Constructive Use of MP/NLOS Bias of GNSS Pseudoranges: Performance Analysis by Type of Environment

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ABSTRACT

The several progress of the free-accessible global navigation satellites system (GNSS) is not without major hurdles and challenges in it course of application in urban setting. Several error sources in these environments such as multipath and non-line-of-sight (NLOS) reception, signal masking and poor constellation geometry hinder the required positioning accuracy by GNSS signals. Facing this pressing need for performance enhancement in NLOS conditions, a new trend of approaches seek a constructive use of these degraded signals by correcting ranging measurements, using a 3D GNSS simulator for instance. However, this approach may engender a great risk of deteriorating PR measurements instead of correcting them if the compensation term is not accurate enough. Therefore, we propose in this paper to address the influence of PR bias estimation on the performances of this positioning method based on the correction of PR measurement. This original study permits us defining the maximum level of inaccuracy on bias estimation that any 3D GNSS simulator, or other tools, mustn't exceed. A detailed study on this most acceptable level of inaccuracy on the PR bias estimation is performed using real GNSS data in Toulouse and encompass analysis by type of environment (Urban, Peri-urban and rural environments) and by type of GNSS signals.

INTRODUCTION

Motivated by the exponential increase of global navigation satellites system (GNSS) applications in urban environments, along with the availability of affordable receiver chipsets, satellite navigation and timing is considered as the preferred localization solution for a plethora of fields such as transportation and location-based-service (LBS) [1]. In these conditions, performance reliability of GNSS is mandatory especially for applications having impacts on financial or safety-of-life aspects such as road user charging (RUC) [2]. Nevertheless, it is acknowledged that reliable GNSS positioning for land navigation is difficult to achieve in harsh setting such as urban environments or roads under heavy foliage canopy. In order to fill the gap between user requirements on one side and the existing technologies performances on the other side, recent attention tend to enhance positioning performances in terms of accuracy, robustness and integrity in urban settings. In fact, these local reception environment encompass many challenges leading to crucial effects on positioning performance, for instance signal blockage, multipath and non-line-of-sight (NLOS) receptions.

The presence of line-of-sight (LOS) blockage deteriorates the positioning accuracy for three reasons. First, it engenders very challenging technical issues for acquiring and tracking highly attenuated GNSS signals received from reflected paths. Hence, the continuity of position estimation cannot be ensured in tunnels, close to tall buildings and foliage which disrupt the GNSS navigation completely. Second, the interaction of the eventual received signal with the environment usually results in the reception of multipath (MP) signals. Besides, if the line of sight is blocked and the satellite signal is eventually received through a reflected non-line-of-sight path, the related pseudo-range (PR) measurement will be affected by an additional, positive and potentially unbounded bias. These combined NLOS and MP biases degrade the position estimation and result in more than tens of meters of position errors in some situations [3]. Third, blocked satellite signals engender an unfavorable constellation geometry that appears as an increased dilution of precision (DOP) which reduce the positioning quality. As these issues hinder GNSS usage in urban environments, effective and timely solutions are very much sought after.

GNSS BASED NAVIGATION IN URBAN ENVIRONMENT: STATE OF THE ART

In order to further expedite the usage of GNSS for land navigation applications, researchers and industrial engineers have shown an increased interest in dealing with the problem of NLOS. Broadly speaking, recent published studies on this field fall under three headings: LOS/NLOS distinction, NLOS elimination and NLOS constructive use. The former deals with the problem of identifying deteriorated NLOS range information among "clean" LOS signals. The literature on this category has highlighted several distinction criteria including using additional hardware for NLOS-LOS distinction, for instance dual polarization antenna [4], a GNSS antenna array and a sky-pointing camera [5]. Without using additional hardware, [6] argues for others simple indicators of NLOS reception such as elevation angle selection, C/N0-based NLOS detection and inter-satellite consistency checking [7]. Assuming that NLOS and LOS range estimates are perfectly distinguished, "unhealthy" measurement may be either discarded [8], down-weighted [9] or used constructively to enhance positioning performances [10-13]. The second category tends to reduce the adverse effect of NLOS errors on location estimation. A considerable amount of literature has been published on Multipath mitigation at the receiver level. Most efficient technics represent standard features of professional grade GNSS receivers, in particularly those based on narrow and double-delta correlators [24]. Other in-receiver MP mitigation methods include strobe correlator [24], the Multipath Estimating Delay Lock Loop (MEDLL) and Fast Iterative Maximum-Likelihood Algorithm (FILMA) [14]. However, these in-receiver techniques are not efficient in case of NLOS reception due to the absence of direct signal. A number of other scientific studies carried out on NLOS elimination at the level of post-receiver, using either robust estimation [15, 16], MP modeling or hybridizations.
To deal with the lack of GNSS signals redundancy, a new trend of techniques attempt to detect these degraded measurements and to use them constructively to enhance positioning performances [10, 13, 17]. In fact, in deep urban canyons characterized by reduced satellite visibility we would like to use constructively these NLOS observables trying to improve the measurements model by correcting the PR measurement via aiding information from a 3D city model combined with a 3D GNSS simulator for example as in [11], [13]. The basis of these approaches is to make use of 3D city models to score an array of candidate positions by comparison between the received observations at the receiver and ones of the information provided by the 3D model such as the sky visibility [18], the NLOS signal delay [19] and the PR measurements [20, 21]. Assuming that building layout is symmetric, which is predominantly present in down-towns of European cities, [22] combine a simplified 3D model of the environment, called urban trench, with a probabilistic method to enhance performances. In order to correct range measurements, we proposes in our approach [13] a range bias correction using bias bounds predicted from a 3D GNSS simulator SPRING [23]. This PR correction step is a sensitive task: poor PR biases prediction engenders an erroneous PR measurement correction and then may sensitively reduce the position estimation instead of enhancing it.
To date, the problem of the influence of NLOS correction on positioning performance has received scant attention in the research literature. The purpose of this paper is to explore the relationship between bias estimation accuracy and the performance of GNSS positioning by range bias correction. In fact, performances of PR measurements-based-correction method are strongly linked to the performances of PR bias estimation. One of the greatest challenges is that generally these biases are environment-dependent and highly time-varying and hence very difficult to be estimated. In this study, we use the 3D GNSS Simulator SPRING [23] to estimate these ranging errors. We distinguish between two kinds of 3D models: ones providing pure geometrical information on the building and street sizes [18] and others combined with 3D GNSS simulators and are more informative providing also simulated GNSS signals at any input position and time using Ray-Tracing techniques [23]. This second kind of cited 3D models are used jointly with a 3D GNSS simulator in order to characterize on-the-fly the measurements errors in urban environments. It is evident that the predicted bias and errors from the 3D propagation model cannot be instantaneous and certainly accurate. The quality and reliability of the PR bias estimation depend on how accurate is the signals propagation model, the 3D city modeling, receiver setting, etc... Therefore, we propose in this paper to address the influence of PR bias estimation on the performances of PR measurement-based-correction method.
In this paper, we seek to find conditions that must verify the PR bias estimation to lead to performances enhancement after range correction. These conditions define the most acceptable/allowed level of inaccuracy on bias estimation that any 3D GNSS simulator must verify

to allow performances improvement by PR measurements correction. First, we give the theoretical study and general formulas that should be verified by the PR bias estimation. Then, we test and confirm these conditions on real data collected in Toulouse (South-west of France) in a simplified case of one faulty ranging measurement. Also, a detailed study and analysis on the most acceptable level of inaccuracy on the PR bias estimation is performed by type of environment (Urban, Peri-urban and rural environments). An investigation on the level of the acceptable PR bias estimation error by satellite elevation and/or CN0 is also performed. The performances comparison to establish the acceptable inaccuracy conditions are defined via a comparison between the PR measurements-based-correction method and a conventional least-square solution. Although, others position estimators could be used. Finally, the performances of bias estimation by 3D simulation with SPRING will be evaluated compared to maximum allowed inaccuracy on bias estimation.

This paper is divided into five main sections. The first one presents the problem of GNSS positioning in urban environments. In the second section, we propose a review of the state of the art on the MP/NLOS problem. In the third section, we establish theoretical conditions that must be verified by PR bias estimation to ensure performances enhancement by range bias correction. The fourth section outlines experimental results of these conditions in different environments and using different signals. Finally, some conclusions are summarized in section 5.

THEORETICAL BIAS ESTIMATION BOUNDS FOR PR MEASUREMENT CORRECTION

GNSS user segment consist of GNSS devices or receivers allowing any user over the globe to receive and process the satellite signals to locate upon a common referential. This dedicated GNSS device process and estimate the time of arrival of signals along a direct line-of-sight (LOS) from at least four satellites. However, more often than not, the propagated GNSS signal is contaminated by additional MP/NLOS path caused by the replicas of the reflected satellite signals from the surfaces surrounding the receiver. Then, the following linearized measurement equation formulates the satellite positioning problem at each time step [24]:

$$\mathbf{y} = \mathbf{H_0}\mathbf{x} + \mathbf{b} + \mathbf{v} \tag{1}$$

Where, throughout this paper, the $M\times 1$ state vector $\mathbf{x} = \left[x, y, z, b_c\right]^{\mathrm{T}}$ contain the three coordinates of the user position (x, y, z) and the receiver clock bias b_c , which is common between all the received satellites. The estimated range measurements will be referred as the $N\times 1$ vector $\mathbf{y}$. $\mathbf{H_0}$ matrix contains the unit line-of-sight vectors between satellite and previous user position, $\mathbf{b}$ refer to the additional measurement bias caused by MP/NLOS receptions [*N*, 1] and is commonly called as PR bias. $\mathbf{v}$ is the measurement noise supposed to be a white Gaussian noise characterized by a covariance matrix $\mathbf{R} = E\left\{\mathbf{v}\mathbf{v}^{\mathrm{T}}\right\}$.

Since urban navigation MP/NLOS errors are usually unknowns, a possible estimation of the state vector is given by the Least Squares (LS) solution:

$$\hat{\mathbf{x}}_{LS} = \mathbf{H}_0^{+}\mathbf{y} \tag{2}$$

Throughout this paper, $\mathbf{H}_0^{+} = (\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}_0)^{-1}\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}$ refers to the pseudo-inverse of $\mathbf{H_0}$ weighted by matrix $\mathbf{R}$. In the case of uncorrelated noise and MP-NLOS bias, The MSE of the LS estimator is:

$$\begin{aligned}\mathbf{MSE}\left[\hat{\mathbf{x}}_{LS}\right] &= E\left[(\hat{\mathbf{x}}_{LS} - \mathbf{x})(\hat{\mathbf{x}}_{LS} - \mathbf{x})^{\mathrm{T}}\right] = \mathbf{H}_0^{+}E\left\{\mathbf{y}\mathbf{y}^{T}\right\}\left(\mathbf{H}_0^{+}\right)^{\mathrm{T}} \\ &= (\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}_0)^{-1} + \mathbf{H}_0^{+}E\left\{\mathbf{b}\mathbf{b}^{T}\right\}\left(\mathbf{H}_0^{+}\right)^{\mathrm{T}}\end{aligned} \tag{3}$$

The overall MSE of this estimator can be written as:

$$\begin{aligned}OMSE\left[\hat{\mathbf{x}}_{LS}\right] &= tr\left\{\mathbf{MSE}\left[\hat{\mathbf{x}}_{LS}\right]\right\} = tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}_0)^{-1}\right\} \\ &+ tr\left\{\mathbf{H}_0^{+}E\left\{\mathbf{b}\mathbf{b}^{T}\right\}\left(\mathbf{H}_0^{+}\right)^{\mathrm{T}}\right\} > OMSE\left[\hat{\mathbf{x}}_{ML}\right] = tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}_0)^{-1}\right\}\end{aligned} \tag{4}$$

Where $\hat{\mathbf{x}}_{ML} = \mathbf{H}_0^{+}(\mathbf{y} - \mathbf{b})$ refers to the maximum likelihood estimate. This previous inequality illustrates the effect of MP-NLOS biases on the final positioning.

We suppose that we can obtain an estimation of the PR bias, using an external information source such as 3D GNSS simulator for instance. This estimation is referred to as $\mathbf{c}$. Also, we suppose that we build a new weighting matrix $\mathbf{R}_b$ based on this predicted PR bias $\mathbf{c}$.

The final solution of problem (1) with measurements correction would be then a corrected least squares (CLS) using the estimation of the PR bias $\mathbf{c}$ and is expressed as:

$$\hat{\mathbf{x}}_{CLS} = \mathbf{H}_b^{+}\mathbf{y}_c = \mathbf{H}_b^{+}(\mathbf{y} - \mathbf{c}) \tag{5}$$

Where $\mathbf{y}_c = \mathbf{y} - \mathbf{c}$ are the corrected PR measurements and $\mathbf{H}_b^{+} = (\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1}\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}$ is the pseudo-inverse of $\mathbf{H}_0$ weighted by matrix $\mathbf{R}_b$, that might be different from $\mathbf{R}$. The error of this estimation is given by:

$$\delta\mathbf{x}_{CLS} = \hat{\mathbf{x}}_{CLS} - \mathbf{x} = \mathbf{H}_b^{+}(\mathbf{b} + \mathbf{v} - \mathbf{c}) \tag{6}$$

If we note $\delta\mathbf{b} = \mathbf{b} - \mathbf{c}$ the error in the PR bias prediction, the accuracy of the CLS estimator is characterized by the Mean Square Error (MSE) expressed as:

$$\begin{aligned}\mathbf{MSE}\left[\hat{\mathbf{x}}_{CLS}\right] &= \mathbf{H}_b^{+}E\left\{\mathbf{y}_c\mathbf{y}_c^{T}\right\}\left(\mathbf{H}_b^{+}\right)^{T} \\ &= (\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1} + \mathbf{H}_b^{+}E\left\{(\delta\mathbf{b})(\delta\mathbf{b})^{T}\right\}\left(\mathbf{H}_b^{+}\right)^{T}\end{aligned} \tag{7}$$

Then, the overall MSE of the CLS estimator can be written as:

$$OMSE\left[\hat{\mathbf{x}}_{CLS}\right] = tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1}\right\} + tr\left\{\mathbf{H}_b^{+}E\left\{(\delta\mathbf{b})(\delta\mathbf{b})^{T}\right\}\left(\mathbf{H}_b^{+}\right)^{T}\right\} \tag{8}$$

Because the weighting matrix $\mathbf{R}_b$ is generally an augmented matrix version of $\mathbf{R}$ and because of the presence of the PR bias prediction error $\delta\mathbf{b}$, this yields the following inequality:

$$OMSE\left[\hat{\mathbf{x}}_{CLS}\right] \geq OMSE\left[\hat{\mathbf{x}}_{ML}\right] = tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}_0)^{-1}\right\} \tag{9}$$

This means that the conventional LS estimator doesn't reach the optimal MSE while the proposed CLS estimator does under the condition of low bias prediction error $\delta\mathbf{b}$. But, the accuracy of the CLS algorithm depends heavily on the PR bias estimation used to correct the PR measurements. Hence, a good estimated PR bias that enhances performance compared to conventional methods must follow as much as possible the true bias as expressed in (8).

Hence, the fundamental question to be addressed is: how much accurate the PR bias estimation, by a 3D simulator or others tools, should be to ensure that the proposed CLS algorithm give better results in term of accuracy than the conventional LS. The following analysis is valid for any source of NLOS bias estimation and prediction, including multisensory navigation, crowd sourced navigation and data base-based errors correction.

This amounts to find the maximum acceptable level of uncertainty on the PR bias prediction required to obtain a performance enhancement compared to conventional positioning algorithms such as the conventional least squares. The maximum acceptable level of inaccuracy in PR bias prediction to achieve better performance by measurements correction compared to conventional LS is defined by using the overall MSE of the estimator as:

$$OMSE[\hat{\mathbf{x}}_{CLS}] = tr\{MSE[\hat{\mathbf{x}}_{CLS}]\} \leq OMSE[\hat{\mathbf{x}}_{LS}] = tr\{MSE[\hat{\mathbf{x}}_{LS}]\}$$

In case of uncorrelated MP-NLOS biases, this relation leads to:

$$\begin{aligned} & tr\left\{\mathbf{H}_b^+ E\{(\delta\mathbf{b})(\delta\mathbf{b})^T\}(\mathbf{H}_b^+)^T\right\} \leq tr\left\{\mathbf{H}_0^+ E\{\mathbf{b}\mathbf{b}^T\}(\mathbf{H}_0^+)^{\mathrm{T}}\right\} - \beta_b \\ & \Rightarrow \sum_k \left[\sum_i \left[(\mathbf{H}_b^+)_{k,i}\right]^2 \left(E[\delta\mathbf{b}\delta\mathbf{b}^T]\right)_i\right] \leq \sum_k \left[\sum_i \left[(\mathbf{H}_0^+)_{k,i}\right]^2 \left(E[\mathbf{b}\mathbf{b}^T]\right)_i\right] - \beta_b \end{aligned} \quad (10)$$

Where $\beta_b = tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1}\right\} - tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}_0)^{-1}\right\}$. In the case of only one faulty measurement in the ranging measurement from satellite j, condition (10) became:

$$\begin{aligned} & \sum_k \left[(\mathbf{H}_b^+)_{k,j}\right]^2 \left(E[\delta\mathbf{b}\delta\mathbf{b}^T]\right)_j \leq \sum_k \left[(\mathbf{H}_0^+)_{k,j}\right]^2 \left(E[\mathbf{b}\mathbf{b}^T]\right)_j - \beta_b \\ & \Rightarrow \left(E[\delta\mathbf{b}\delta\mathbf{b}^T]\right)_j \leq \frac{\sum_k \left[(\mathbf{H}_0^+)_{k,j}\right]^2}{\sum_k \left[(\mathbf{H}_b^+)_{k,j}\right]^2} \left(E[\mathbf{b}\mathbf{b}^T]\right)_j - \frac{\beta_b}{\sum_k \left[(\mathbf{H}_b^+)_{k,j}\right]^2} \end{aligned} \quad (11)$$

From last condition, if we define the dumping coefficient $\varepsilon_j = \sum_k \left[(\mathbf{H}_0^+)_{k,j}\right]^2 \Big/ \sum_k \left[(\mathbf{H}_b^+)_{k,j}\right]^2$, then we can express condition (11): $\left(E[\delta\mathbf{b}\delta\mathbf{b}^T]\right)_j < \varepsilon_j \left(E[\mathbf{b}\mathbf{b}^T]\right)_j - \left(\beta_b \Big/ \sum_k \left[(\mathbf{H}_b^+)_{k,j}\right]^2\right)$.

This dumping coefficient appears because we have augmented the noise covariance matrix using the bias prediction as explained in (6).

If we haven't use this augmentation, then the dumping coefficient will be equal to 1 and $\beta_b = 0$. Thus, the condition (11) became $\left(E[\delta\mathbf{b}\delta\mathbf{b}^T]\right)_j < \left(E[\mathbf{b}\mathbf{b}^T]\right)_j$. This condition means that the bias bound prediction error must have a lower variation than the true unknown PR bias variation to obtain better performance by correcting the PR measurement. The dumping coefficient allows widening the admissible region of bias estimation inaccuracy since it is higher than 1, in general.

The condition (10) is a general condition that any positioning algorithm based on the PR measurements correction must verify to ensure decreasing estimation errors than conventional least squares algorithm without PR measurement correction. This condition defines the maximum acceptable level of uncertainty on the PR bias prediction in term of accuracy.

EXPERIMENTAL BIAS ESTIMATION BOUNDS BY TYPE OF ENVIRONMENT

To evaluate experimentally the bias estimation bounds, a dynamic positioning test was conducted in Toulouse (South-West of France). GPS L1 C/A code PR measurements were recorded along different environments in Toulouse using an AsteRx3 SEPTENTRIO receiver, at a rate of 10 Hz, and a SPAN Novatel system including a DGPS receiver tightly integrated with an IMU-FSAS (from iMAR). The trajectory provided by the Novatel system is considered as the reference trajectory in this analysis section. Fig. 1 shows an image of the test environment.

Fig. 1. Dynamic test in Toulouse. White line indicate the reference trajectory.

The following table summarizes the set of received signals during this measurement campaign:

TABLE I. RECEIVED SIGNALS IN THE URBAN SECTION

	PRN 22	PRN 12	PRN 28	PRN 24	PRN 13	PRN 15
Elevation (°)	5.93	21.47	26.06	47.23	52.47	82.29
C/N$_0$ (dB-Hz)	35.5	33.5	27.75	46.25	42	47.75
Mean bias (m)	6.69	6.48	3.57	0.24	3.07	0
Maxi bias (m)	33.29	15.95	23.98	6.51	11.56	0

A. Experimental Computation of Maximum Acceptable Uncertainty on Bias Estimation

In this sub-section, we aim to verify the condition (11) using real data collected in Toulouse. First, we consider the case of only one faulty measurement in the ranging measurement obtained from satellite j. To do that, we correct for all PR measurement using the bias estimation algorithm proposed in [25], expect for PR measurement from satellite j. Then, we model the bias prediction error of the measurement from this satellite $(\delta\mathbf{b})_j$ follows a Gaussian distribution $(\delta\mathbf{b})_j \sim N(\mu,\sigma)$. Finally, we compute the values of mean and variance (μ,σ) of the considered Gaussian distribution $N(\mu,\sigma)$ verifying: $OMSE[\hat{\mathbf{x}}_{CLS}] = OMSE[\hat{\mathbf{x}}_{LS}]$. The OMSE is function of the bias prediction errors as:

$$\begin{aligned} OMSE(\mu,\sigma) &= tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1}\right\} + \left(E\left[\delta\mathbf{b}\delta\mathbf{b}^T\right]\right)_j \sum_i \left[\left(\mathbf{H}_b^{+}\right)_{i,j}\right]^2 \\ &= tr\left\{(\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1}\right\} + \sum_i \left[\left(\mathbf{H}_b^{+}\right)_{i,j}\right]^2 \left(\sigma + \mu^2\right) \end{aligned} \quad (12)$$

It can be easily verified that if the error in the bias prediction $(\delta\mathbf{b})_j$ increase, i.e. μ and σ are high, $OMSE(\mu,\sigma)$ increase, hence the accuracy decrease.

In this particular case, the condition defining the acceptable bias prediction error can be written as the following:

$$\left(\sigma + \mu^2\right) < \varepsilon_j \left(E\left[\mathbf{b}\mathbf{b}^T\right]\right)_j - \beta_b \Big/ \sum_k \left[\left(\mathbf{H}_b^{+}\right)_{k,j}\right]^2 \quad (13)$$

In case of equal augmentation matrix $\mathbf{R}_b = \mathbf{R}$, i.e. $\varepsilon_j = 1$ and $\beta_b = 0$, the value $\left(E\left[\delta\mathbf{b}\delta\mathbf{b}^T\right]\right)_j^{Exp} = \left(\sigma + \mu^2\right)$ verifying $OMSE(\mu,\sigma) = OMSE[\hat{\mathbf{x}}_{LS}]$ is considered as the experimental maximum acceptable level of uncertainty on the PR bias prediction for satellite j required to obtain a performance enhancement compared to conventional least squares. This value can be computed by varying the couple (μ,σ) using a grid of simulation points until reaching the condition $OMSE(\mu,\sigma) = OMSE[\hat{\mathbf{x}}_{LS}]$.

The value $\left(E\left[\delta\mathbf{b}\delta\mathbf{b}^T\right]\right)_j^{Theo} = \left(E\left[\mathbf{b}\mathbf{b}^T\right]\right)_j$ is considered as the corresponding theoretical maximum acceptable level of uncertainty on the bias prediction for satellite j required to achieve better performance compared to conventional least squares. To sum up, the two defined experimental and theoretical maximum acceptable level of uncertainty on the bias prediction for satellite j are:

$$\begin{cases} \left(E\left[\delta\mathbf{b}\delta\mathbf{b}^T\right]\right)_j^{Exp} = \left(\sigma + \mu^2\right) & s.t\ OMSE(\mu,\sigma) = OMSE\left[\hat{\mathbf{x}}_{LS}\right] \\ \left(E\left[\delta\mathbf{b}\delta\mathbf{b}^T\right]\right)_j^{Theo} = \left(E\left[\mathbf{b}\mathbf{b}^T\right]\right)_j & \end{cases}$$

These two experimental and theoretical values will be compared using real GNSS data in the following sub-sections.

B. Maximum Acceptable Uncertainty on Bias Estimation in Urban Areas by Elevation Angles

In this sub-section, we will evaluate theoretical and experimental maximum acceptable uncertainty levels for different range bias in an urban environment characterized by narrow streets and tall buildings. We analyze these maximum acceptable uncertainty levels following the elevation angles of different satellite. In general, the higher is the elevation angle, the less likely the signal is to be blocked or reflected by a building. Hence, the maximum acceptable uncertainty level should decreases when the elevation angle increases. Fig. 2 gives the variation of this theoretical and experimental maximum acceptable uncertainty level versus satellite elevation angle in an urban environment.

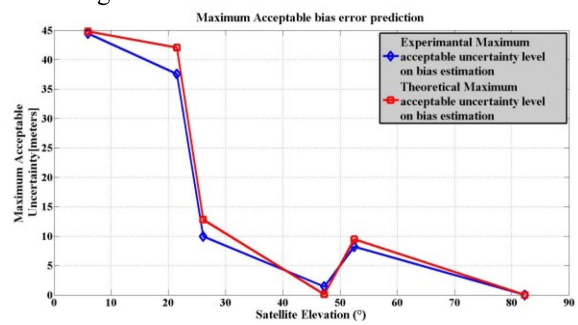


Fig. 2. Experimental and theoretical maximum acceptable bias estimation uncertainty in urban environment.

If we take into account the limitation due to the number of grid point used in simulation, we note that experimental and theoretical maximum acceptable bias estimation uncertainty are close. This study allow to identify PR measurements that are very difficult to be corrected, those of good quality, and hence those who should not be estimated using the 3D GNSS simulator. In this case these signals are usually those having very high satellite elevation.

Satellite elevation is not an absolute criterion for signal quality in urban environment. In fact, the configuration of the urban environment may induce that high elevation signals still be reflected or received in NLOS situation if there is a tall building nearby. But, in general, we observe that Fig. 2 shows the expected behavior of maximum acceptable bias estimation uncertainty towards satellite elevations, especially for low elevation satellites.

C. Maximum Acceptable Uncertainty on Bias Estimation in Urban Areas by C/N0 ratios

In this sub-section, we will evaluate theoretical and experimental maximum acceptable uncertainty levels for different range bias in an urban environment. We analyze these maximum acceptable uncertainty levels following the elevation angles of different satellite. In general, C/N0 ratio is a good indicator for satellite signal quality since reflected signals are usually attenuated. Hence, the maximum acceptable uncertainty level should decreases when the C/N0 ratio increases. Fig. 3 gives the variation of this theoretical and experimental maximum acceptable uncertainty level versus satellite C/N0 ratio in the considered urban environment.

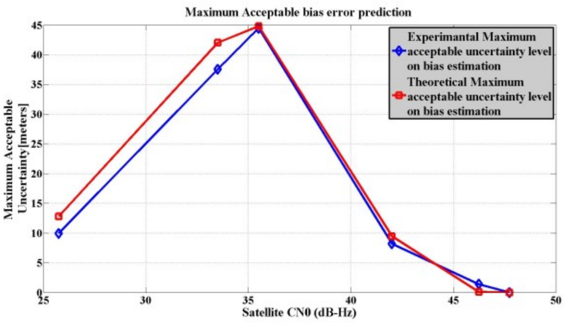


Fig. 3. Experimental and theoretical maximum acceptable bias estimation uncertainty in urban environment.

Making decision on the signal quality in urban environment using only C/N0 ratio is very difficult. In fact, smooth reflecting surfaces, for instance wet surface, may increase the power of reflected signals making them as strong as direct signal. Besides, satellite signal power depends on the antenna gain pattern and on the phase of the received signal. Generally speaking, we note that we have almost the predicted variation for high C/N0 signals. Also, the experimental and theoretical maximum acceptable bias estimation uncertainty are close, if we take into account the limitation due to the consequent number of grid point in simulation. This study allow to identify PR measurements that are very difficult to be corrected, those of good quality, and hence those who should not be estimated using the 3D GNSS simulator. In this case, these signals are usually those having very high C/N0 ratios.

D. Maximum Acceptable Uncertainty on Bias Estimation by Environment

In this sub-section, we will evaluate theoretical and experimental maximum acceptable uncertainty levels for different range bias in different environment. We analyze these maximum acceptable uncertainty levels in an urban, peri-urban and an open-sky environment. Since GNSS signals are usually of good quality in open-sky environments, maximum acceptable uncertainty levels on bias estimation should be lower than those in urban environments. Fig. 3 gives the experimental maximum acceptable uncertainty level on bias estimation for two satellites in these environments.

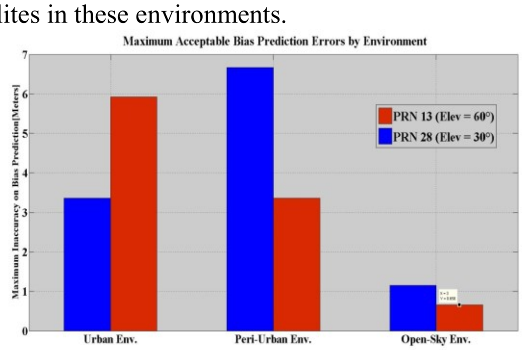


Fig. 4. Experimental maximum acceptable bias estimation uncertainty in different environments for two GNSS satellites.

It can be seen from the previous figure that GNSS signals are of good quality, hence are hard to be corrected, which explain the low value of the maximum acceptable bias estimation uncertainties in this kind of environment. However, the problem of satellite signal degradation is much more prominent in urban and peri-urban setting as oppose to rural environments. This explains the fact that the maximum acceptable bias estimation uncertainties are higher in these environments. Then, it is interesting to use 3D GNSS simulator to correct PR measurement in these kinds of environments with high theoretical acceptable inaccuracy on bias estimation. However, in open sky environments with a small theoretical acceptable inaccuracy on bias estimation, 3D GNSS simulator should not be used since there is a great risk of deteriorating PR measurements by modifying them.

E. Bias Estimation Using 3D GNSS Simulator SPRING

In this sub-section, we compare the bias estimation using the 3D GNSS simulator SPRING [23] with theoretical and experimental maximum acceptable uncertainty levels on bias estimation in an urban environment. This comparison allows concluding if the use of the 3D GNSS simulator for range bias correction in this environment will enhance positioning performance or not. Fig. 4 gives the variation of experimental maximum acceptable uncertainty level on bias estimation and bias estimation performance using SPRING versus satellite elevation angle in an urban environment.

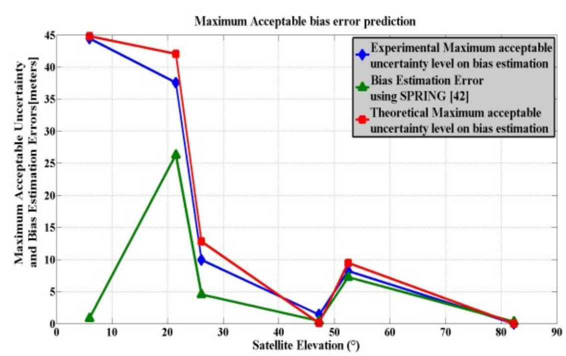


Fig. 5. Experimental maximum acceptable bias estimation uncertainty and bias estimation error using SPRING [23].

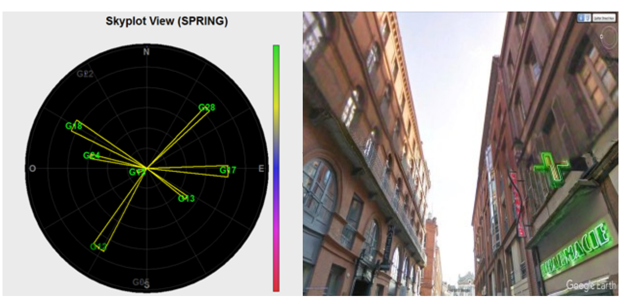
These result show that the level of bias estimation uncertainty using the simulator SPRING [23] is under the maximum allowed level in this case of environment. Hence, the level of accuracy on bias estimation of this simulator allows bias range correction and performance enhancement in these kind of harsh environment.

This study allows defining metric requirements on NLOS bias estimation by 3D GNSS simulation permitting the Classification of different 3D GNSS simulators.

Taken into account that the 3D simulator SPRING is under permanent improvement and evolution by CNES, these results show the usefulness and the potential of these tools for positioning enhancement in presence of MP/NLOS biases.

F. Positioning in urban environment using Bias Correction via the 3D GNSS Simulator SPRING

In this sub-section, we use the 3D simulator SPRING for ranging measurement correction in a deep-urban environment. As shown in the last sub-section, bias estimation uncertainty using the 3D GNSS simulator SPRING is under the maximum allowed level in this case of environment. For bias estimation, a grid of 30 array positions is considered at each time step and the bias is considered as the mean of the obtained biases in each input point as explained in [13]. A 3 min trajectory along a deep urban environment is selected. This is a relatively short data of 1800 samples but without loss of generality of the comparison. This is only a limitation from the computational resources on the simulator computer. Actually, the simulator has to generate signals from all available satellites (i.e. performing ray-tracing interaction with 3D model for each point among the 30 array position considered in this scenario). A street view on this urban section and a sky plot is provided in the following figure:



(a) (b)

Fig. 6. 6(a) Sky-plot of GPS satellites in the deep urban section (a mask elevation of 10° is applied); 6(b) a street and a sky view of the considered trajectory.

The algorithm in [13] is based on bias bounds obtained using these array positions at each time step. Performing bias prediction using 3D GNSS simulator on these input positions, we bound the MP-NLOS bias, i.e. we obtain the following inequality for each time step and for each received PR signal:

$$(\mathbf{l})_n \leq (\mathbf{b})_n \leq (\mathbf{u})_n \text{ , } \forall n = 1, 2, \ldots, N$$

Where $\mathbf{l}$ refers to the lower bound of the PR bias over the considered 30 array positions and $\mathbf{u}$ is the upper bound of the PR bias over these array positions.

We assume that the bias is Gaussian distributed between these two bounds. As the measurement noise and the MP-NLOS bias are independent, the total noise $\mathbf{b}+\mathbf{v}$ have a non-zero Gaussian distribution with a covariance matrix equal to:

$$\mathbf{R}_b = \mathbf{R} + diag\left\{\left[(u_n - l_n)/6\right]^2\right\}_{n=1,\ldots,N}$$

We perform PR measurement correction by subtracting the mean value of the total noise distribution $(\mathbf{u}+\mathbf{l})/2$ from the PR measurement vector when estimating the state vector. Hence, we obtained a new corrected LS estimation with an augmented covariance matrix and PR measurements correction using PR bias bounds:

$$\begin{aligned}\hat{\mathbf{x}}_{CLS} &= \arg\min_{\mathbf{x}} \left\|\mathbf{y} - (\mathbf{u}+\mathbf{l})/2 - \mathbf{H}_0\mathbf{x}\right\|^2_{\mathbf{R}_b^{-1}} \\ &= (\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\mathbf{H}_0)^{-1}\mathbf{H}_0^{\mathrm{T}}\mathbf{R}_b^{-1}\left(\mathbf{y} - (\mathbf{u}+\mathbf{l})/2\right)\end{aligned}$$

The original study presented in the third section permits to identify environments where it is interesting to use a 3D GNSS simulator for estimating the bias PR and NLOS correction. Hence, it allow to create a map of environments where is interesting to use a bias correction by 3D simulation, or other tools. These maps will be called “Maps of PR bias Correction Availability”.

Therefore, we can consider three different types of environment depending on this information on bias correction availability: the first kind of environment is typically the rural environment characterized by a good redundancy, i.e. high number of available signals in the order of 7 GNSS satellites, and a low percentage of degraded signals. Generally in this first kind of environment, the percentage of deteriorated PR measurements is less than 50%. As shown in the sub-section D, PR measurement correction is hard to be performed in this environment. Hence, in this type of environment, bias estimation using SPRING simulation is not necessary and we propose to use a robust Kalman estimation as in [16].

The second type of environments is those characterized with constrained signal availability, generally in the order of 4 to 6 satellites. However, the environment geometry doesn’t deteriorate all the received signals. A percentage between 50% and 70% of these received signals are probably received in MP and NLOS situations. This is typically the case of peri-urban environments. In such situation, a signal correction using 3D bias estimation is necessary but must be performed only on medium to low-elevation satellite as shown in Fig. 4.

The last type of environments is typically the urban environment. This constrained environment is characterized with a low signal availability combined with a very high percentage of degraded signals, generally more than 70%. In this kind of environment, even high elevation satellite can be degraded as shown in Fig. 2 for SV13. We propose to use constructively signal degradation by PR measurement correction method described above (CLS) in this kind of harsh environment.

The proposed intelligent positioning algorithm depending on the type of environment is shown in Fig. 7.

The environment checking test T0 is performed using the “Maps of PR bias Correction Availability” and the initial conventional position computed using a conventional EKF for instance: using this position and the “Maps of PR bias Correction Availability” we decide if it is useful to use a PR measurement correction or not. C/N0 threshold on data checking test T1 can be set to 40 dB-Hz. Elevation angle threshold on data checking test T2 can be set to 60°.

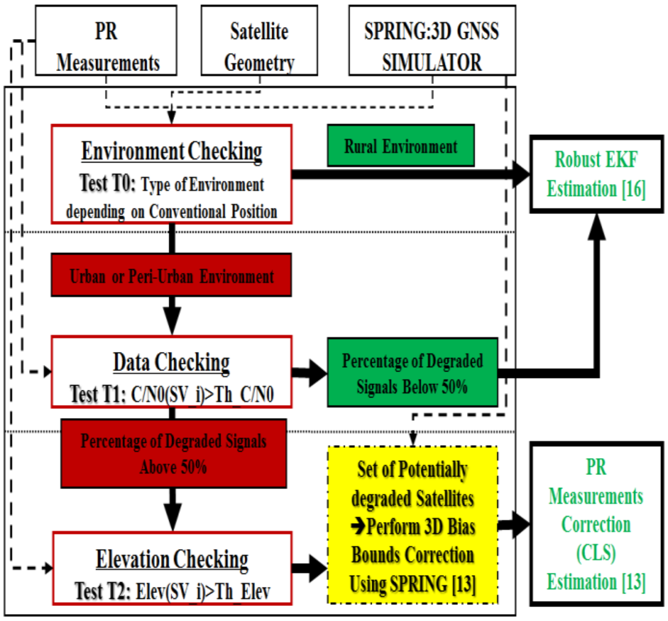


Fig. 7. Positioning Algorithm depending on the environment ("Maps of PR bias Correction Availability")

To assess the positioning performance of this positioning algorithm, we compare the conventional LS estimator, a robust version of the LS estimator using [16] and a LS with bias correction [13]. The cumulative distribution function is shown in Fig. 8.

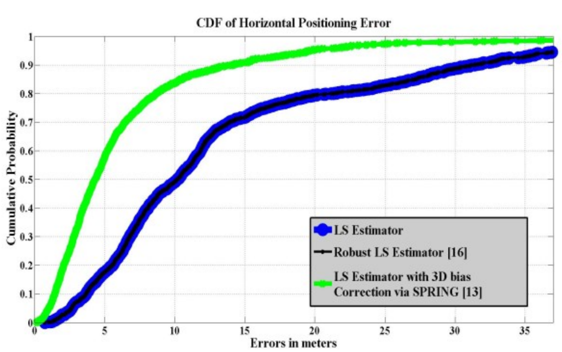


Fig. 8. CDF of horizontal Positioning in deep urban environment using bias correction via 3D GNSS Simulator.

According to Fig. 8, it apparent that ranging measurement correction using the 3D Simulator SPRING gives better positioning performance compared to the conventional stand-alone LS. By measurements correction using SPRING, the CLS achieve less than 10 meters of positioning errors in 85% of case, against 27 meters for robust Least-Squares.

The robust LS estimator have almost the same performance as the conventional LS since in this kind of harsh environment it is difficult to distinguish between healthy and corrupted signals which represents the limitation of such robust approaches. In fact, robust estimation methods are able to detect blunder measurements if there are less than 50% of unhealthy measurements, which is not the case in deep urban canyons.

CONCLUSIONS

In this paper, we are addressing the question of the merit of integrating a 3D simulator in the GNSS solution. This study allows defining the maximum level of inaccuracy on bias estimation that any 3D GNSS simulator mustn't exceed. It permits also to find the areas where a PR measurement correction is not interesting or difficult obtain; i.e. when bias correction will probably engender more performance degradation than enhancement. It can be also used to find PR measurements that are very difficult to be corrected (since they are already of good quality: generally satellites with high elevation and/or high C/N0).

In this study, we push forward our previous study on degraded PR measurements correction using a 3D GNSS simulator by defining the theoretical level of maximum acceptable inaccuracy on bias estimation. Extensive measurement campaign may be conducted to produce a map of bias correction in the city by producing a map of PR bias correction availability for each zone of the traveled trajectory. In environments where we have a high theoretical acceptable inaccuracy, 3D GNSS simulator can be used for PR measurements correction. If we are travelling across an environment with a small theoretical acceptable inaccuracy, 3D GNSS simulator should not be used to correct PR measurements, because there is a great risk of deteriorating PR measurements instead of correcting them.

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