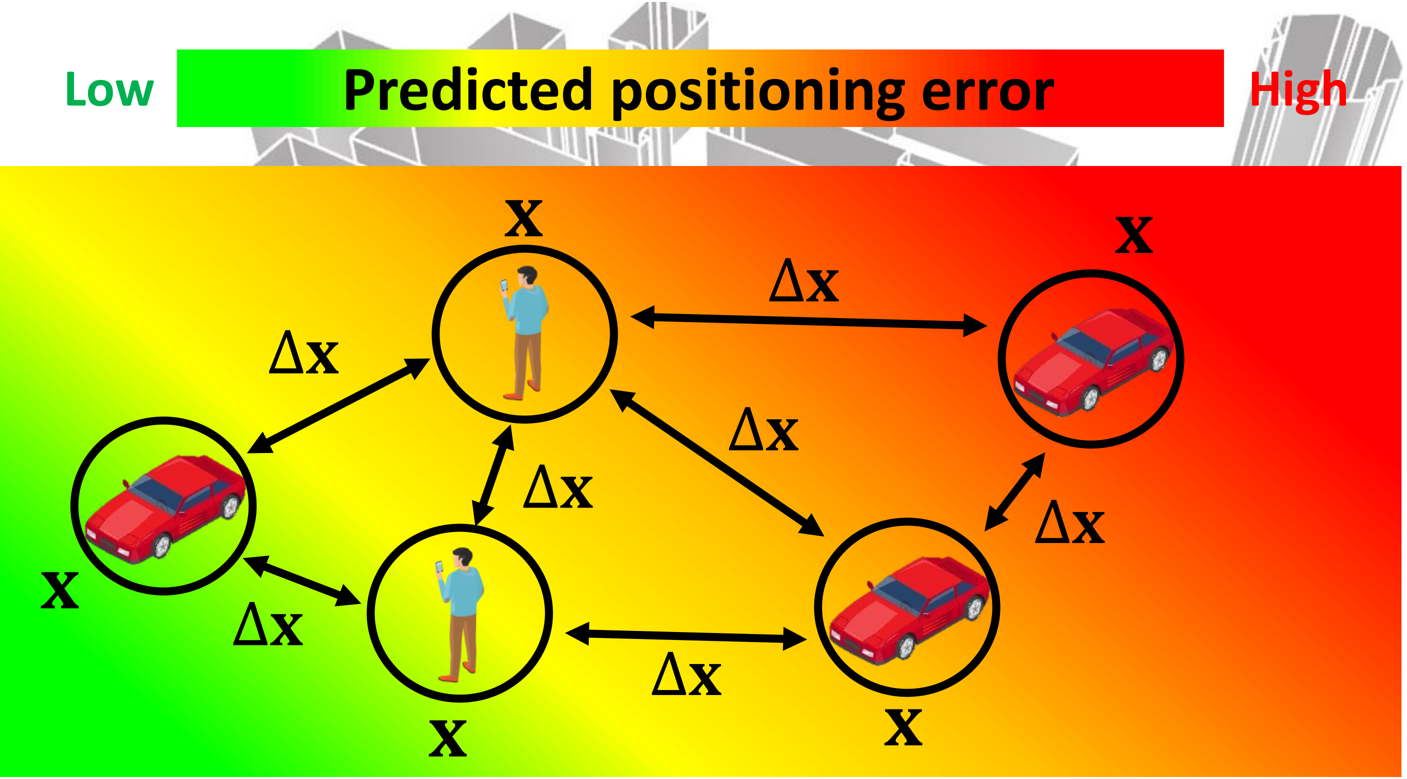
Limited measurements after NLOS exclusion!

LS: Least square positioning
SDM-CP: Shadow matching NLOS-excluded cooperative positioning

Challenges of GNSS Cooperative Positioning

		Proposed solution
• Limited common LOS satellite for cooperative positioning in urban	⇨	Use ray-tracing algorithm to correct NLOS instead of exclusion
• Single anchor-based method is not robust for urban	⇨	Use factor graph optimization to consider all available constraints

Challenges of GNSS Positioning in Urban



Environment information

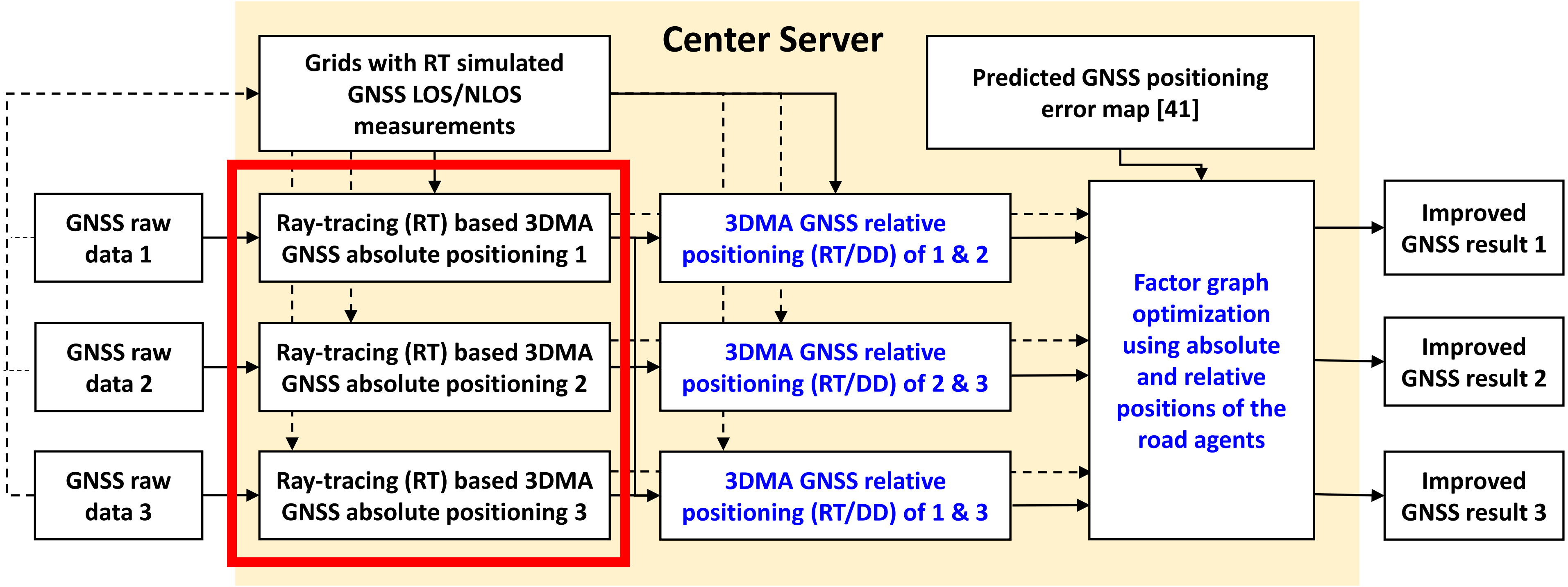
⇩

Factor graph optimization

⇩

Each user's position

Flowchart of the proposed algorithm



Ray-tracing algorithm (Hsu, Gu et al. 2016)

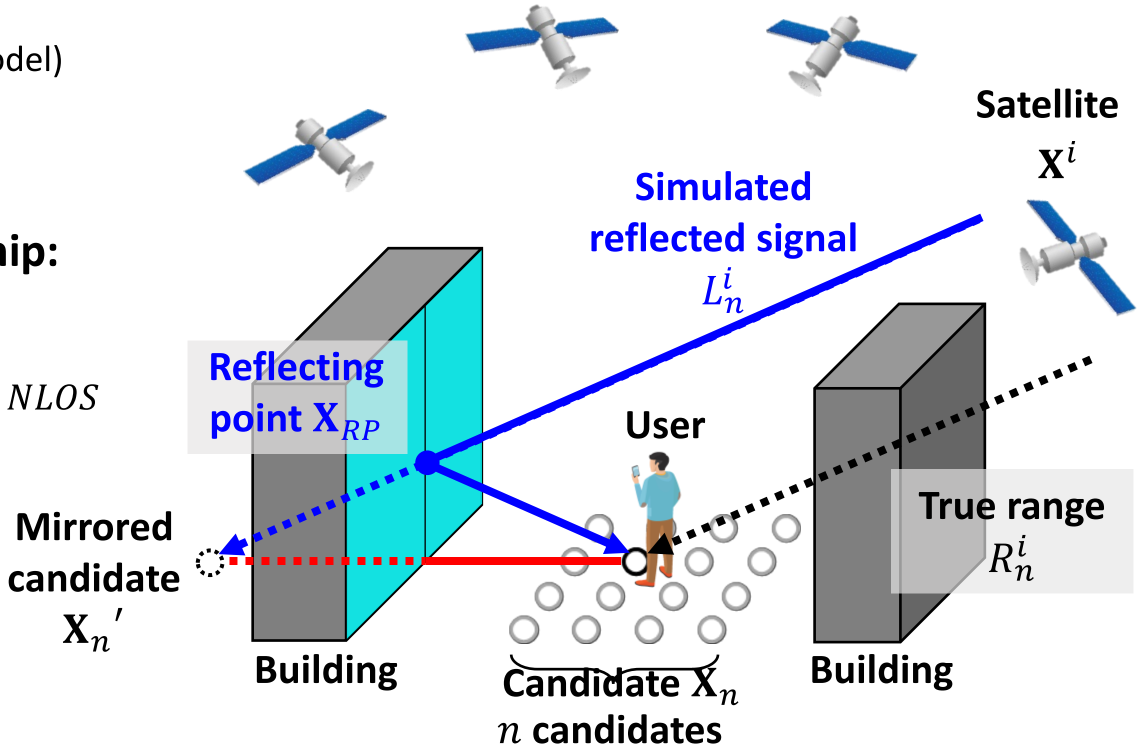
1. Sample candidates (digital terrain model)

2. Simulate GNSS measurements with NLOS geometrical relationship:

$$L_n^i = \begin{cases} \|\mathbf{X}_n - \mathbf{X}^i\|, & i \in LOS \\ \|\mathbf{X}_{RP} - \mathbf{X}^i\| + \|\mathbf{X}_n - \mathbf{X}_{RP}\|, & i \in NLOS \end{cases}$$

3. GNSS measurement correction sets:

$$\delta\rho_n^i = L_n^i - R_n^i$$



Ray-tracing algorithm (Hsu, Gu et al. 2016)

4. Simulation-measurement similarity estimation:

(single differenced to cancel receiver clock offset)

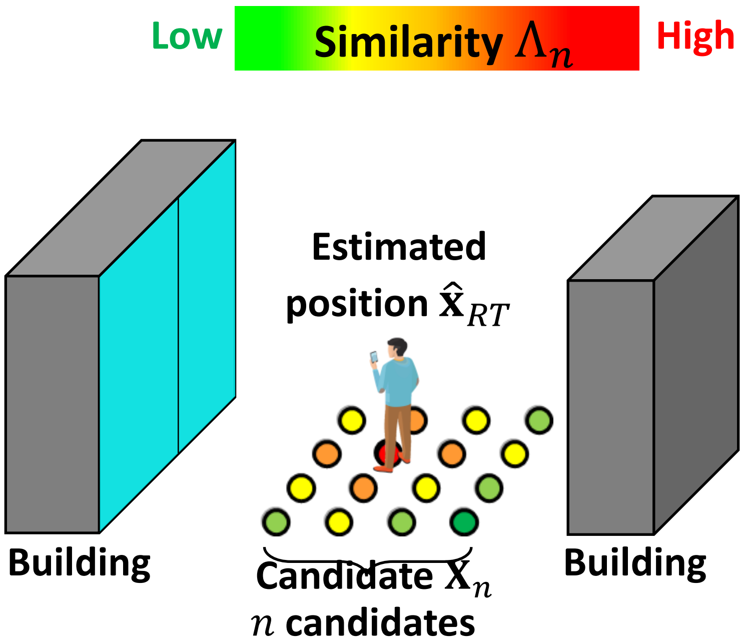
Simulation: $\hat{S}_n^i = L_n^i - L_n^m$

Measurement: $\tilde{S}^i = \rho^i - \rho^m$

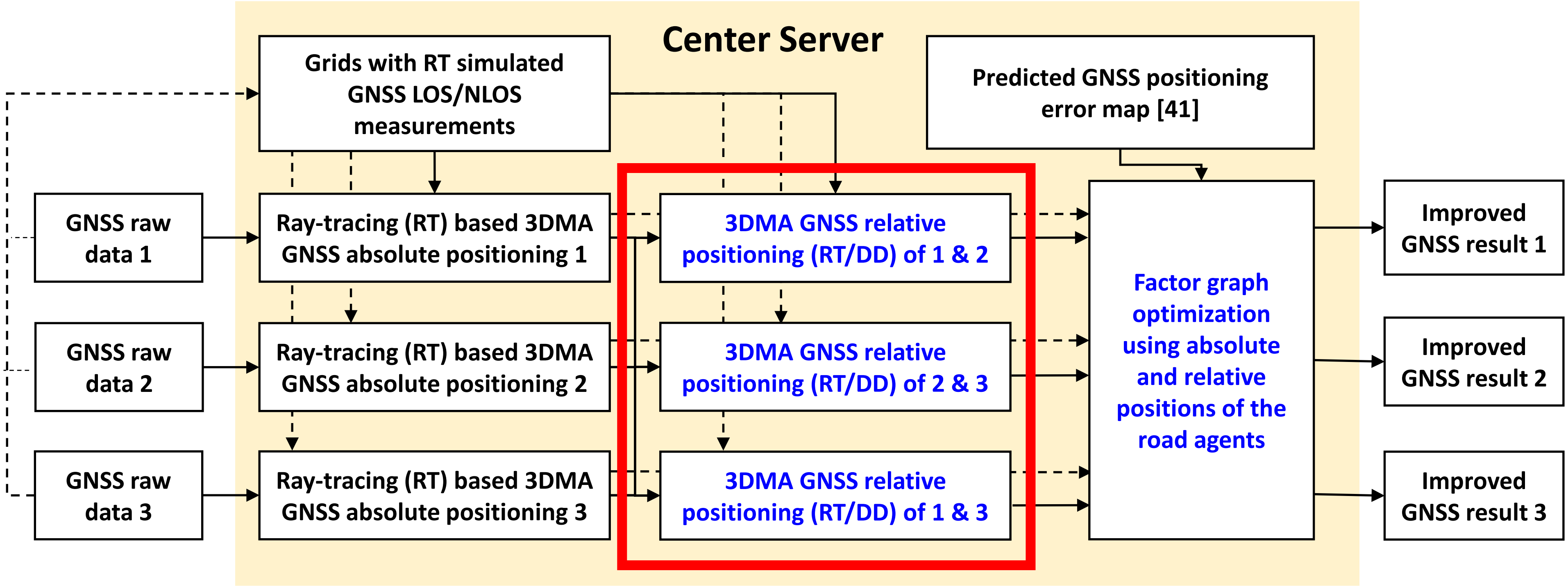
Average difference: $\delta S_n = \frac{\sum_i \left|\hat{S}_n^i - \tilde{S}^i\right|}{i}$

$$\Lambda_n = e^{-(\delta S_n - \delta S_{min})/(\delta S_{max} - \delta S_{min})}$$

5. Weighted averaging candidate positions: $\hat{\mathbf{x}}_{RT} = \frac{\sum_n \Lambda_n \cdot \mathbf{x}_n}{\sum_n \Lambda_n}$



Flowchart of the proposed algorithm



3DMA Double Difference with Ray-tracing

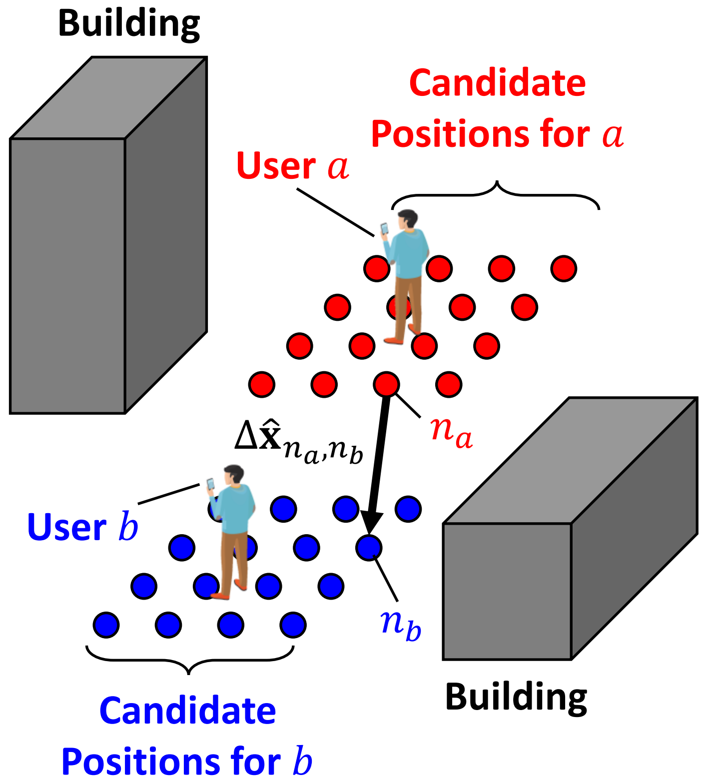
1. Sample candidates for different user

2. Pair each candidates from different user

3. Apply ray-tracing NLOS-corrected double difference relative positioning for each pair:

$$\boldsymbol{\rho}_{n_a}{}^{*} = \widetilde{\boldsymbol{\rho}}_{n_a} - \delta\boldsymbol{\rho}_{n_a}$$

$$\Delta\hat{\mathbf{x}}_{n_a,n_b} = \left(\mathbf{G}^{\mathrm{T}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{T}}\mathbf{D}^{*}_{n_a,n_b}$$



3DMA Double Difference with Ray-tracing

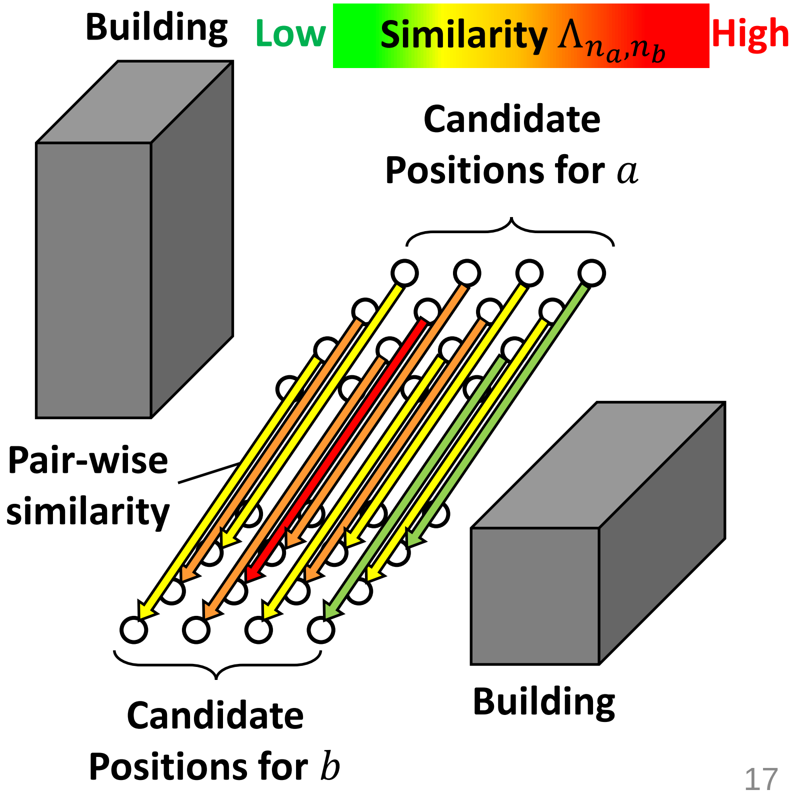
4. Pair-wise simulation-measurement similarity estimation:

$$\delta\Delta\mathbf{x}_{n_a,n_b} = \left\|\left(\mathbf{x}_{n_b} - \mathbf{x}_{n_a}\right) - \Delta\hat{\mathbf{x}}_{n_a,n_b}\right\|$$

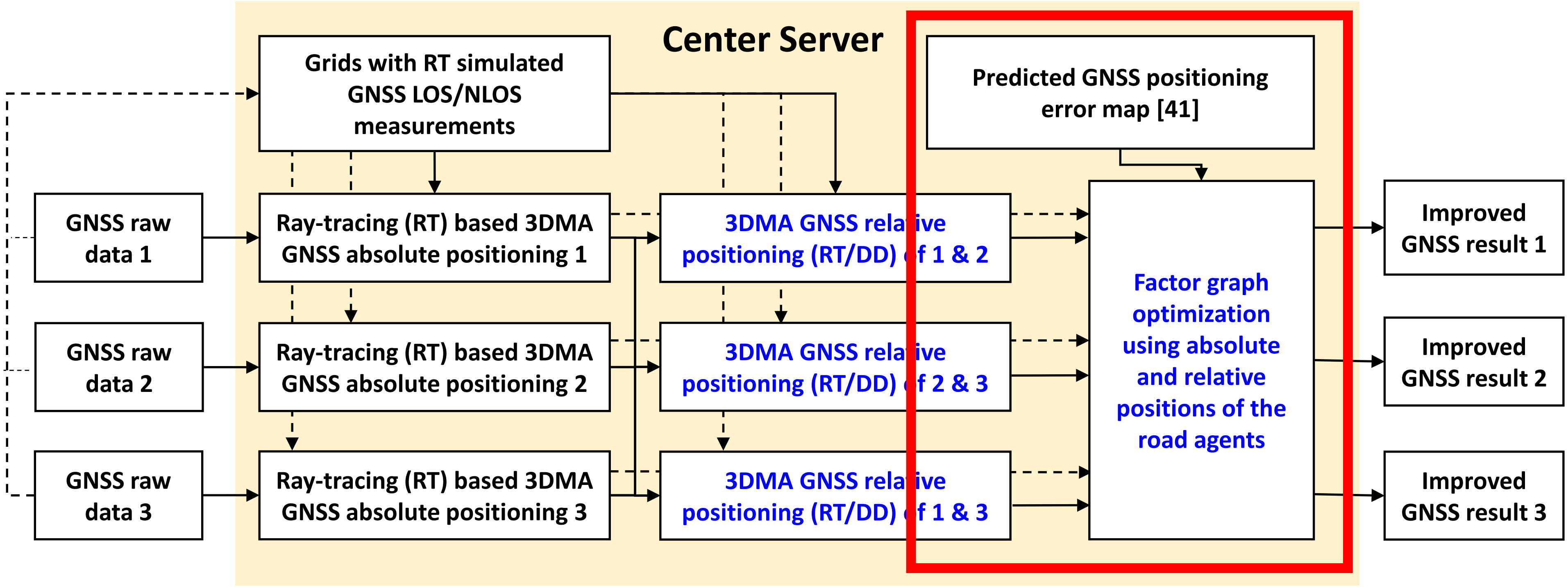
$$\Lambda_{n_a,n_b} = e^{-\left(\delta\Delta\mathbf{x}_{n_a,n_b} - \delta\Delta\mathbf{x}_{min}\right)/\left(\delta\Delta\mathbf{x}_{max} - \delta\Delta\mathbf{x}_{min}\right)}$$

5. Pair-wise similarity-weighted averaging relative position:

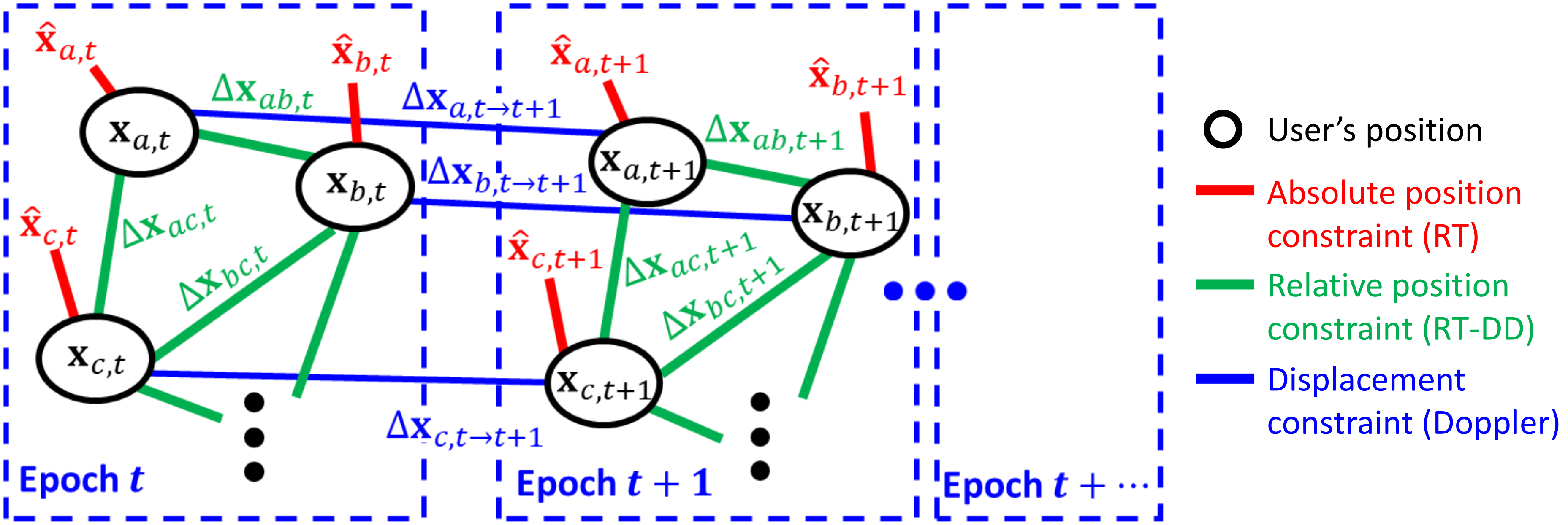
$$\Delta\hat{\mathbf{x}}_{ab} = \frac{\sum_{n_a}\sum_{n_b}\Lambda_{n_a,n_b}\Delta\mathbf{x}_{n_a,n_b}}{\sum_{n_a}\sum_{n_b}\Lambda_{n_a,n_b}}$$



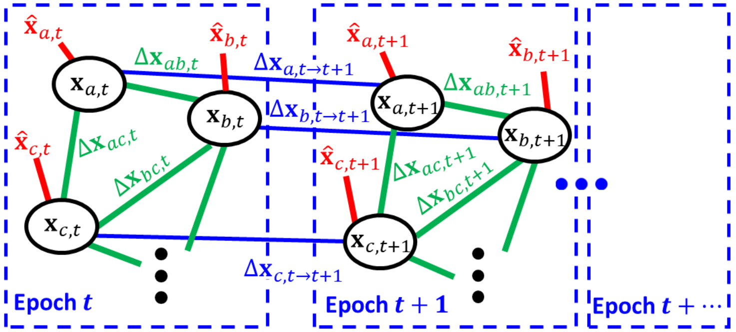
Flowchart of the proposed algorithm



Factor Graph Optimization



Factor Graph Optimization



ε – cost function $\quad\quad$ $\mathbf{\Omega}$ – covariance matrix

Absolute position constraint:

$$\varepsilon_{a,t} = \mathbf{H}(\mathbf{x}_{a,t}) - \hat{\mathbf{x}}_{a,t} \qquad \mathbf{\Omega}_{\mathbf{x}_a}^{abs} = \begin{bmatrix} \left(\overline{\mathrm{err}}_{\mathbf{x}_a}^{east}\right)^2 & 0 \\ 0 & \left(\overline{\mathrm{err}}_{\mathbf{x}_a}^{north}\right)^2 \end{bmatrix}$$

Relative position constraint:

$$\varepsilon_{ab,t} = \mathbf{H}(\mathbf{x}_{b,t}) - \mathbf{H}(\mathbf{x}_{a,t}) - \Delta\hat{\mathbf{x}}_{ab,t} \qquad \mathbf{\Omega}_{\Delta\hat{\mathbf{X}}_{ab}}^{rel} = \begin{bmatrix} \left(\overline{\mathrm{err}}_{\mathbf{x}_a}^{east}\right)^2 + \left(\overline{\mathrm{err}}_{\mathbf{x}_b}^{east}\right)^2 & 0 \\ 0 & \left(\overline{\mathrm{err}}_{\mathbf{x}_a}^{north}\right)^2 + \left(\overline{\mathrm{err}}_{\mathbf{x}_b}^{north}\right)^2 \end{bmatrix}$$

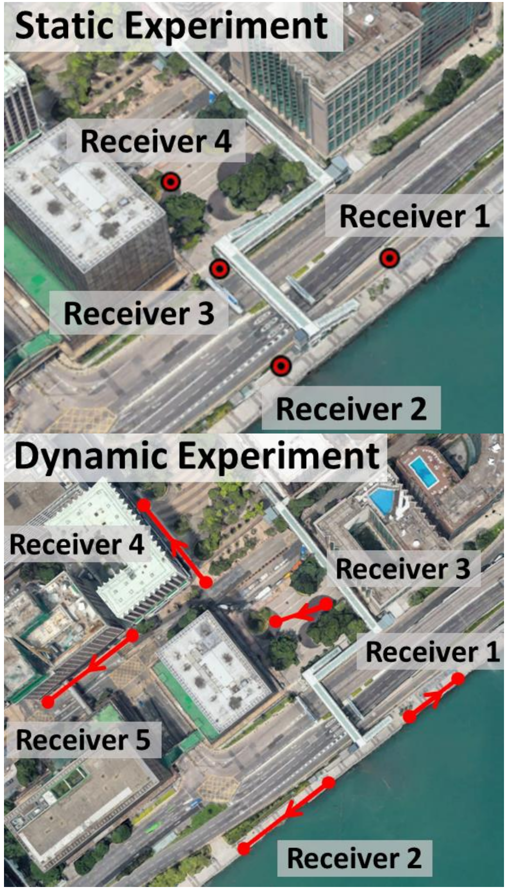
Displacement constraint:

$$\varepsilon_{a,t\to t+1} = \mathbf{H}(\mathbf{x}_{a,t+1}) - \mathbf{H}(\mathbf{x}_{a,t}) - \Delta\hat{\mathbf{x}}_{a,t\to t+1} \qquad \mathbf{\Omega}_{\mathbf{x}_a,\mathrm{t\to t+1}}^{displacement} = \begin{bmatrix} \sigma_{a,t\to t+1} & 0 \\ 0 & \sigma_{a,t\to t+1} \end{bmatrix}$$

Overall objective function: $\chi^* = \underset{\chi=[\mathbf{x}_1 \;\cdots\; \mathbf{x}_N]^{\mathrm{T}}}{\arg\min} \sum_k \|\varepsilon_k\|_{\mathbf{\Omega}_k^{-1}}^2$

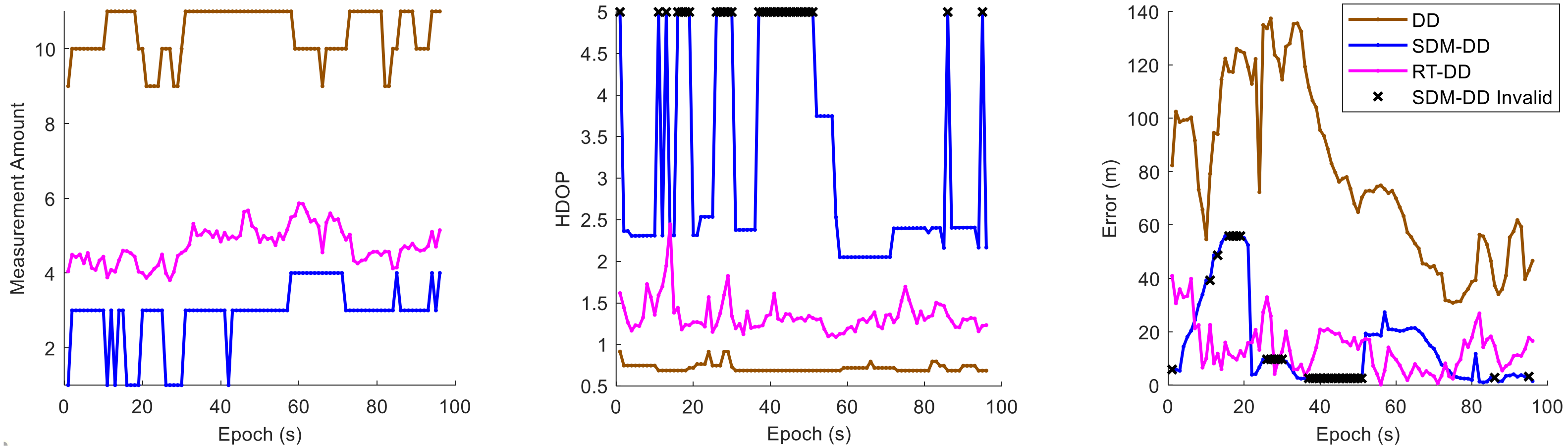
Experiment Setup

Experiment		Static	Dynamic
Receiver type		Ublox EVK-M8T	
Constellation		GPS/GLONASS	GPS/BDS
Environment	Receiver 1	Open sky	Open sky
	Receiver 2	Open sky near bridge	Open sky
	Receiver 3	Building corner under bridge	Between buildings
	Receiver 4	Between buildings	One side building
	Receiver 5		Urban canyon



Experiment Result — Static Experiment

Relative positioning performance between Receiver 1 (healthy) and Receiver 4 (degraded)

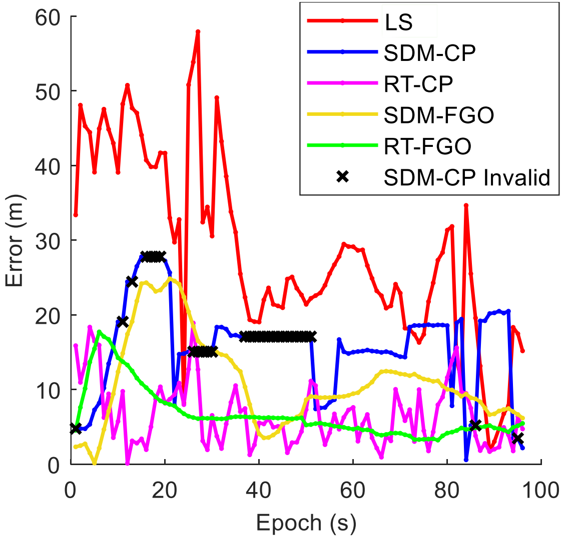


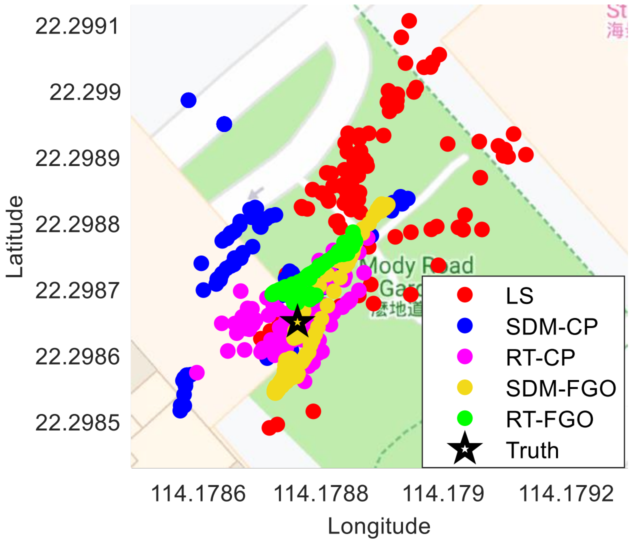
Method	Measurement amount	HDOP	RMSE (m)	Availability
DD	10.4	0.72	84.6	100%
SDM-DD	2.9	2.41	20.3	70%
RT-DD	4.7	1.34	16.3	100%

DD: Double difference positioning
SDM-DD: Shadow matching NLOS-excluded DD
RT-DD: Ray-tracing NLOS-corrected DD

Experiment Result — Static Experiment

Absolute positioning performance Receiver 4 (degraded)





Method	RMSE (m)
LS	30.9
RT	10.4
SDM-CP	16.2 (70%)
RT-CP	7.8
SDM-FGO	12.6
RT-FGO	7.4

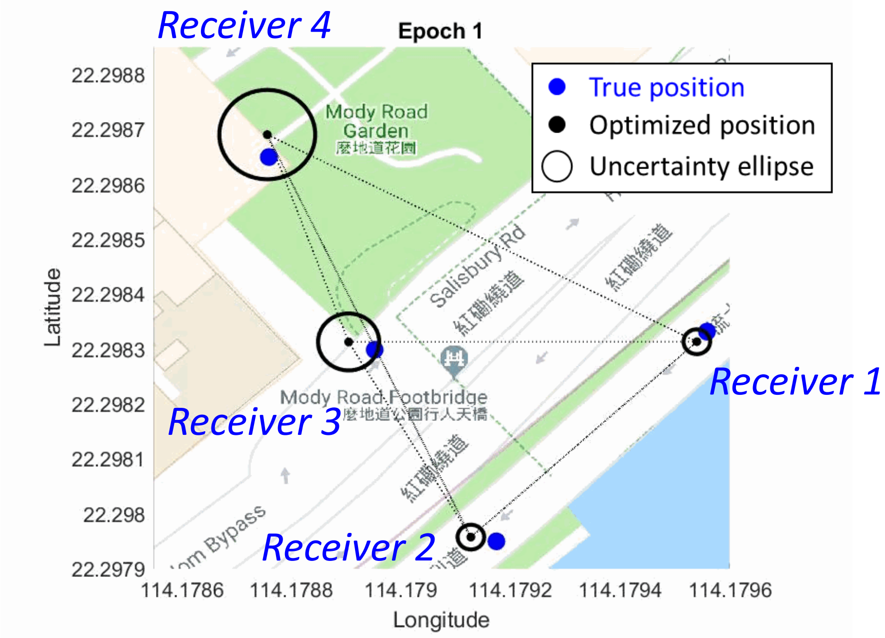
LS: Least squares positioning
RT: Ray-tracing
SDM-FGO: SDM-CP with factor graph

SDM-CP: Shadow matching NLOS-excluded cooperative positioning (Zhang, Wen et al. 2018 on ION GNSS+ 2018)
RT-FGO: RT-CP with factor graph

RT-CP: Ray-tracing NLOS-corrected cooperative positioning

Experiment Result — Static Experiment

Absolute positioning performance



Absolute Positioning RMSE (m)

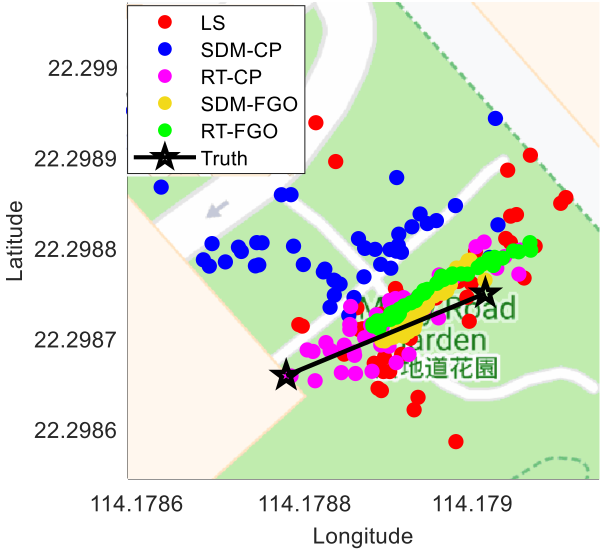
Receiver	1	2	3	4
LS	3.7	5.0	14.7	30.9
RT	2.7	3.1	14.9	10.4
SDM-CP	4.2 (100%)	4.7 (100%)	14.2 (96%)	16.2 (70%)
RT-CP	2.3	3.5	12.5	7.8
SDM-FGO	2.3	2.6	14.7	12.6
RT-FGO	2.7	4.1	8.4	7.4

LS: Least squares positioning
RT: Ray-tracing
SDM-FGO: SDM-CP with factor graph
SDM-CP: Shadow matching NLOS-excluded cooperative positioning (Zhang, Wen et al. 2018 on ION GNSS+ 2018)
RT-FGO: RT-CP with factor graph
RT-CP: Ray-tracing NLOS-corrected cooperative positioning

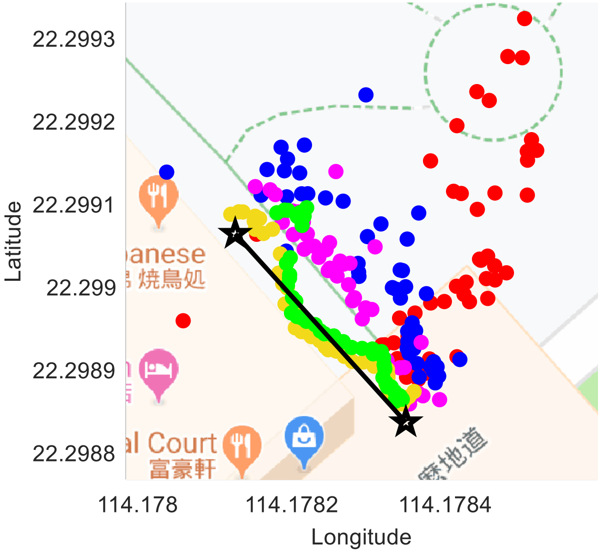
Experiment Result – Dynamic Experiment

Absolute positioning performance

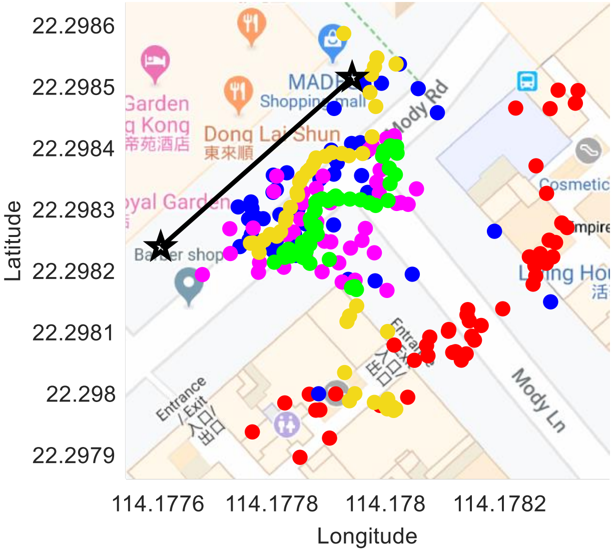
Receiver 3



Receiver 4



Receiver 5



LS: Least squares positioning

SDM-CP: Shadow matching NLOS-excluded cooperative positioning (Zhang, Wen et al. 2018 on ION GNSS+ 2018)

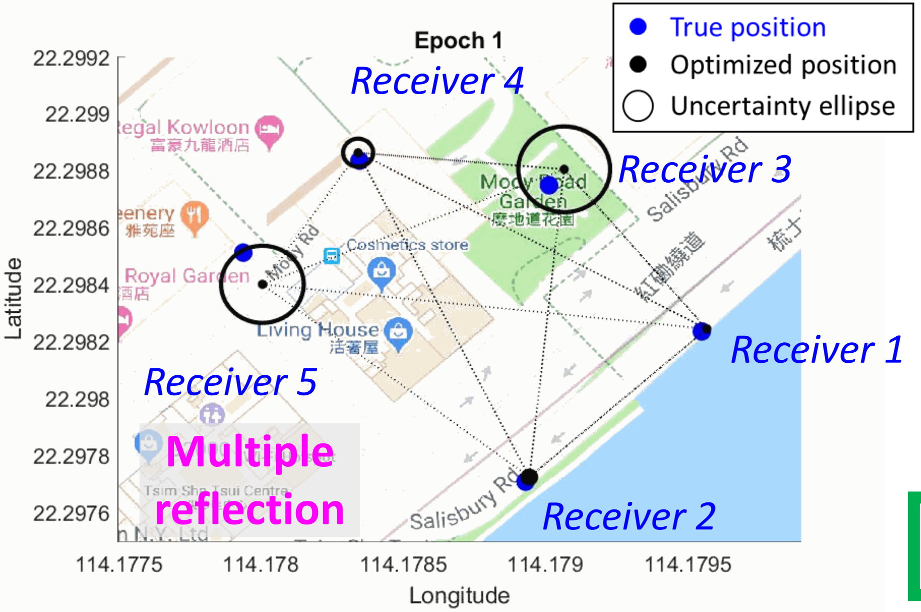
RT-CP: Ray-tracing NLOS-corrected cooperative positioning

SDM-FGO: SDM-CP with factor graph

RT-FGO: RT-CP with factor graph

Experiment Result — Dynamic Experiment

Absolute positioning performance



Absolute Positioning RMSE (m)

Receiver	1	2	3	4	5
LS	4.3	2.0	14.6	25.3	46.5
RT	5.1	3.1	8.5	10.6	20.1
SDM-CP	4.9	2.4	14.7	12.0	18.3
RT-CP	5.4	2.5	5.3	7.6	19.3
SDM-FGO	5.6	1.7	7.5	3.4	25.5
RT-FGO	5.1	2.1	8.1	4.2	18.6

PEM: Positioning error map prediction
LS: Least squares positioning
RT: Ray-tracing
SDM-FGO: SDM-CP with factor graph

SDM-CP: Shadow matching NLOS-excluded cooperative positioning (Zhang, Wen et al. 2018 on ION GNSS+ 2018)
RT-FGO: RT-CP with factor graph

RT-CP: Ray-tracing NLOS-corrected cooperative positioning

Conclusion

- The proposed ray-tracing NLOS-corrected DD method improves the relative positioning performance in dense urban.

  (factor of 4 comparing to conventional DD with 100% availability)
- The factor graph optimization can improve the robustness by considering all the available constraints. (through space and time)
- The proposed 3DMA cooperative positioning algorithm with factor graph optimization can improve the positioning performance in dense urban.

  (25.3m → 4.2m for degraded Receiver 4).

Future Works

- The scalability of the proposed algorithm.
- Mitigate other types of error.
  (Multipath, double reflected NLOS reception, etc)
- The computation load for pair-wise candidate matching is large and needs to be reduced.

Q & A

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