Prediction of GNSS Signal Bias Using a 3D Model in Urban Environments

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***Abstract* – In this paper, we address the problem of characterization of the GNSS pseudorange error in urban canyons. The goal of this work is to study the reliability of predicting the observation bias with a 3D GNSS simulation model. Comparison between simulated and real pseudorange bias allows the evaluation of the realism of the simulation model. We use the 3D multipath simulations into a mathematical reconstruction of the correlation function to estimate the bias at the output of the code tracking step, which provides an estimation of pseudorange error.**

The characteristics of the used 3D software, the collected real data and the comparison results are presented. We finish the paper by discussing different possibilities of integrating this kind of 3D city model inside the receiver processing.

BIOGRAPHIES

Aude Bourdeau received an engineer degree in mathematics and numerical modelling from INSA Toulouse in 2010. Since October 2010, she is preparing PhD at the French Institute of Aeronautics and Space (ISAE). Her research interest includes signal processing, GNSS navigation in challenging environment and GNSS signal tracking.

Mohamed Sahmoudi received a PhD in signal processing and communications from Paris Sud University and Telecom Paris in 2004, and an M. S. degree in statistics from Pierre and Marie Curie University in 2000. During his PhD, he was an assistant lecturer at Ecole Polytechnique, then a lecturer at Paris Dauphine University. From 2005 to 2007, he was a post-doc researcher on GPS signal processing at Villanova University, PA, USA. In august 2007, he joined the ETS School of Engineering at Montreal, Canada, to work on GNSS RTK for precise positioning. In december 2009, he became an associate professor at the French Institute of Aeronautics and Space (ISAE), Toulouse, France. His research interest includes weak multi-GNSS signals processing, multipath mitigation and multi-sensor fusion.

Jean-Yves Tourneret (SM'08) received the Ingénieur degree in electrical engineering from the ENSEEIHT (Ecole Nationale Supérieure d'Electronique, d'Electrotechnique, d'Informatique, d'Hydraulique, et des Télécommunications de Toulouse), France, in 1989 and the Ph.D. degree from the National Polytechnic Institute, Toulouse, France, in 1992. He is currently a Professor in the University of Toulouse (ENSEEIHT), France, and a member of the IRIT laboratory (UMR5505 of the CNRS). His research activities are centered around statistical signal processing, with a particular interest to Bayesian and Markov chain Monte Carlo methods. Dr. Tourneret has been involved in the organization of several conferences, including the European Conference on Signal Processing (EUSIPCO) in 2002 (as the program chair), the International Conference on Acoustics, Speech and Signal Processing (ICASSP) in 2006 (in charge of plenaries) and the Statistical Signal Processing Workshop (SSP) in 2012 (for international liaisons). He has been a member of different technical committees, including the Signal Processing Theory and Methods (SPTM) Committee of the IEEE Signal Processing Society from 2001 to 2007 and from 2010 to present. He served as an Associate Editor for the IEEE TRANSACTIONS ON SIGNAL PROCESSING from 2008 to 2011.

I. INTRODUCTION

The number of global navigation satellite system (GNSS) applications has steadily increased over the last decades, in particular for personal mobility (e.g., GNSS-enabled mobile phones, smartphones and services). Intelligent systems of transportation are also an important segment of the GNSS market including in-car navigation and road user charging. However, the urban environment presents significant challenges for satellite positioning.

GNSS positioning is based on the trilateration principle. This means that the main information needed are the geometrical distances between the receiver and the satellites. These distances are calculated from the time of flight of the signals emitted by the satellites. However the measurement of the time of flight can be inconsistent with the real geometrical distance for several reasons [1], [2]. In urban environment, two reasons are predominant. On the one hand, multipath signals, which are added to the line-of-sight (LOS) signal but have a time of flight longer because of reflexion or diffraction, can disturb the measurement. On the other hand, LOS signal may be blocked by an obstacle, and the receiver measures only non-line-of-sight (NLOS) signal. This NLOS signal has been reflected or diffracted on some surface/edge and so travelled a distance longer than the direct path between satellite and receiver antenna.

In order to deal with the NLOS and the LOS measurements highly affected by multipath, a first category of solutions consists in rejecting bad measurements [3]. This is a good solution when available measurements are redundant, but it is not applicable with too few signals because the receiver needs at least four measurements to compute a position.

Another kind of solutions tries to compute the actual distance between satellite and receiver. Two different approaches can be adopted for this purpose. The first one consists in using a measurement process which is not disturbed by multipath. The second one estimates the bias due to multipath in order to compensate their effects in the measurement processing. The first approach is the most currently used, as it needs no external information and uses robust algorithms of signal processing for position computation. Examples of efficient in-receiver multipath mitigation methods include the narrow correlator, the strobe correlator, the multipath estimating delay lock loop, the multipath elimination technology, the vision correlator and the fast iterative maximum-likelihood algorithm (see [1], [4] and [5] for more details). However, these solutions can be applied only if the LOS signal is present. Since our main interest is focused on exploiting also NLOS signals, we investigate the second approach.

To estimate the bias of a NLOS measurement, a stand-alone GNSS receiver may be not sufficient. The difficulty consists in modelling the length of the indirect paths. In [6], a geometric path model is used whose parameters are estimated by a nonlinear filter. In [7], multipath parameters are calculated using environment information obtained from a laser scanner. In [8] and [9], we have proposed a new navigation strategy based on the augmentation of GNSS measurements by a 3D model of the environment. This approach is also used in [10], with a comparison to a statistical model-based method. Using a 3D simulator of GNSS reception is well adapted for the bias estimation of NLOS measurements, but can also be applied for the estimation of the bias due to multipath in the LOS measurements. However, before using 3D estimations in a GNSS navigation algorithm, we have to check if the 3D simulations are realistic and provide information with enough accuracy. This issue is the main focus of this paper, in which we show the valuable use of the 3D model as priori information to characterize the additional multipath bias. In this study, we use the SE-NAV simulator provided by a French company [11].

The paper is organized as follows. In section II, first the mathematical reconstruction of multipath effects on the pseudorange measurements is presented. Then the characteristics of the 3D simulator software SE-NAV [11] are given. Section III deals with the comparisons between real and simulated pseudorange errors and presents experimental results. Finally, section IV concludes about the realism of SE-NAV simulations and about potential future applications for improving accuracy and integrity of the GNSS positioning in NLOS and multipath environments.

II. Modelling GNSS Signals with a 3D Model of the Environment

A. Mathematical modelling of GNSS measurements

Pseudorange measured by the receiver can be expressed as

$$\rho_m = \rho_{strong} + b_{MP} + n \qquad (1)$$

where ρ_{strong} denotes the distance travelled by the strongest signal received (SSR), b_{MP} is the bias due to the effects of all other signal replicas and n is the additive error due to thermal noise and other non-modelled noise sources. In the LOS case, ρ_{strong} is the geometrical distance between the receiver and the satellite. In the NLOS case, ρ_{strong} is the distance travelled by the strongest multipath reaching the receiver as this will be the signal tracked by the receiver. In this case, we can write

$$\rho_{strong} = \rho_{direct} + \rho_{NLOS} \qquad (2)$$

where ρ_{direct} is the geometrical distance between the receiver and the satellite, and ρ_{NLOS} is the extra distance travelled by the SSR. To estimate ρ_{NLOS} with a 3D simulator software, we need to know which multipath is the ray with maximum power and what is its length. The power information is only used to discriminate the different simulated multipath signals. The additional distance ρ_{NLOS} can then be deduced by subtracting ρ_{direct} from ρ_{strong} provided by SE-NAV.

The determination of b_{MP} requires both geometrical information and signal amplitudes. Indeed, an acceptable approximation of the correlation function in presence of multipath [12] is expressed as

$$C(\tau) = R(\tau) + \sum_{i=1}^{m} \alpha_i R(\tau - \delta\tau_i), \qquad (3)$$

where $R(\tau)$ is the correlation function of the SSR, τ is the delay between the SSR code and the local replica code, m is number of multipath signals, α_i is the amplitude of the i^{th} multipath relative to the SSR amplitude, and τ-$\delta\tau_i$ is the delay between the i^{th} multipath code and the local replica code.

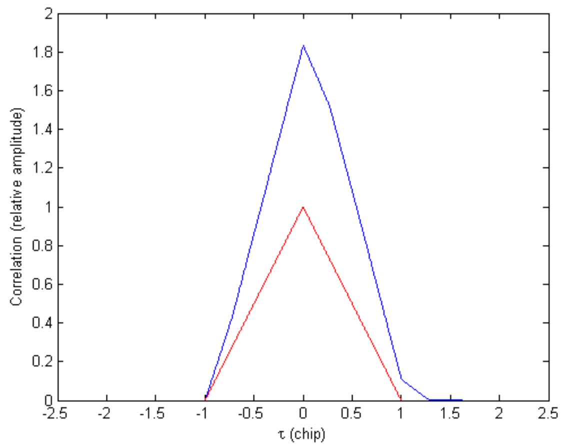

Figure 1: Correlation function of GPS L1 C/A signal without noise (red) and its version distorted by multipath (blue).

Fig. 1 shows the typical shapes of the theoretical correlation function R(τ) (red curve) and its disturbed version C(τ) (blue curve) obtained after taking into account all multipath delay $\delta\tau_i$ simulated by the SE-NAV software (for a given satellite at a given position), and using the amplitude information α_i delivered by SE-NAV (see section II.B). SE-NAV simulates around forty multipath signals for this situation.

To compute the bias due to multipath, we need to know the discriminator function used by the receiver. Since the objective of this paper is to assess how closed is the simulator bias prediction to a real pseudorange error as computed by a standard receiver, we use a simple discriminator. In our case, it is a non-coherent early-late normalized envelope discriminator expressed as

$$D(\tau) = \frac{1}{2}\frac{\|C(\tau-d\tau)\|-\|C(\tau+d\tau)\|}{\|C(\tau-d\tau)\|+\|C(\tau+d\tau)\|} \qquad (4)$$

where dτ is the correlators spacing and ||.|| denotes the modulus, as the output of the correlator is in reality a complex number. However, using a complex version of C(τ) for the mathematical model is useful only if multipath polarization and phase information are taken into account. As it is not the case in equation (3) we use in this work, C(τ) is real and the modulus is replaced by the absolute value. You should note that we do not aim to mitigate multipath in this work. Indeed our purpose is to compare real with simulated multipath bias. Thus we use a half chip value for dτ as in a wide correlators. When C(τ)=R(τ) the output of the discriminator is D(τ)=τ in the linear region within ±0.5 chip of input error. This discriminator is convenient because it gives directly the delay of the local code replica in absence of noise.

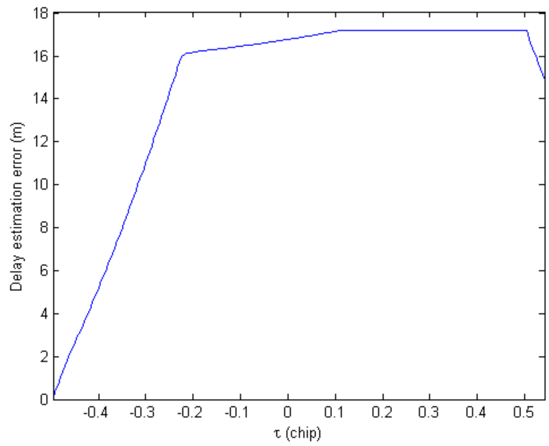

Figure 2: Output of the discriminator: Delay estimation error due to multipath.

When C(τ) is subjected to multipath, it can be shown that $D(\tau)=\tau+b_{MP}$. Because of normalization, D(τ) is not a linear function of $\tau-\delta\tau_i$ and so b_{MP} cannot be expressed with a simple closed-form expression. Thus we propose to calculate D(τ) using (4) and to compute b_{MP} by subtracting τ. Fig. 2 shows how b_{MP} depends on τ for the same simulation as in Fig. 1. The purpose of the tracking step is to estimate the code delay τ using the output of the discriminator. In consequence, without the knowledge of τ, we retain the mean value of $b_{MP}(\tau)$ as our estimation of the bias due to multipath.

B. SE-NAV Software

In the previous section, we have shown that we need two kinds of information to be able to estimate the bias due to multipath, i.e., the length and power (or amplitude) of multipath. A software modelling signal propagation geometrically is necessary for obtaining the first information whereas a software modelling signal propagation physically is necessary for the second information. Moreover, a simulation software able to work with 3D maps of real environments is necessary to compare simulations and real measurements on a same trajectory.

All the previous requirements are not presently combined in a single software. However, the SE-NAV software considered in this study [11] is a geometry based software, working with 3D maps of real environments. This software provides approximations of the signal power thanks to simplified models of the GNSS signals interaction with the environment. This is why we have chosen this software for our study.

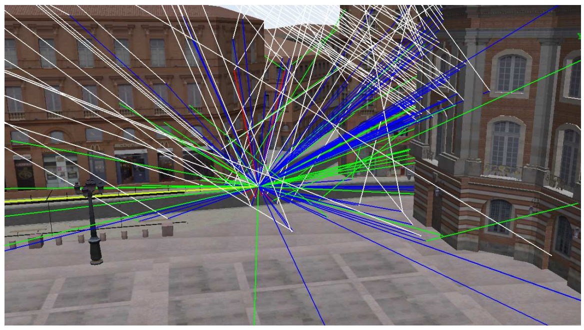

Figure 3: SE-NAV simulation in Toulouse Downtown by OKTAL-SE.

SE-NAV simulates the propagation of GNSS signals in constrained environment. This software, developed by the company OKTAL Synthetic Environment, embeds a GPU Raytracing kernel to compute the masks and the multipath signals (reflections, transmission and diffractions) generated by the objects/buildings near the receiver. Fig. 3 shows an example of result obtained from an SE-NAV simulation.

SE-NAV uses geometrical optics to model reflections and transmissions and uniform theory of diffraction to detect signal diffractions on the edges of the objects. It is based on a deterministic method, that is used to calculate and display the geometry of each ray reaching the receiver and then to compute the errors needed to forecast the local pseudorange. SE-NAV computes a link budget and provides in output the received power per multipath signal and per channel. To do so, SE-NAV assesses the main source of attenuations during the propagation of the signal in the environment.

Cabling losses, antenna gain (satellite and receiver), free space losses, tropospheric losses and multipath losses are taking into account. The software computes the complete field (modulus and phase) and therefore models interferences and fading effects.

III. Comparison between 3D predicted GNSS Signals and Real Measurements

A simulation software cannot compute a perfect reconstruction of the real received signals for several reasons. The first reason is the high variability of the reception environment while the 3D map captures only a static image (i.e., buildings and summer vegetation). Other vehicles present in the scene cannot be modelled since these vehicles change with time. Vegetation foliage evolves over the year, and even the building surface characteristics may change, e.g. when a shutter is open or closed. Another limitation is the precision of the 3D map. Building walls can be modelled accurately through a measurement campaign, e.g. with a laser. However, modelling the geometry of the roofs is more complicated while these are key elements for multipath re-tracing. A last constraint is the complexity of the electromagnetic signal propagation. All these physical effects cannot be precisely modelled if we want to keep a reasonable computation time.

For all these reasons, simulations conducted with software such as SE-NAV only provide approximations. The realism of these approximations has to be validated before using them in a navigation algorithm.

A. Real data

Our study is performed using a data set recorded in Toulouse downtown, France, around the Capitole square. This data set is composed of baseband measurements (I & Q signals), at a frequency of 25MHz. It was acquired with a Novatel antenna and a CRISTALINA bit-grabber. We have developed a Matlab software receiver allowing pseudoranges to be computed from this data set, with a control on all signal processing elements.

An interesting property of this measurement campaign is the availability of a highly accurate reference trajectory. This trajectory was established thanks to the loose fusion of data from an inertial unit (3 accelerometers, 3 gyrometers), an odometer and a DGNSS (GPS+GLONASS) receiver. The reference trajectory is used to compute the actual pseudoranges (that are corrected from Earth rotation effects, ionospheric delay and tropospheric delay). A comparison between the actual and measured pseudoranges allows us to compute the remaining bias on the measurement. In urban environment, this bias is mainly due to the multipath. The trajectory used for our evaluations is depicted in Fig. 4 (yellow curve). Note that this trajectory is almost a loop beginning at the top left of the scene.

Figure 4: Aerial view (in SE-NAV) of the trajectory in Toulouse downtown.

B. Results

In order to validate the accuracy of SE-NAV simulations, we compare real pseudorange errors and simulated SE-NAV errors. Real pseudorange errors can be known with a good precision, as explained in Section III.A. SE-NAV simulated errors are calculated as presented in section II.A, from signals simulated by SE-NAV along the reference trajectory (at the time instants corresponding to real measurements).

1) Comparison using reference trajectory

Fig. 5 shows that the real measurements (red points), are not available in some parts of the trajectory. These parts correspond to a very narrow street, where no satellite was visible. For these parts, the simulations (blue points) are very noisy, which is consistent with a blocked situation where only very weak signals reach the receiver antenna. When real error information is available, simulated errors are almost constants and consistent with the real errors.

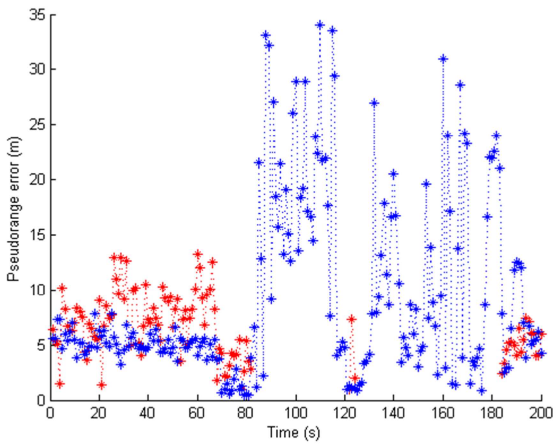

Figure 5: Comparison between real pseudorange errors (red dots) and pseudorange errors simulated by SE-NAV (blue dots), for a given satellite. (no noise on the receiver positions)

To summarize the comparison for all the satellites in visibility during the trajectory, we have computed the differences between simulated and real pseudorange errors. The results are displayed as boxplots shown in Fig. 6.

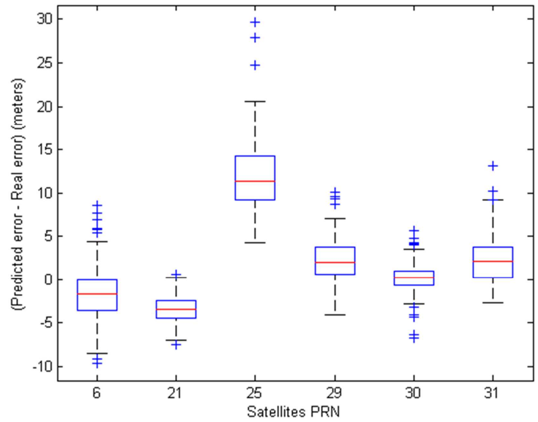

Figure 6: Boxplots of the differences between simulated and real pseudorange errors. (median in red, crosses correspond to the outliers) (no noise on the receiver positions)

The red lines of these boxplots correspond to the error difference medians whereas the blue boxes have bounds at the first (lower) and third (higher) quartiles. The quartiles of a set of values are the three points that divide the data set into four equal groups, each representing a fourth of the population being sampled. The interquartile range (IQR) is equal to the difference between the upper and lower quartiles. The outliers (indicated by blue crosses) are data lower than 1.5 IQR of the lower quartile, or higher than 1.5 IQR of the upper quartile. Note that satellites #21 and #30 are the closest to the zenith (elevation above 60°) during the whole trajectory.

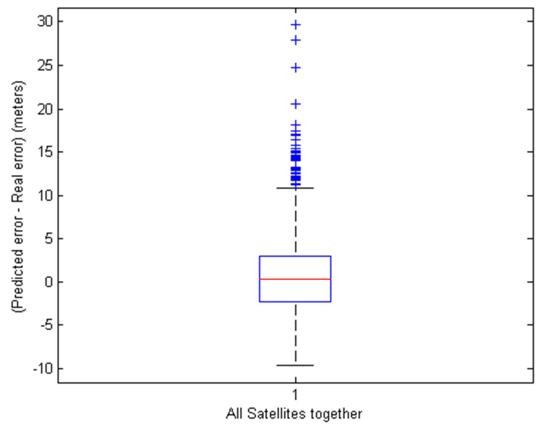

Figure 7: Boxplot for all the differences between simulated and real pseudorange errors. (median in red, crosses correspond to the outliers) (no noise on the receiver positions)

Fig. 6 shows that the error differences for these satellites are very low and with very limited dispersion. On the other hand, satellites #6 and #25 are the closest to the horizon (elevation under 30°) yielding larger errors with more significant dispersions (note however that the differences are acceptable, especially for satellite #6). Fig. 7 aggregates the error differences in a unique boxplot. This boxplot shows that fifty percent of the differences are between -2.3m and 3.1m, with a median closed to 0m.

2) Comparison using a noisy trajectory

It is worthy to remind that the previous figures have been produced using the actual position of the receiver as computed by the reference system However, in a navigation algorithm, the estimated position is never exactly equal to the actual receiver position. With a basic receiver, the error on the position can be of several meters. In order to verify the robustness of SE-NAV simulations to positioning errors, we have added some noise to the reference trajectory with a uniform distribution [-8m; +8m].

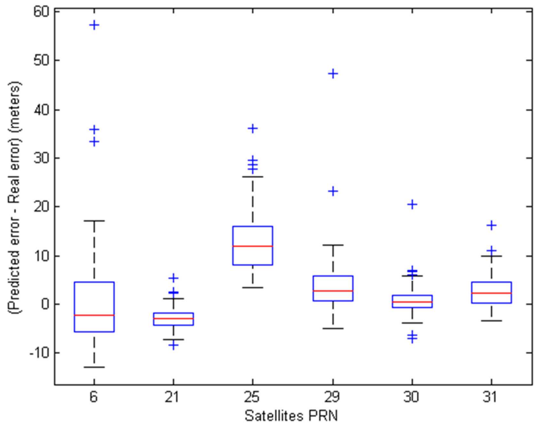

Figure 8: Boxplots of the differences between simulated and real pseudorange errors. (median in red, crosses correspond to the outliers) (receiver positions corrupted by a noise uniform in [-8m ; +8m]).

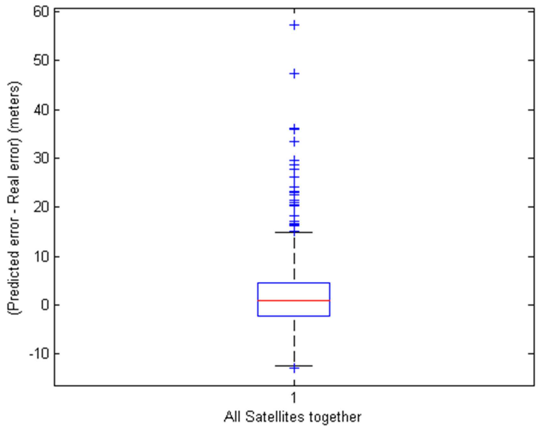

Figure 9: Boxplot for all the differences between simulated and real pseudorange errors. (median in red, crosses correspond to the outliers) (receiver positions corrupted by a noise uniform in [-8m ; +8m]).

The differences between simulated and real errors are then reprocessed with new SE-NAV simulations. Fig. 8

is similar to Fig. 6, but corresponds to noisy receiver positions. For the satellites closed to the zenith, error difference distributions are very similar to the ones displayed in Fig. 6. For the other satellites, the distributions are more scattered, but with a majority of error differences less than ten meters. This results is illustrated in Fig. 9 (which is similar to Fig. 7 but with noisy receiver positions). Fifty percent of the differences are between -2.3m and +4.6m, which is a promising result for more investigation on the topic of using a 3D model to assist the GNSS receiver in urban canyons.

3) SE-NAV prediction quality

Here we are interested to evaluate whether SE-NAV simulations can improve pseudorange measurement precision to be integrated in a navigation algorithm. For this evaluation, we compute the relative differences between simulated and real errors defined as

$$Diff = \frac{|Simulated\ error - Real\ error|}{|Real\ error|} \qquad (6)$$

When Diff<1, the use of simulated error to correct pseudorange measurement is useful. When Diff<0.5, the final error is divided at least by two when using simulated errors. The first column of Tab. 1 shows the percentage of cases where the use of simulated information is helpful whereas the second column of this table corresponds to the percentage of cases where the final error is divided at least by two. Even in a degraded condition with prior position of high uncertainty, showed in the third line, using SE-NAV simulations remains useful in approximately sixty percent of the cases. In a such situation, SE-NAV still allows a very important decrease of the error in thirty percent of the cases. Comparing the results of Tab. 1 with the one presented in Fig. 8 and Fig. 10, we can conclude that SE-NAV simulations are statistically close to the real measurements, with the upper error differences almost in the range of real measurement errors.

Table 1: SE-NAV prediction accuracy

	SE-NAV predictions improving real measurement error [%]	**Final error divided at least by two [%]**
No noise on receiver position	66.4	34.51
Receiver position with a noise on [-4m ; +4m]	64.71	31.74
Receiver position with a noise on [-8m ; +8m]	59.5	29.91

IV. CONCLUSION

We have presented the comparison between real and simulated pseudorange errors. Simulated errors are calculated using the information delivered by the SE-NAV software and computed by a mathematical modelling of the multipath effects. Comparison results have shown that simulated pseudorange errors are good in more than sixty percent of the time. Given the limitations inherent in the use of a 3D model, this score validates the SE-NAV's ability to realistically simulate the signals.

Based on this validation study, approach developed in [9] will be assessed using real data.

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