Advanced Signal Processing Methods for GNSS Positioning with NLOS/MP Signals

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Plan

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Global Navigation Satellite Systems

GNSS: Satellite radio navigation system used to estimate the position of a receiver by means of constellation of multiple satellites.

Each GNSS system contains 3 major components:

- Space Segment
- Control Segment
- User Segment

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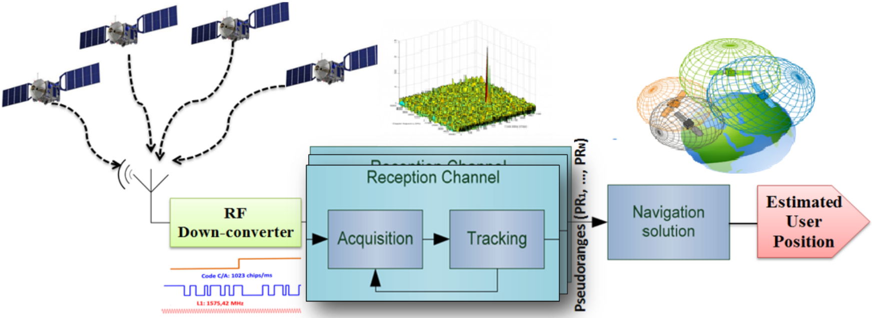
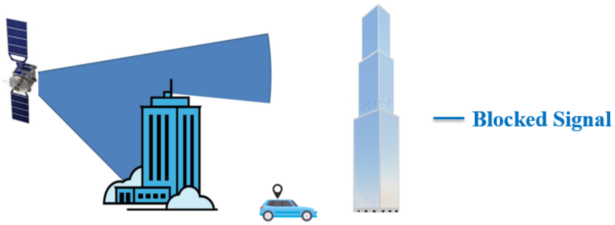
GNSS Architecture



GNSS quality in urban areas

- Masking effect and Limited satellite visibility $\Rightarrow$ High DOP
- Signal reflections $\Rightarrow$ additional Pseudoranges bias



Can an external information about the receiver environment of reception be used to assist GNSS in MP/NLOS situations?

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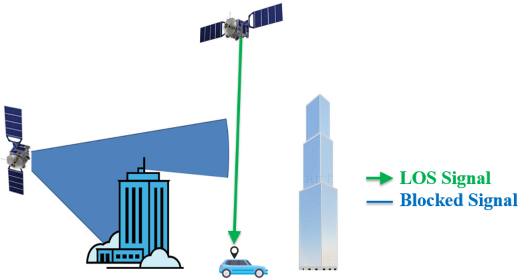

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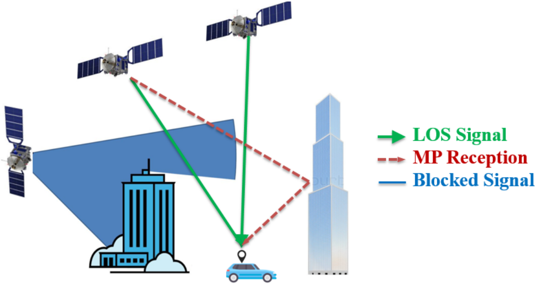

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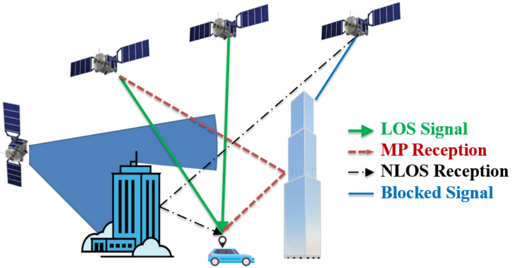

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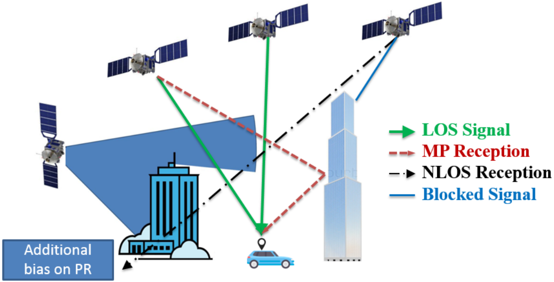


Can an external information about the receiver environment of reception be used to assist GNSS in MP/NLOS situations?

Objectives

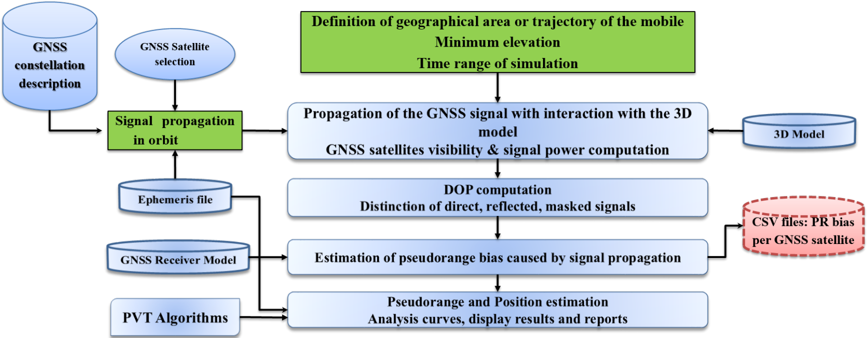
1. **Find out the benefits of using an additional geometrical information of the reception environment to assist the GNSS receiver**
   $\Rightarrow$ For this purpose, we have used the 3D GNSS signal propagation Simulator SPRING (provided by the CNES)
2. **What is the maximum achievable positioning accuracy level reached by GNSS positioning in MP/NLOS settings?**
   $\Rightarrow$ An analysis based on lower bounds computation

Plan

SPRING Architecture

3D GNSS signal propagation Simulator

3D GNSS simulator = 3D city model + GNSS signal propagation + GNSS receiver model → We have **SPRING (CNES)**



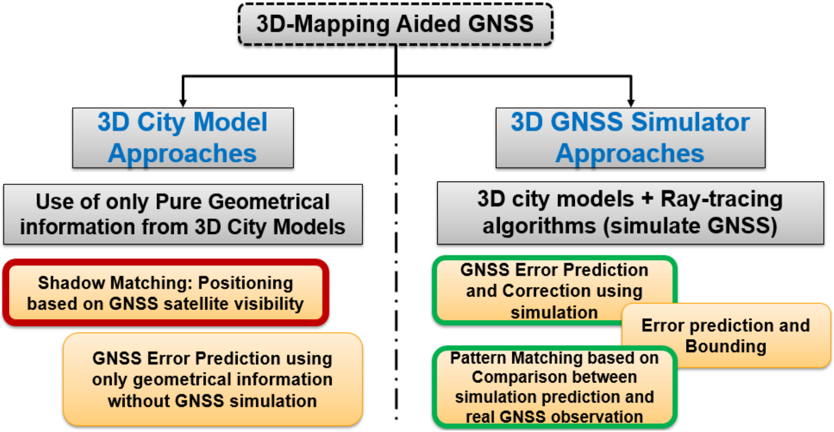
PR bias prediction using SPRING

PR bias prediction using 3D GNSS signal propagation simulation

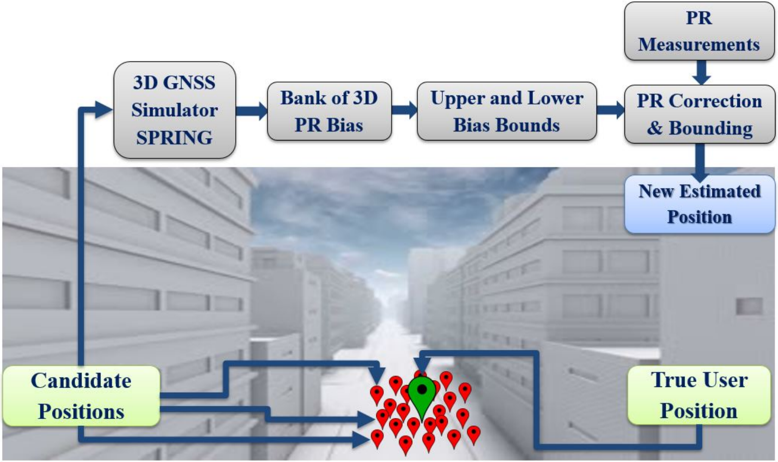
1. Compute satellite positions based on satellite ephemeris
2. Determine LOS distance between each satellite and the input position
3. Predict received PR measurements using ray-tracing algorithm
4. Compute PR bias by difference between predicted PR and LOS distances

SPRING Illustration

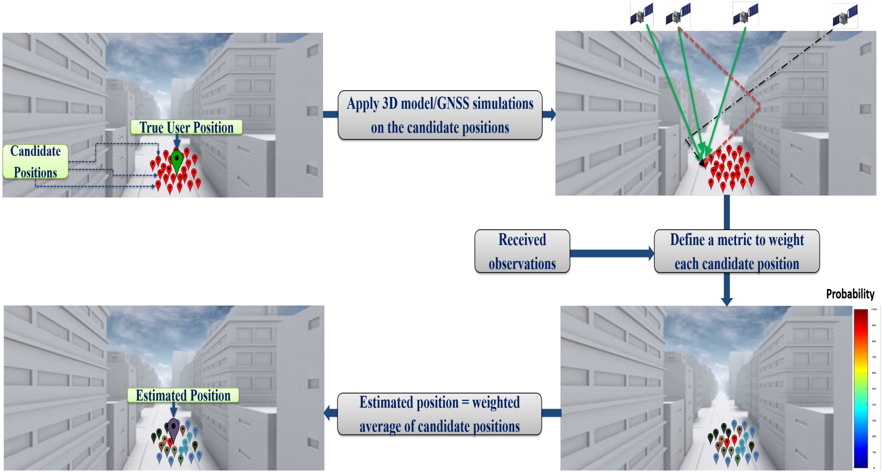
GNSS/3D Maps Fusion for localization



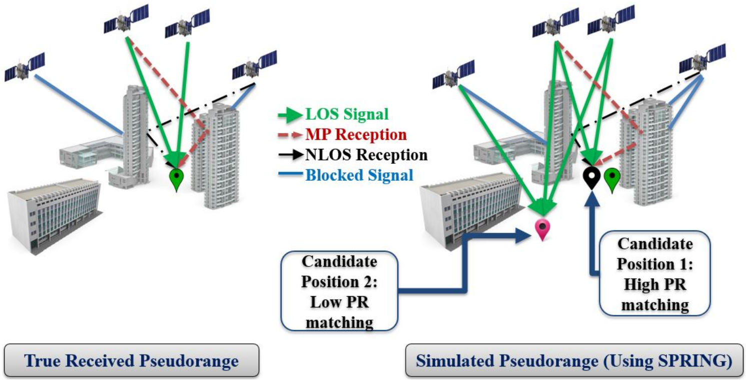
Proposed approach



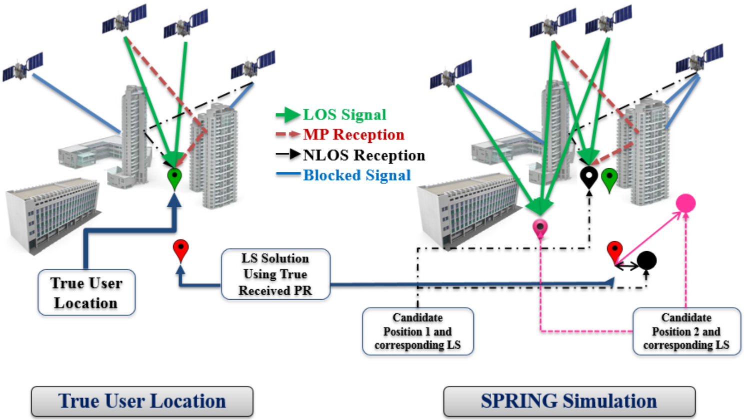
Overview of Pattern matching methods



Proposed Approaches: AML-3D



Proposed Approaches: Position Matching-3D



Architecture of the proposed approaches

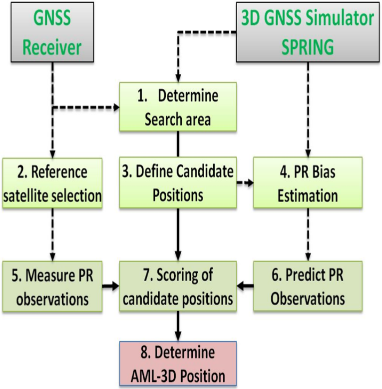


Figure: Our AML-3D Block Diagram

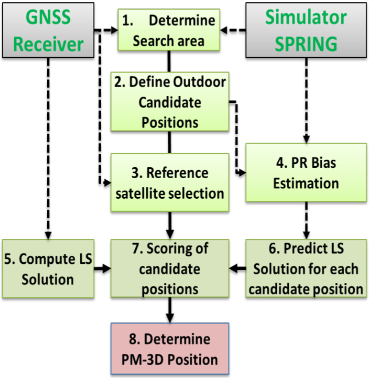
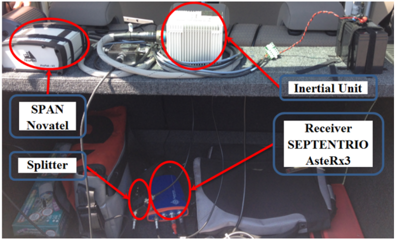


Figure: Our PM-3D Block Diagram

Experimental settings

General Experimental Setup

Environment: Urban area Toulouse, France
Date: 18/03/2015
Mode: Dynamic
GNSS Receiver: AsteRx3 Receiver
Recording Frequency: 10 Hz
Reference: SPAN NOVATEL(IMU-FSAS +RTK)

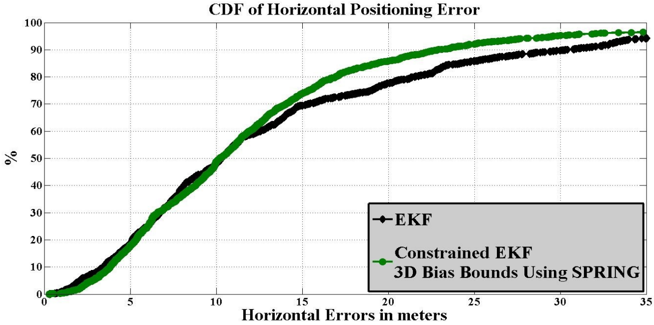


	GPS 22	GPS 12	GPS 28	GPS 24	GPS 13	GPS 15	GPS 18	GLO 08	GLO 09	GLO 11
Elevation (°)	5.9	21.4	26	47.2	52.4	82.2	26.3	62	35	25.5
$C/N0$ (dB-Hz)	35.5	33.5	27.7	46.2	42	47.7	35.2	34	24	28

Candidate Point selection

1. 2D area selection using Q-GIS Software
2. Height extrusion
3. Selection of a grid of point and elimination of indoor points

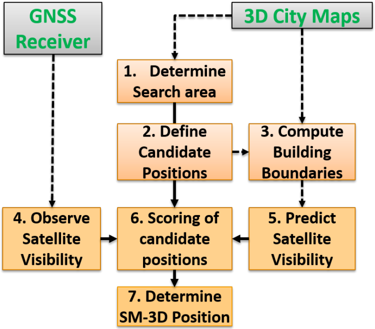
Results of 3D bias bounding approach



Comparison algo: Shadow Matching SM-3D

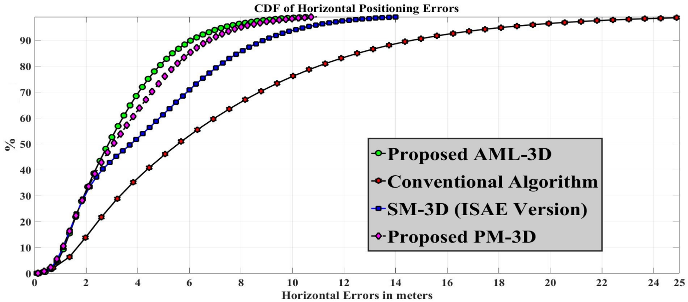
Shadow Matching Principle

Satellite visibility is a valuable information for positioning



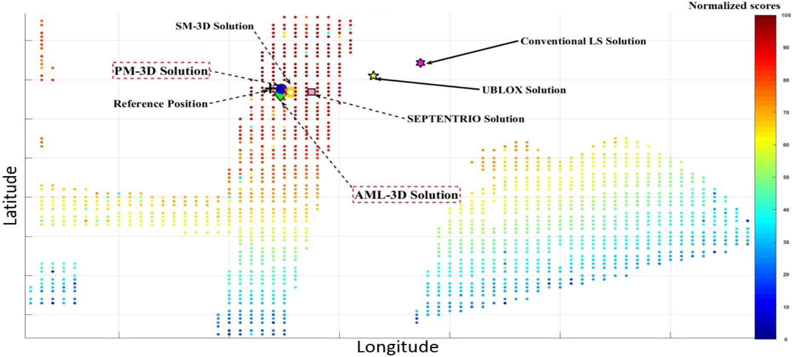
1. **Define a grid of candidate positions**
2. **Building Boundaries (BB) computation:** For each candidate position, predict building edges using the 3D city model
3. **Predict satellite visibility:** For each candidate position, predict satellite visibility using the Building Boundaries
4. **Measure satellite visibility:** Use $C/N0$ ratios to determine the observed satellite visibility
5. **Scoring of candidate positions:** Based on matching between predicted and measured sat visibility, score each point
6. **Final position estimation:** Estimate the final user position based on weighting of position having the highest scores

Performance of Algorithms Based On Candidate Positions Scoring



	AML-3D	PM-3D	SM-3D	UBLOX	Least-squares
Mean of HPE (m)	3.18	3.41	4.22	7.27	6.6
HPE AT 95% (m)	5.86	6.36	7.95	11.65	14.66
HPE AT 97% (m)	6.66	6.5	9.15	11.85	15.78

Performance of Algorithms Based On Candidate Positions Scoring



Computational loads

Proposed methods (with SPRING simulations) have a computation time 3 times greater than the SM-3D

Conclusions of this part

Reminder of objectives

- **Determine the benefits of using a 3D GNSS propagation simulator to assist the GNSS receiver**

1. Errors on PR bias prediction using SPRING simulations are unavoidable
2. Methods based on PR measurements correction are very sensitive to the PR bias correction provided by SPRING simulations
3. Proposed algorithms give comparable results compared to Shadow matching algorithm, but with more computational loads

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Conclusions of this part

PR errors prediction, using GNSS signal propagation simulations, requires:

- 3D mapping accurate to cm level (not the case)
- Accurate GNSS signal propagation simulation (very complicated)
- Cm-level accurate receiver position (Impossible)
- Use of the same design information (receiver design, correlator design, pre-correlation bandwidth,...) for the receivers used in the experiments: these information are a trade secret.

$\rightarrow$ **PR errors predicted by SPRING simulator will have a low level of correspondence to those experienced by the actual receiver.**

Plan

Previous proposed method based on PR measurements correction from PR bias bounds is very sensitive to the PR correction.

Problematic

How much the inaccuracy on the prediction of PR bias impacts the positioning performance of algorithms based on PR measurements?

Objectives

- How accurate the PR bias prediction should be to ensure that algorithms based on PR correction give better positioning accuracy compared to conventional positioning algorithms?
- What is the acceptable/allowed level of imprecision on PR bias prediction that any 3D GNSS signal propagation simulators must not exceed?

GNSS Navigation Equation

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} + \mathbf{b} \qquad (1)$$

- $\mathbf{y}$: PR innovation measurements
- $\mathbf{x}$: State vector to be estimated
- $\mathbf{b}$: MP and NLOS bias (PR bias)
- $\mathbf{H}$: Observation matrix
- $\mathbf{n}$: Measurement Noise with a zero-mean Gaussian distribution with covariance matrix $\mathbf{R}$

WLS Estimator: $\mathbf{x}_{WLS} = (\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1}\mathbf{H}^T\mathbf{R}^{-1}\mathbf{y} = \mathbf{H}^+\mathbf{y}$

$$\rightarrow \delta\mathbf{x}_{WLS} = \mathbf{x}_{WLS} - \mathbf{x} = \mathbf{H}^+(\mathbf{b} + \mathbf{n})$$

Corrected-LS Estimator: $\mathbf{x}_{CLS} = \mathbf{H}_\mathbf{b}^+(\mathbf{y} - \mathbf{c})$

$$\rightarrow \delta\mathbf{x}_{CLS} = \mathbf{H}_\mathbf{b}^+(\mathbf{b} + \mathbf{n} - \mathbf{c}) = \mathbf{H}_\mathbf{b}^+(\delta\mathbf{b} + \mathbf{n});$$

$$\delta\mathbf{b} = \mathbf{b} - \mathbf{c}; \quad \mathbf{H}_\mathbf{b}^+ = (\mathbf{H}^T\mathbf{R}_\mathbf{b}^{-1}\mathbf{H})^{-1}\mathbf{H}^T\mathbf{R}_\mathbf{b}^{-1}; \quad \mathbf{R}_\mathbf{b} \neq \mathbf{R}$$

MSE Definition

$$\mathbf{MSE}[\mathbf{x}_{LS}] = E[\delta\mathbf{x}_{LS}\delta\mathbf{x}_{LS}^T] \quad (2)$$

Acceptable condition for accuracy improvements compared to LS

$$OMSE[\mathbf{x}_{CLS}] = \mathrm{Tr}\{MSE(\mathbf{x}_{CLS})\} \leq OMSE[\mathbf{x}_{LS}] = \mathrm{Tr}\{MSE(\mathbf{x}_{LS})\} \quad (3)$$

Hypotheses: uncorrelated MP/NLOS bias $\mathbf{b}$ between satellites, one bias from one satellite j and $\mathbf{R_b} = \mathbf{R}$:

$$(E\{\delta\mathbf{b}\delta\mathbf{b}^T\})_j \leq (E\{\mathbf{b}\mathbf{b}^T\})_j \quad (4)$$

First remarks

- For better accuracy by PR measurement correction compared to LS, bias bound prediction errors must have a lower correlation matrix than the true unknown PR bias variation

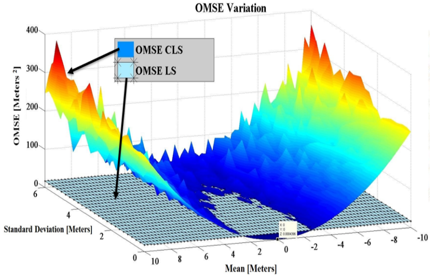
Objective: Validation of theoretical acceptable levels of PR bias inaccuracy

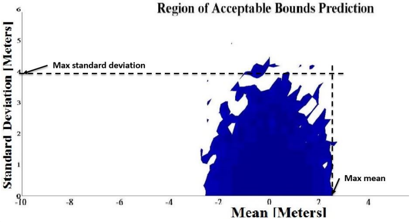
1. Correction of PR measurements bias of all satellites using method in [a].
2. The error on the prediction of PR bias of the satellite under study $(\delta\mathbf{b})_j$ is assumed to be Gaussian distribution with a variable mean and variance, i.e. $(\delta\mathbf{b})_j \sim \mathcal{N}(\mu,\, \sigma^2)$.

$$(E\{\delta\mathbf{b}\delta\mathbf{b}^T\})_j = (\sigma^2 + \mu^2)$$

3. The mean μ and the variance σ^2 of this Gaussian distribution (of $(\delta\mathbf{b})_j$) are varied until reaching the condition of equality between the positioning errors of LS and CLS solutions, i.e. $OMSE[\mathbf{x}_{CLS}] = OMSE(\mu, \sigma) = OMSE[\mathbf{x}_{LS}]$.

[a] T. Iwase, N. Suzuki, and Y. Watanabe, Estimation and exclusion of multipath range error for robust positioning, GPS solutions, vol. 17, no. 1, 2013.





- Region of the maximum acceptable error on PR bias prediction using a 3D GNSS signal propagation simulator
  → Minimum 3D modelling realism to correct PR measurements

Determination of Maximum acceptable level of PR bias uncertainty for all satellites and comparison with SPRING PR bias prediction error

	Average Satellite Elevation (°)	**Average PR Bias Estimation Error using SPRING Simulation [Meters]**	**Average Experimental Maximum Acceptable Uncertainty Level on PR bias Estimation [Meters]**
GPS 22	5.93	0.83 !!!	44.45
GPS 12	21.47	26.30	37.53
GPS 28	26.35	4.53	9.94
GPS 24	47.23	0.39	1.38
GPS 13	52.47	7.22	8.2
GPS 15	82.29	0.25	0

PR bias prediction error using SPRING simulation is lower than the maximum acceptable on PR bias prediction error in this case
$\rightarrow$ Confirm the previous result: PR measurement correction using SPRING prediction will slightly enhance the positioning performance

Potential applications of this study / Conclusions

- Identify environments where it is useful to use a 3D GNSS signal propagation simulator to predict PR biases in order to correct PR measurements.
  $\rightarrow$ Map representing the environments where it is useful to use a correction of PR measurements by prediction of PR biases
- production of a requirement metric on PR bias prediction by 3D GNSS signal propagation simulation
  $\rightarrow$ Validation and classification of 3D GNSS signal propagation simulators

Plan

GNSS observation model with LOS signals only:

$$s(t) = \sum_{k=0}^{K-1} \alpha_k . c_k(t - \tau_k) . e^{2i\pi f_k t} + n(t)$$

- α_k complex satellite signal amplitude
- $c_k(t)$ transmitted complex baseband navigation signal
- $n(t)$ additive complex zero-mean Gaussian noise
- and τ_k, f_k the delay and Doppler frequency shift of the k-th satellite signal

GNSS observation model with LOS signals only:

$$s(t) = \sum_{k=0}^{K-1} \alpha_k . c_k(t - \tau_k).e^{2i\pi f_k t} + n(t)$$

$$\Downarrow$$

Case N snapshots sampled at a $F_s = \frac{1}{Ts}$ rate from $s(t)$:

$$\mathbf{s} = \mathbf{s}(\boldsymbol{\theta}_d) = \mathbf{A}(\boldsymbol{\eta})\boldsymbol{\alpha} + \mathbf{n}, \qquad \boldsymbol{\theta}_d = (\boldsymbol{\eta}^T, \boldsymbol{\alpha}^T)^T$$

- $\mathbf{x} = (x(0), \ldots, x((N-1)T_s))^T$,
- $\mathbf{A} = [\mathbf{a}_0, \ldots, \mathbf{a}_{K-1}]$ is the manifold corresponding to all in-view satellite signals, with $\mathbf{a}_k = (c_k(-\tau_k), \ldots, c_k((N-1)T_s - \tau_k).e^{2i\pi f_k (N-1)T_s})^T$,
- $\boldsymbol{\eta} = (\tau_1, \ldots, \tau_K, f_1, \ldots, f_K)^T$ is the vector of unknown deterministic parameters of primary interest (delays, Doppler-frequency shifts,...).
- $\boldsymbol{\alpha} = (\alpha_0, \ldots, \alpha_{K-1})^T$ and,
- $\mathbf{n} = (n(0), \ldots, n((N-1)T_s))^T$

GNSS observation model with LOS and MP signals:

$$s(t) = \sum_{k=0}^{K-1} \alpha_k . c_k(t - \tau_k) . e^{2i\pi f_k t} + \sum_{i=1}^{N_{MP}} \alpha_{r,i} . c_k(t - \tau_{r,i}) . e^{2i\pi f_{r,i} t} + n(t)$$

- $\alpha_{r,i}$ each complex satellite signal amplitude after signal reflections, supposed to be random and unknown,
- and $\tau_{r,i}$, $f_{r,i}$ the delay and Doppler frequency shift after signal reflections, observed from the receiver, and supposed to be random and unknown.

GNSS observation model with LOS and MP signals:

$$s(t) = \sum_{k=0}^{K-1} \alpha_k . c_k(t - \tau_k).e^{2i\pi f_k t} + \sum_{i=1}^{N_{MP}} \alpha_{r,i}.c_k(t - \tau_{r,i}).e^{2i\pi f_{r,i} t} + n(t)$$

$$\Downarrow$$

$$\mathbf{s} = \mathbf{s}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_r) = \mathbf{A}(\boldsymbol{\eta})\boldsymbol{\alpha} + \mathbf{m}(\boldsymbol{\eta}_r, \boldsymbol{\alpha}_r) + \mathbf{n}; \qquad \boldsymbol{\theta}_d = (\boldsymbol{\eta}^T, \boldsymbol{\alpha}^T)^T, \quad \boldsymbol{\theta}_r = (\boldsymbol{\eta}_r^T, \boldsymbol{\alpha}_r^T)^T$$

Where, $\mathbf{m}(\boldsymbol{\eta}_r, \boldsymbol{\alpha}_r) = \sum_{i=1}^{N_{MP}} \mathbf{B}_i(\boldsymbol{\eta}_{r,i})\boldsymbol{\alpha}_{r,i}$ represents the contribution of all MP and:

- $\forall i \in [1, N_{MP}]$, $\mathbf{B}_i$ manifold corresponding to transmitted signal after signal reflections for the i-th multipath (may be different from MP to MP).
- $\boldsymbol{\eta}_r = (\eta_{r,1}, \ldots, \eta_{r,N_{MP}})^T$ unknown nuisance parameters (delay and the Doppler frequency shift, of each MP after reflections).
- $\boldsymbol{\alpha}_r = (\alpha_{r,1}, \ldots, \alpha_{r,N_{MP}})^T$ GNSS signal amplitudes of each MP after reflections.

Non-Gaussian errors in MP situations

Non-Gaussian p.d.f. in case of MP

In case of MP situations, the p.d.f. of GNSS problem is:

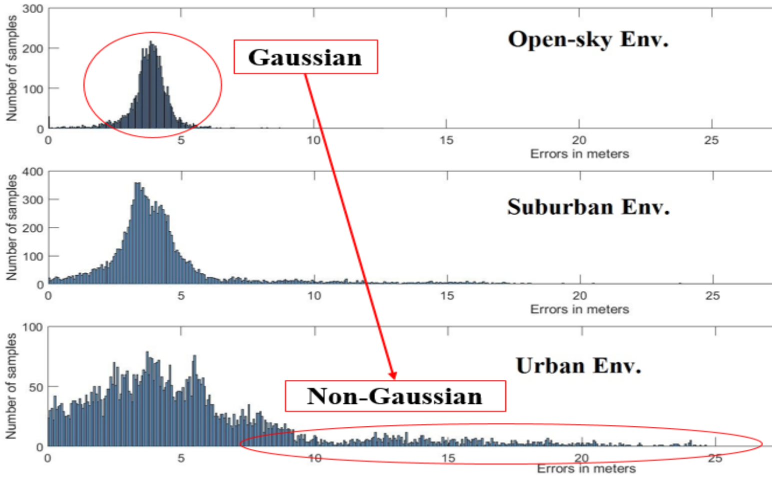
- non-Gaussian
- results from the marginalization of a joint p.d.f. depending on random variables as well (the delays, Doppler frequency shifts and amplitudes of MPs)

$$p(\mathbf{s};\boldsymbol{\theta}_d) = \int p(\mathbf{s}|\boldsymbol{\theta}_r;\boldsymbol{\theta}_d)\, p(\boldsymbol{\theta}_r;\boldsymbol{\theta}_d)\, d\boldsymbol{\theta}_r;$$

$$p(\mathbf{s}|\boldsymbol{\theta}_r;\boldsymbol{\theta}_d) = p(\mathbf{s}|\boldsymbol{\eta}_r,\boldsymbol{\alpha}_r;\boldsymbol{\eta},\boldsymbol{\alpha}) = \mathcal{CN}\left(\mathbf{A}(\boldsymbol{\eta})\boldsymbol{\alpha} + \mathbf{m}(\boldsymbol{\eta}_r,\boldsymbol{\alpha}_r), \sigma^2\mathbf{I}\right)$$

This will be illustrated with real GNSS data

Non-Gaussian errors in MP situations



Non-Gaussian errors in MP situations

Why Lower Bounds?

1. ***Relative information:*** *benchmark different estimators*
2. ***Absolute information:*** *performance limit of all estimators (mean to characterize the limit of estimation precision)*

Raised questions

1. *Can standard lower bounds (LBs) be computed in these environments?*
2. *If standard LBs can not be computed, can we derive modified LBs that are computable?*

Problematic

Problem formulation

$$p(\mathbf{s};\boldsymbol{\theta}) = \int_{\Theta_r} p(\mathbf{s},\boldsymbol{\theta}_r;\boldsymbol{\theta})\, d\boldsymbol{\theta}_r,$$

$$p(\mathbf{s},\boldsymbol{\theta}_r;\boldsymbol{\theta}) = p(\mathbf{s}|\boldsymbol{\theta}_r;\boldsymbol{\theta})\, p(\boldsymbol{\theta}_r;\boldsymbol{\theta}),$$

where $p(\mathbf{s}|\boldsymbol{\theta}_r;\boldsymbol{\theta})$ is the conditional probability density function (p.d.f.) of $\mathbf{s}$ given $\boldsymbol{\theta}_r$, and $p(\boldsymbol{\theta}_r;\boldsymbol{\theta})$ is the prior p.d.f. of $\boldsymbol{\theta}_r$, parameterized by $\boldsymbol{\theta}$.
We distinguish two subsets:

- the subset of " standard" deterministic estimation problems for which a closed-form expression of $p(\mathbf{s};\boldsymbol{\theta})$ is available
- the subset of " non-standard" deterministic estimation problems for which only an integral form of $p(\mathbf{s};\boldsymbol{\theta})$ is available.

$\rightarrow$ **Objective:** Compute lower bounds (LBs) on the estimation errors.

Case of standard estimation

McAulay-Seidman bound

The MSE of a particular estimator $\widehat{\theta^0} \in \mathcal{L}_2(\mathcal{S}_\mathcal{S})$ of θ^0, i.e., $\widehat{\theta^0} \triangleq \widehat{\theta^0}(\mathbf{s})$, where θ^0 is a selected value of the parameter θ can be bounded as follows:

$$MSE_{\theta^0}\left[\widehat{\theta^0}\right] = \left\|\widehat{\theta^0}(\mathbf{s}) - \theta^0\right\|^2_{\theta^0} \geq \boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right)^T \mathbf{R}^{-1}_{\boldsymbol{\upsilon}_{\theta^0}} \boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right);$$
$$\left(\mathbf{R}_{\boldsymbol{\upsilon}_{\theta^0}}\right)_{n,m} = E_{\mathbf{s};\theta^0}\left[\upsilon_{\theta^0}(\mathbf{s};\theta^m)\,\upsilon_{\theta^0}(\mathbf{s};\theta^n)\right]$$

Where $\boldsymbol{\theta}^N = \left(\theta^1, \ldots, \theta^N\right)^T \in \Theta_d^N$ is a vector of N selected values of the parameter θ (aka test points),
$\boldsymbol{\upsilon}_{\theta^0}\left(\mathbf{s};\boldsymbol{\theta}^N\right) = \left(\upsilon_{\theta^0}(\mathbf{s};\theta^1), \ldots, \upsilon_{\theta^0}(\mathbf{s};\theta^N)\right)^T$: Likelihood ratios associated to $\boldsymbol{\theta}^N$, $\xi(\theta) = \theta - \theta^0$ and $\boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right) = \left(\xi(\theta^1), \ldots, \xi(\theta^N)\right)^T$.
$\rightarrow$ Any Lower Bound is a Linear Transformations of the McAulay-Seidman Bound.

Case of standard estimation

Standard LBs in GNSS harsh environments

- Presence of non-Gaussian MP fluctuation p.d.f. in harsh environments $\rightarrow$ the marginal p.d.f. of the GNSS observations has not an analytical form.
- Standard LBs on MSE cannot be computed in this case.

Solution: embed the initial observation space in a hybrid one where any standard LB can be transformed into a modified one fitted to non-standard deterministic estimation.

Case of non-standard estimation

Methodology: Look for LBs based on $p(\mathbf{s}, \boldsymbol{\theta}_r; \theta)$ instead of $p(\mathbf{s}; \theta)$.

Modified MSB:

$$MSE_{\theta^0}\left[\widehat{\theta^0}\right] \geq \boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right)^T \mathbf{R}^{-1}_{\boldsymbol{\upsilon}_{\theta^0}} \boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right)$$

$$\left(\mathbf{R}_{\boldsymbol{\upsilon}_{\theta^0}}\right)_{n,m} = E_{\mathbf{s},\boldsymbol{\theta}_r;\theta^0}\left[\upsilon_{\theta^0}\left(\mathbf{s}, \boldsymbol{\theta}_r; \theta^m\right) \upsilon_{\theta^0}\left(\mathbf{s}, \boldsymbol{\theta}_r; \theta^n\right)\right]$$

$$\rightarrow \quad ModifiedLB$$

"Standard" MSB:

$$MSE_{\theta^0}\left[\widehat{\theta^0}\right] \geq \boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right)^T \mathbf{R}^{-1}_{\boldsymbol{\upsilon}_{\theta^0}} \boldsymbol{\xi}\left(\boldsymbol{\theta}^N\right)$$

$$\left(\mathbf{R}_{\boldsymbol{\upsilon}_{\theta^0}}\right)_{n,m} = E_{\mathbf{s};\theta^0}\left[\upsilon_{\theta^0}\left(\mathbf{s}; \theta^m\right) \upsilon_{\theta^0}\left(\mathbf{s}; \theta^n\right)\right]$$

$$\rightarrow \quad StandardLB$$

Case of non-standard estimation

- The previous result is general for all LBs
- **For example with CRB:**
  MCRB is obtained directly from the CRB:

$$\mathbf{CRB}_\theta = E_{\mathbf{s};\theta}\left[\frac{\partial \ln p(\mathbf{s};\theta)}{\partial\theta}\frac{\partial \ln p(\mathbf{s};\theta)}{\partial\theta^T}\right]^{-1}$$

$$\rightarrow \mathbf{MCRB}_\theta = E_{\mathbf{s},\boldsymbol{\theta}_r;\theta}\left[\frac{\partial \ln p(\mathbf{s},\boldsymbol{\theta}_r;\theta)}{\partial\theta}\frac{\partial \ln p(\mathbf{s},\boldsymbol{\theta}_r;\theta)}{\partial\theta^T}\right]^{-1}$$

with $\mathbf{CRB}_\theta \geq \mathbf{MCRB}_\theta$

Case of non-standard estimation

Difference between MLBs and LBs

1. Larger vector space:
   - LBs are for unbiased estimates belonging to $\mathcal{L}_2\left(\mathcal{S}_{\mathcal{S}}\right)$
   - MLBs are for unbiased estimates belonging to $\mathcal{L}_2\left(\mathcal{S}_{\mathcal{S},\Theta_r}\right)$
     $\rightarrow$ Computability of MLBs at the possible expense of tightness
     $\rightarrow$ It is possible to increase the tightness of MLBs by adding constraints in order to restrict the class of viable estimators $\widehat{\theta^0} \in \mathcal{L}_2\left(\mathcal{S}_{\mathcal{S},\Theta_r}\right)$
2. MLB is obtained from the LB by substituting d.p.p.
   $\rightarrow$ Any standard LB can be transformed into a modified one fitted to non-standard deterministic estimation

Plan

Main Conclusions

Objectives/Conclusions

The benefits of 3D GNSS signal propagation simulators:

- PR bias prediction using 3D GNSS simulators is a mere approximation
- Proposed algorithms give comparable results compared to a state-of-the-art method, with more computational loads.

The acceptable level of accuracy of 3D GNSS simulators:

- A study to define the allowed level of imprecision on PR bias prediction in order to improve the positioning performance by correcting PR.
- SPRING PR bias prediction is slightly below this acceptable level.

Modified lower bounds of estimation accuracy:

- General framework to transform standard LBs into a modified ones at the expense of tightness.

Future Works

1. Evaluation of the proposed approaches in other urban settings and using more measurements
2. Reduction of computational loads related to 3D GNSS signal propagation
3. 3D Simulator/GNSS fusion at the receiver level: track MP/NLOS signals in the GNSS receiver using the help of 3D GNSS simulators/3D city models.
4. 3D Simulator/GNSS fusion using Doppler measurements: use of 3D models/3D GNSS simulators to estimate the Doppler effects and aid the GNSS receiver estimation.

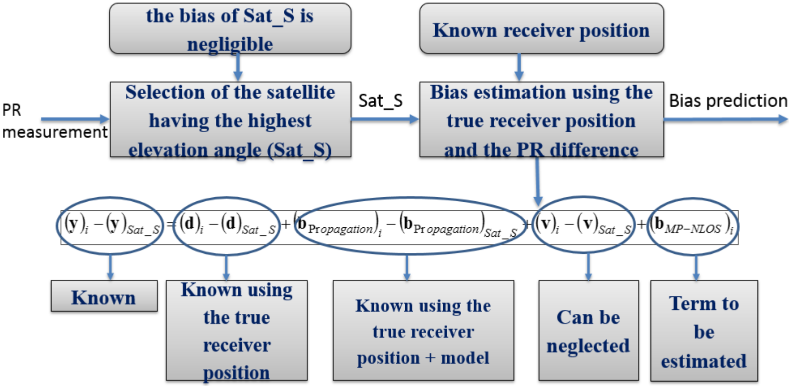
Publications

1. **Journal Papers**
   [1] N. Kbayer, J. Galy, E. Chaumette, F. Vincent, A. Renaux and P. Larzabal, "On Lower Bounds for Nonstandard Deterministic Estimation," in **IEEE Transactions on Signal Processing**, vol. 65, no. 6, 15 March 2017.
   [2] N. Kbayer, M. Sahmoudi, "Performances Analysis of GNSS NLOS Bias Correction in Urban Environment Using a 3D City Model and GNSS Simulator," in **IEEE Transactions on Aerospace and Electronic Systems**, 2018.
2. **International Conferences**
   [1] N. Kbayer, M. Sahmoudi, E. Chaumette, "Robust GNSS Navigation in Urban Environments by Bounding NLOS Bias of GNSS Pseudoranges Using 3D City Model," Proceedings of **ION GNSS+** conference, September 2015.
   [2] N. Kbayer, M. Sahmoudi, "Constructive Use of MP/NLOS Bias of GNSS Pseudoranges: Performance Analysis by Type of Environment," Proceedings of ION ITM conference, January 2017.
   [3] N. Kbayer, J. Galy, E. Chaumette, F. Vincent, A. Renaux, P. Larzabal, "Estimation Accuracy Of Non-Standard Maximum Likelihood Estimators," On **ICASSP** 2017.
   [4] N. Kbayer, M. Sahmoudi, H. Ortega-Gonzàlez, C. Rouch, "Approximate Maximum Likelihood Estimation Using a 3D GNSS Simulator for Positioning in MP/NLOS Conditions," Proceedings of **ION GNSS+** conference 2017.

Thank you for your attention

BACK-UP

PR bias estimation using reference trajectory



[1]

[1] T. Iwase, N. Suzuki, and Y. Watanabe, Estimation and exclusion of multipath range error for robust positioning, GPS solutions, vol. 17, no. 1, 2013.

Non-standard lower bounds (NSLB)

Non-standard McAulay-Seidman bound

$$E_{\boldsymbol{\theta}_r;\theta}\left[\mathbf{C}_{\phi}\left(\widehat{\phi}_{MSB}\right)\right] = \boldsymbol{\Xi}\left(\phi^N\right)\mathbf{R}_{\upsilon_\phi}^{-1}\left(\phi^N\right)\boldsymbol{\Xi}\left(\phi^N\right)^T \leq \min_{\widehat{\phi}\in\mathcal{U}_S(\mathcal{S}_S)}\left\{E_{\mathbf{s},\boldsymbol{\theta}_r;\theta}\left[\left(\widehat{\phi}-\phi\right)\left(\widehat{\phi}-\phi\right)^T\right]\right\}.$$

$\phi^N = \left[\phi^1 \ldots \phi^N\right]$ is a vector of N selected values of the parameter θ (aka test points) and $\boldsymbol{\Xi}\left(\phi^N\right) = \left[\phi^1 - \phi \ldots \phi^N - \phi\right]$

$\rightarrow$ **NSMSB** is a LB for $\widehat{\phi} \in \mathcal{U}_S\left(\mathcal{S}_S\right)$, i.e., strict-sense unbiased estimates, whereas the **MMSB** is a LB for $\widehat{\phi} \in \mathcal{U}_W\left(\mathcal{S}_{\mathcal{X},\Theta_r}\right)$, i.e., wide-sense unbiased estimates.

$\rightarrow$ Any Non-standard Lower Bound is a Linear Transformations of the McAulay-Seidman Bound.

NSLB and MLB comparison

- In general, we cannot compare the NSLB and the MLB
- If $p(\boldsymbol{\theta}_r; \boldsymbol{\theta}_d)$ does not depend on $\boldsymbol{\theta}_d$

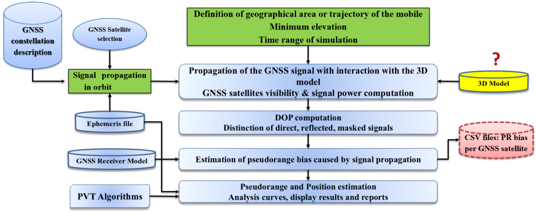
$$\underbrace{\boldsymbol{\Xi}\left(\boldsymbol{\theta}^N\right)\mathbf{R}_{\boldsymbol{\upsilon}_\theta}^{-1}\left(\boldsymbol{\theta}^N\right)\boldsymbol{\Xi}\left(\boldsymbol{\theta}^N\right)^T}_{\textbf{MMSB}} \leq \underbrace{E_{\boldsymbol{\theta}_r;\theta}\left[\boldsymbol{\Xi}\left(\boldsymbol{\phi}^N\right)\mathbf{R}_{\boldsymbol{\upsilon}_\phi}^{-1}\left(\boldsymbol{\phi}^N\right)\boldsymbol{\Xi}\left(\boldsymbol{\phi}^N\right)^T\right]}_{\textbf{NSMSB}}.$$

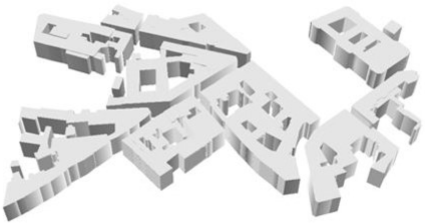
GNSS estimation accuracy depends on:

- **Dilution Of Precision (DOP):** The geometry between each satellite and the receiver.
  $\Rightarrow$ The DOP is a pure geometrical factor.
- **User Equivalent Range Error (UERE):** The satellite signal state and health (Presence of errors on measurements).
  - Satellite-based errors: satellite clock errors, orbits errors...
  - Propagation-based errors: ionospheric, tropospheric errors...
  - Receiver-based errors: multipath, receiver noise...

Position Error = DOP x UERE

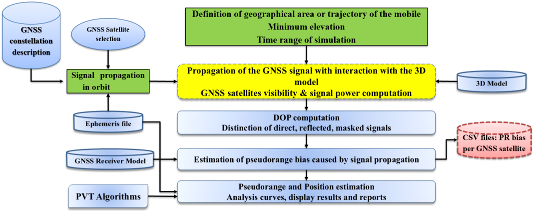
SPRING Architecture

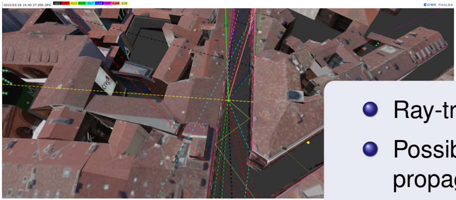




Toulouse 3D model provided by IGN: City model with roof structures and boundary surfaces.

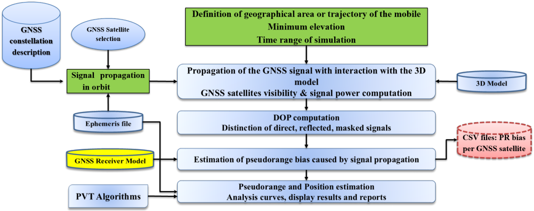
SPRING Architecture

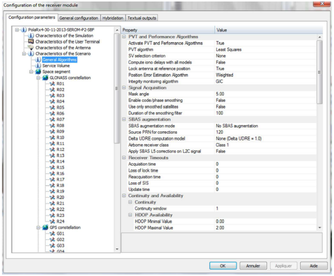




- Ray-tracing algorithm with a propagation model
- Possibility of selecting different propagation phenomena
- Reflection coefficients are set by users
- All building have the same materials

SPRING Architecture



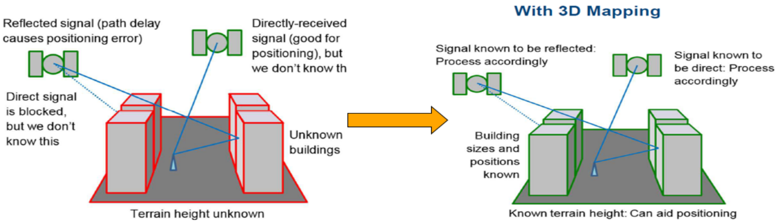


- Parameters of the Rx correlator are set by users
- Pseudorange error: error between input LOS pseudorange and computed pseudorange

Our use of SPRING

- **First step:** Configure SPRING parameters to give the most reliable approximation of GNSS signals propagation:
  - GNSS constellation configuration
  - 3D modelling configuration
  - GNSS propagation parameters
  - GNSS Rx parameters (signal acquisition and tracking)
- **Second step:** Study the reliability of SPRING simulations.
- **Third step:** Analyse the output 3D PR bias provided by SPRING simulation.

Shadow Matching SM-3D



[2]

Shadow Matching Principle

Use of masked and NLOS Satellite as additional information: Satellite visibility is a valuable information for positioning

[2] M. Adjrad and P. D. Groves, Intelligent Urban Positioning: 3D Mapping-Aided GNSS as Solution to the Urban Positioning Problem, GDR-ISIS Seminar, 27/10/2016, Toulouse

GNSS principles

- Multilateration method: find out the user position by knowing ranging to at least three known satellites in view (**Pseudoranges**).
- Additional measurement to solve synchronization between GNSS receiver clock and satellite clocks.

$\Rightarrow$ Four ranges (surface of spheres) of four satellites are needed: three for calculating the position in 3D and the fourth one for time synchronization.

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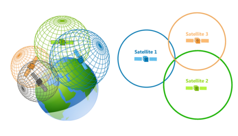


3D model Overview

3D city models

3D city models are digital representations of buildings and other objects presents in cities.

- More and more precise
- Widely available for most big cities
- Free of charge
- Different Levels of details

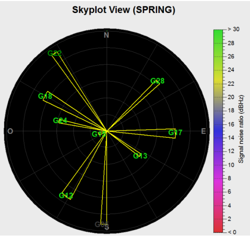
3D GNSS signal propagation Simulator

3D GNSS simulator = 3D city model + GNSS signal propagation + GNSS receiver model
$\rightarrow$ We have used the 3D GNSS signal propagation Simulator **SPRING (CNES)**

Experimental settings

General Experimental Setup

Environment: Urban area Toulouse, France
Date: 18/03/2015
Mode: Dynamic
GNSS Receiver: AsteRx3 Receiver
Recording Frequency: 10 Hz
Reference: SPAN NOVATEL(IMU-FSAS +RTK)



	GPS 22	GPS 12	GPS 28	GPS 24	GPS 13	GPS 15	GPS 18	GLO 08	GLO 09	GLO 11
Elevation (°)	5.9	21.4	26	47.2	52.4	82.2	26.3	62	35	25.5
$C/N0$ (dB-Hz)	35.5	33.5	27.7	46.2	42	47.7	35.2	34	24	28