Performance Assessment of Navigation Signals in Realistic Multipath Environments

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ABSTRACT

A major error source within global navigation satellite systems, such as the Global Positioning System or the future European satellite navigation system Galileo, comes from multipath, the reception of additional signal replica due to reflections caused by the receiver environment. The reception of multipath introduces a bias into the time delay estimate of the delay lock loop of a conventional navigation receiver, which finally leads to a bias in the receiver's position estimate. To mitigate and to reduce the impact of multipath on navigation receivers, the problem is approached from several directions, including the development of novel signal processing techniques as well as the design of more robust navigation signals. In this context hardware simulator has become a valuable tool for the test, assessment and validation of novel algorithms, signals and receivers under controllable environments. To allow hardware tests under realistic propagation conditions it is required to implement complex channel models, such as the one introduced by the German Aerospace Center DLR in 2005, into the existing hardware simulators, which is today still and unsolved challenge, since the number of available hardware taps is usually much smaller than the number of coexistent rays of the original channel models. In this paper the impact of model reduction is studied, whereas two reduction techniques are considered. To take the evolution with respect to future navigation signals and receiver algorithms into account the analysis is carried for the BPSK, BOC(1,1), and CBOC signal, whereas three types of receiver signal processing algorithms are considered, including the Narrow correlator, a maximum likelihood estimator, and a Bayesian minimum mean square error estimator. The results confirm the benefits of novel navigation signals and advanced mitigation techniques and reveal that a model reduction could be possible with moderate errors.

INTRODUCTION

In 2002 the German Aerospace Center (DLR) performed a measurement campaign for the assessment of the satellite navigation land mobile multipath channel. Based upon the analysis of the measurement data a parametric channel model was developed [1], which simulates the time-variant channel impulse response for a dynamic user within an artificial scenery using both deterministic and stochastic processes. This model is about to become a reference propagation channel model at the ITU panel: ITU-R P.681 "Propagation data required for the design of earth-space land mobile telecommunication systems" [2]. This new type of channel model is representative of real propagation conditions and can be use to test future navigation signal's resistance to multipath and to assess receiver's multipath mitigation techniques. In order to assess receiver performance in realistic multipath conditions, a time variant channel scenario is studied in this paper. To consider realistic channel dynamics, a time-variant speed signature obtained from a measured vehicle trajectory serves as input for the channel simulation. The selected scenario is investigated with various signal modulations: BPSK(1), BOC(1,1) and CBOC under the same reception conditions (power, bandwidth, code length, chipping rate, …). The performances of classical mitigation technique such as narrow correlation [3] is compared to advanced channel estimation based mitigation algorithms, including the Maximum Likelihood (ML) estimator [5] and a minimum mean square error (MMSE) estimator. As the MMSE estimator requires the computation of the posterior density of the channel parameters, a particle filter is used to implement the recursive Bayesian filter [17].
In addition the influence of the number of echoes produced by the channel model on the error distribution at the receiver level is studied. The aim of this study is to evaluate if a reduced version of the channel model, which may be synthesized by hardware simulators, is sufficient to test receivers in realistic environments. Two simplification methods are implemented: the simplest one keeps only the most powerful echoes and the second one aggregates the least powerful echoes with their nearest neighbors in time delay. The simulations are done using the J-GNSS software receiver developed by the French Centre National d'Etudes Spatiales (CNES). It has been adapted to be able to apply the DLR channel model defined in the selected scenario to the selected signals modulations. The pseudorange errors obtained with the different signal modulations and receiver architectures are finally compared.

DLR CHANNEL MODEL

The aim of the DLR channel model is to fulfill the requirements for realistic and precise modeling of the multipath propagation effects for satellite navigation applications. The basic concept for this channel model is a combination of deterministic and statistical modeling, which takes the crucial correlations between receiver and channel dynamics into account. The time variant user (receiver) speed and heading, and the satellite elevation and azimuth are required inputs to the motion model. The motion model drives an artificial scenery, where the receiver moves along a street. In the scenery obstacles (in particular house fronts, trees, and lamp posts), which may cause shadowing and diffraction of the direct path, are generated statistically. To model the multipath components the channel model creates a time variant number of reflectors at positions which follow an empiric likelihood distribution. The powers, bandwidths, Rice factors and life spans of the resulting echoes follow these statistics, too. Figure 1 illustrates the concept of the model. Detailed information about the model is provided in [1]. A free version of the model is available for download via [3].

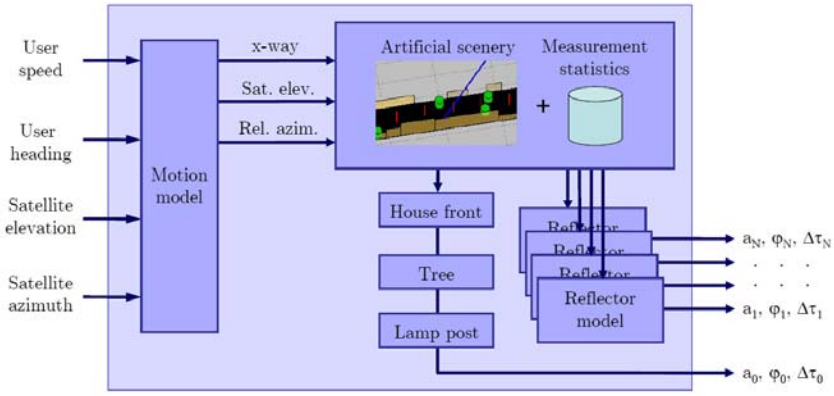

Figure 1: DLR land mobile channel model according to [1].

MODEL COMPLEXITY REDUCTION

In standard condition of reception, receivers usually provide similar performances, the differences are however noticeable in degraded environment where the availability is poor and the signals is affected by path loss and multipath. The test of receivers in severe conditions is of great importance for application's sizing and validation. An alternative to costly field testing is the development in laboratory of representative, repeatable and controlled test environments. The modeling of the propagation channel is the most challenging part of the overall process: the created synthetic environment shall produce realistic degradations at receiver level and should be synthesizable with RF simulators. RF simulators usually provide limited number of channels and consequently a limited number of paths can be generated. The land mobile channel model is a very detailed and accurate channel model but the high number of generated echoes (up to 40 or 50) makes it too complex to be synthesized directly by an RF simulator. In this paper two simplification methods have been investigated, and the receiver behavior under these lower complexity models were compared to the full model. This has been done for a traditional narrow correlator receiver architecture, as well as for receiver architectures that implement complex multipath mitigation algorithms.

Reduction Methods

In general there are several reduction approaches to be distinguished, e.g. the objective can be to preserve some properties of the channel with respect to the temporal behavior, the delay profile or the frequency domain. Spectral properties of the signal that gets transmitted through the channel may be taken into account as well as the architecture of the receiver, e.g. its reception bandwidth. Generally a limited bandwidth may allow for grouping several closely spaced taps into a representative tap. Furthermore the power and phase of the original taps may be expected to have a large impact. Given the channel model links the time-variant impulse response to specific reflectors it may be even possible to remove complete reflectors from the model. In our study we restrained to reduction methods in the delay domain, which are independent of the receiver and the used signals, and which are purely based on the realization of the particular channel response, i.e. for each temporal consecutive realization of the channel response the reduction is applied independently.

Selection Method

By far the simplest method of channel reduction is to neglect those echoes, which have weak power. For the investigation done within the scope of this paper this approach will serve as baseline method. To reduce the channel we just preserve the most powerful echoes of the original channel response. This approach will be referred to as the (power) selection method.

Aggregation Method

A more advanced reduction method based on the aggregation of echoes was proposed recently in [19]. We have basically followed this approach for our study. To briefly summarize the method it works as follows: In the first step the echo with the smallest power is determined. In a second step this echo is aggregated coherently with its nearest neighbor with respect to the delay domain. The resulting reduced channel response serves now as starting point for a further iteration following the aforementioned two steps. Finally the iteration is carried out until the channel is reduced to the desired number of echoes. A detailed description of the algorithm is available in [19].

MULTIPATH MITIGATION

Multipath is today still one of the most crucial problems in GNSS, as the error is caused locally and can not be corrected through the use of correction data, which is provided by reference receiver stations or networks. The advances in the development of signal processing techniques for multipath mitigation have led to a continual improvement of performance, whereas basically two major approaches can be distinguished: The class of techniques that actually mitigate the effect of multipath by modifications of the antenna pattern (either by means of hardware design or with signal processing techniques) or by aligning the more or less traditional receiver components (e.g. the early/late correlator) and the class of multipath estimation techniques, which treat multipath (in particular the delay of the paths) as something to be estimated from the received signal, so that its effects can be trivially removed at a later processing stage. Most of the conventional mitigation techniques are in some way aligning the discriminator of the delay lock loop (DLL) to the signal received in the multipath environment. Well-known examples of this category are amongst others the Narrow Correlator [4] and the Strobe Correlator [6]. For the estimation techniques static and dynamic approaches can be distinguished, according to the underlying assumption of the channel dynamics. Examples for static multipath estimation are those belonging to the family of maximum likelihood (ML) estimators [8], where the probably best-known technique is the multipath estimating delay lock loop (MEDLL) [5]. For static channels without availability of prior information, the ML approach is optimal and performs significantly better than other techniques, especially if the echoes have short delay. Finally, sequential estimators that target the computation of the posterior probability density function (PDF) of the signal parameters conditioned on the received channel output sequence at the receiver have been considered for time-variant channel scenarios [17].

Multipath Signal Model

Assume that the complex valued baseband-equivalent received signal is equal to

$$z(t) = \sum_{i=0}^{N} e_i(t) a_i(t) s(t - \tau_i(t)) + n(t)\,, \tag{1}$$

where $s(t)$ is the transmitted navigation signal, N is the total number of paths reaching the receiver, $a_i(t)$ and $\tau_i(t)$ are their individual complex amplitudes and time delays, and $e_i(t)$ is a binary function controlling the activity of the paths, respectively. The signal is disturbed by additive white Gaussian noise, $n(t)$. Grouping blocks of L samples at times $(n+kL)T_s$, n=0,…,L-1, together into vectors $\mathbf{z}_k$, k=0,1,…, this can be rewritten as

$$\mathbf{z}_k = \sum_{i=0}^{N} e_{k,i} a_{k,i} \mathbf{s}(\tau_{k,i}) + \mathbf{n}_k = \mathbf{S}(\boldsymbol{\tau}_k)\mathbf{A}_k + \mathbf{n}_k\,. \tag{2}$$

In the compact form on the right hand side the samples of the delayed signals are stacked together as columns of the matrix $\mathbf{S}(\boldsymbol{\tau}_k)$, $\boldsymbol{\tau}_k=(\tau_{k,1},\ldots,\tau_{k,N_k})^T$, and the amplitudes and the path activity parameters are collected in the vectors $\mathbf{a}_k=(a_{k,1},\ldots,a_{k,N_m})^T$ and $\mathbf{e}_k=(e_{k,1},\ldots,e_{k,N})^T$, $e_{k,i} \in [0,1]$. It is assumed in (2) that the parameters $\boldsymbol{\tau}_k$, $\mathbf{e}_k$, and $\mathbf{a}_k$ are constant within the corresponding time interval, where $\mathbf{A}_k=\mathbf{a}_k \odot \mathbf{e}_k$ with the element-wise vector (Hadamard) product. Since the noise is assumed to be Gaussian σ^2 with variance the likelihood function for the considered problem is given by:

$$p(\mathbf{z}_k \mid \boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k) = \frac{1}{(2\pi)^{L/2}\sigma^L} \exp\left[-\frac{1}{2\sigma^2} \left(\mathbf{y}_k - \mathbf{S}(\boldsymbol{\tau}_k)\mathbf{A}_k\right)^H \left(\mathbf{y}_k - \mathbf{S}(\boldsymbol{\tau}_k)\mathbf{A}_k\right) \right]. \tag{3}$$

Since a direct computation of the likelihood is numerically to onerous due to the bandwidth of navigation signals the concept of signal compression [10][15][16] is valuable for practical implementations. According to this concept the output of a bank of correlators represents a sufficient statistic for the signal parameters to be estimated, such that evaluations of the likelihood can take place based on the set of correlator outputs. In this paper a bank of 35 complex correlators is used as illustrated in Figure 2, such the main and side peaks of the correlation function are covered.

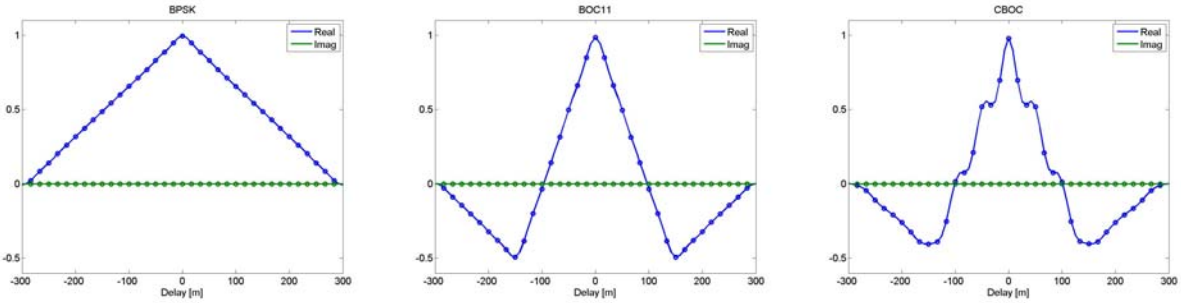

Figure 2: Sampled correlation functions as provided by correlator banks for BPSK, BOC(1,1) and CBOC(6,1,1/11,'-') signal, noise free normalized case.

Maximum Likelihood Estimation

Several strategies have been proposed in the literature to implement the ML time-delay estimator with low complexity [5][11][13][14]. Using (3) the ML estimation criteria for our problem is given by

$$\left\{\hat{\boldsymbol{\tau}}_k^{ML}(\mathbf{e}_k), \hat{\mathbf{a}}_k^{ML}(\mathbf{e}_k)\right\} = \underset{\mathbf{a}_k, \boldsymbol{\tau}_k}{\arg\max}\, p(\mathbf{z}_k \mid \boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k)\,, \tag{4}$$

whereas the number of active paths, i.e. $\mathbf{e}_k$, is assumed to be known. The number of received paths is commonly obtained through a detection test [12]. In such a test different path hypotheses are e.g. compared based upon the statistics of their ML estimation residuals

$$\varepsilon(\mathbf{e}_k) = p(\mathbf{z}_k \mid \hat{\boldsymbol{\tau}}_k^{ML}(\mathbf{e}_k), \mathbf{e}_k, \hat{\mathbf{a}}_k^{ML}(\mathbf{e}_k))\,, \tag{5}$$

whereas models having a larger number of active paths are penalized through the test metrics. For the simulations done in this paper we followed the ML approach introduced in [11], which is based on optimization of (3) via a Newton-type method. To estimate the number of paths a likelihood ratio test [12] was implemented, whereas the decision threshold has been adjusted a posteriori such that the variance of the line-of-sight (LOS) delay estimate is minimized.

Bayesian Minimum Mean Square Error Estimation

Even more advanced than the ML estimator is the usually computationally more complex Bayesian a-posteriori minimum mean square error (MMSE) estimator [8]. Similar to the ML estimator the MMSE estimator also a mitigation technique based on signal parameter estimation. Since the Bayesian MMSE estimator is based on the concept of sequential Bayesian estimation [7], estimates are not obtained independently for each observation interval, but rather at each time step prior knowledge, which is derived from the past observation interval, is used to improve the quality of the estimates. In particular the objective of the Bayesian approach is to estimate the parameters $\boldsymbol{\tau}_k$, $\mathbf{e}_k$, and $\mathbf{a}_k$ for each time instance k in terms of PDFs, namely the posteriors $p(\boldsymbol{\tau}_k,\mathbf{e}_k,\mathbf{a}_k|\mathbf{Z}_k)$, $\mathbf{Z}_k=\{\mathbf{z}_k,\ldots,\mathbf{z}_0\}$. The sequence of posterior PDFs can be computed recursively by alternating calculation of the prediction (Chapman-Kolmogorov) equation

$$p(\boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k \mid \mathbf{Z}_{k-1}) = \int\limits_{\mathbf{a}_{k-1}, \mathbf{e}_{k-1}, \boldsymbol{\tau}_{k-1}} p(\boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k \mid \boldsymbol{\tau}_{k-1}, \mathbf{e}_{k-1}, \mathbf{a}_{k-1})\, p(\boldsymbol{\tau}_{k-1}, \mathbf{e}_{k-1}, \mathbf{a}_{k-1} \mid \mathbf{Z}_{k\text{-}1}) \mathrm{d}\mathbf{a}_{k-1} \mathrm{d}\mathbf{e}_{k-1} \mathrm{d}\boldsymbol{\tau}_{k-1}\,, \tag{6}$$

which makes use of the statistical dependencies between successive observation intervals through the transition density $p(\boldsymbol{\tau}_k,\mathbf{e}_k,\mathbf{a}_k|\boldsymbol{\tau}_{k-1},\mathbf{e}_{k-1},\mathbf{a}_{k-1})$, and the computation of the update step

$$p(\boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k \mid \mathbf{Z}_k) = \frac{p(\mathbf{z}_k \mid \boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k)\, p(\boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k \mid \mathbf{Z}_{k\text{-}1})}{p(\mathbf{z}_k \mid \mathbf{Z}_{k\text{-}1})}\,, \tag{7}$$

in which the likelihood (3) is joined with the prior density (7). The posterior Bayesian MMSE time-delay estimate is then given by

$$\hat{\boldsymbol{\tau}}_k^{MMSE} = \int\limits_{\mathbf{a}_k, \mathbf{e}_k, \boldsymbol{\tau}_k} \boldsymbol{\tau}_k \cdot p(\boldsymbol{\tau}_k, \mathbf{e}_k, \mathbf{a}_k \mid \mathbf{Z}_k) d\mathbf{a}_k d\mathbf{e}_k d\boldsymbol{\tau}_k \tag{8}$$

To implement the Bayesian recursion for the MMSE estimator we have used a marginalized particle filter. Details on the filter algorithm can be found in [17].

SIMULATIONS SET UP

In order to assess receiver performance in realistic multipath conditions, a time variant channel scenario was selected. The full channel as well as two reduced versions of it were applied to three signal waveforms: the actual BPSK(1) signal, the BOC(1,1) and the optimized CBOC. The signals and the propagation channel were generated in software and received using the J-GNSS software receiver.

Multipath Scenario

A realistic scenario has been selected to perform the simulations. It was generated by the DLR channel model with the following inputs: the receiver movement in terms of speed and heading and the satellite elevation. The receiver movement was derived from a time-variant speed signature obtained from a measured vehicle trajectory, and a high elevation satellite (50°) case was selected. The resulting scenario used for the simulations is 400 seconds long and is sampled at 1000 Hz. It exhibits realistic movement with both static and dynamic conditions and alternating LOS and non LOS conditions occurred. The receiver to satellite range is illustrated in Figure 3, (left). The LOS and non LOS cases are more visible on Figure 3 (middle), which shows the total power of the LOS and of the echoes.

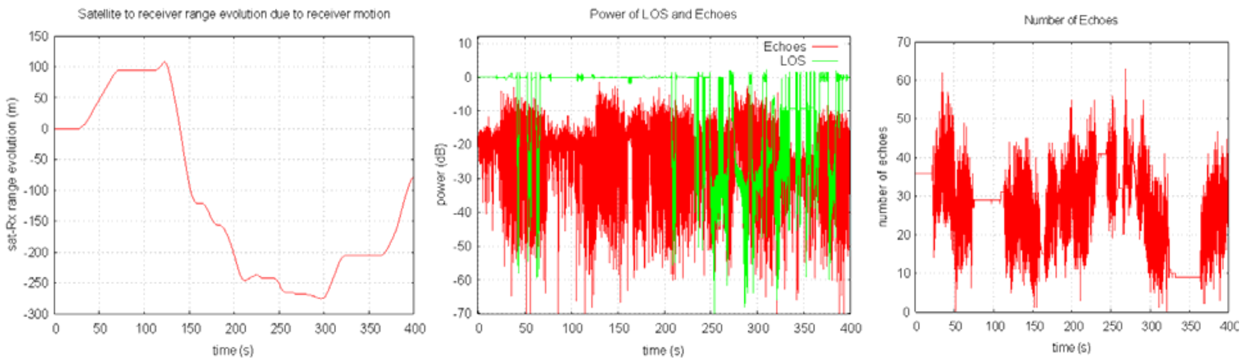

Figure 3: Range evolution (left), LOS and echo power (middle) and number of echoes (right).

The two channel simplification methods descried above have been applied to the full model with the only constraint that the total number of taps shall not be higher than 8. For the selection method, only the 8 most powerful paths were kept, and for the aggregation method the least powerful echoes are aggregated with their closest neighbor in time delay until 8 taps are obtained. The receiver to satellite range variation of the LOS and the echoes, and the power delay distribution are presented in Figure 4 and Figure 5 for the complete channel model and the two simplified ones. It can be seen that after simplification the number of long delay paths is highly reduced. The mean delay is much shorter and mean power higher (see Table 1).

	Mean Delay [m]	Mean Power [dB]
Full Channel	43,7	-35.8
Selection Method	15,8	-26,8
Aggregation Method	20,4	-25,8

Table 1: Mean delay and power values according to Figure 5

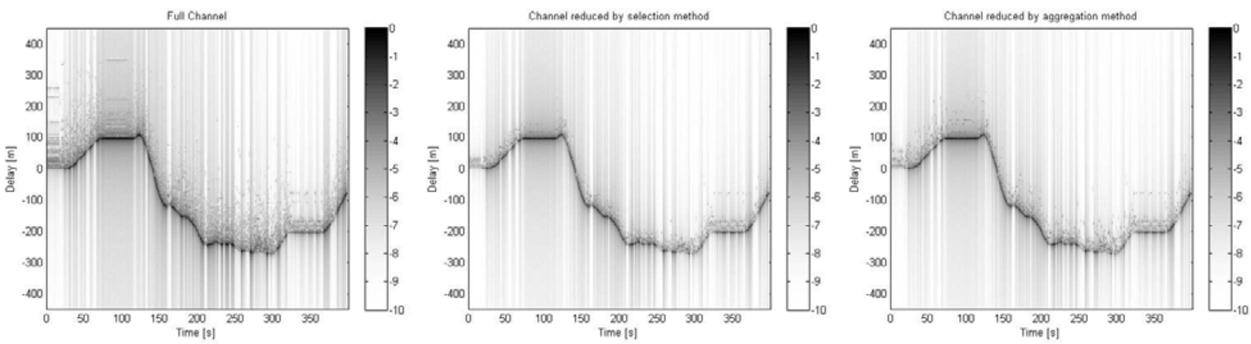

Figure 4: Channel profiles for original channel (left), channel reduced by selection method (middle), and aggregation method (right).

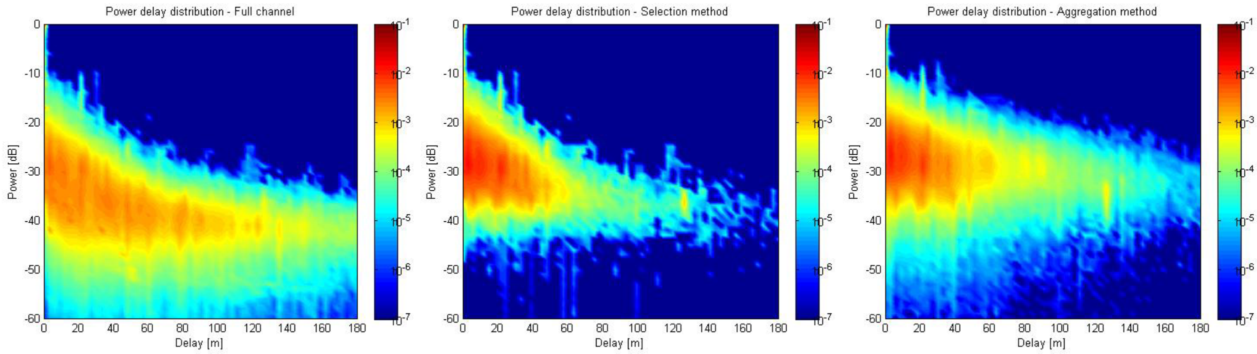

Figure 5: Power delay distributions (bottom) for original channel (left), channel reduced by selection method (middle), and aggregation method (right).

Signals

A way to limit degradation at receiver level is to use navigation signals that are more robust to multipath. Current signals use BPSK modulation, the baseline for the future E1 OS Galileo signal was the BOC(1,1) modulation before the optimized CBOC signal, that exhibits better multipath rejection, was proposed [20]. The selected scenario is used with the three modulations BPSK(1), BOC(1,1) and CBOC under the same reception conditions. For the purpose of these simulations the same PRN code was used for the three modulations: a gold code of length 1023 and chip rate of 1.023 Mchip/s, without secondary code and data. A front end filter with 8MHz one-sided bandwidth was selected in order to take advantage of the wide bandwidth of the CBOC (Figure 6).

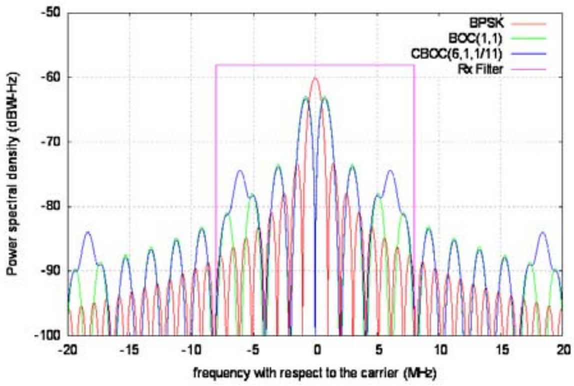

Figure 6: Signal spectra and Rx filter.

Tools

The simulations have been done using the J-GNSS software receiver developed by CNES, which is a “bit-true” simulator. The GNSS SW receiver is based on the open source tool Juzzle (www.juzzle.org), it is written in C ANSI and is multiplatform compatible. The different modules of the simulator include signal acquisition and tracking, and a signal emulator performing signal generation, propagation channel application and RF stage emulation. The signal generator provides a highly configurable satellite model, covering various signal configurations of Galileo and GPS IIF. The propagation module applies the Doppler and delay due to the satellite motion and a multipath module has been developed to interface with the Land mobile channel model. The channel impulse response is applied to the signal by using delay lines and multiplication by complex gains. Thermal noise is added to the signal at sample level. The same noise samples are added from one simulation to the other to allow fair comparison. The RF stage components of the receiver are modeled including Rx Filter, AGC, and A/D converter. The front-end filter is modeled by a Root Raised Cosine filter with a roll-off factor of 0.1 and a cut-off frequency of 8 MHz. The SW receiver comprises acquisition and tracking modules and a controller module performing autonomously the transition between acquisition and tracking mode. The acquisition is FFT based and is activated in case of loss of lock detection. The tracking architecture was common for the three types of received signals (Figure 7); only the correlators and the discriminator normalization differ. Only the pilot channel was tracked, the local replicas are respectively PRN+BPSK(1), PRN+BOC(1,1) and PRN+CBOC(6,1,1/11,”-“). For the simulations a simple loss of lock detector based on the C/N0 value was used, whereas loss of lock was declared when C/N0 was below 10 dB-Hz.

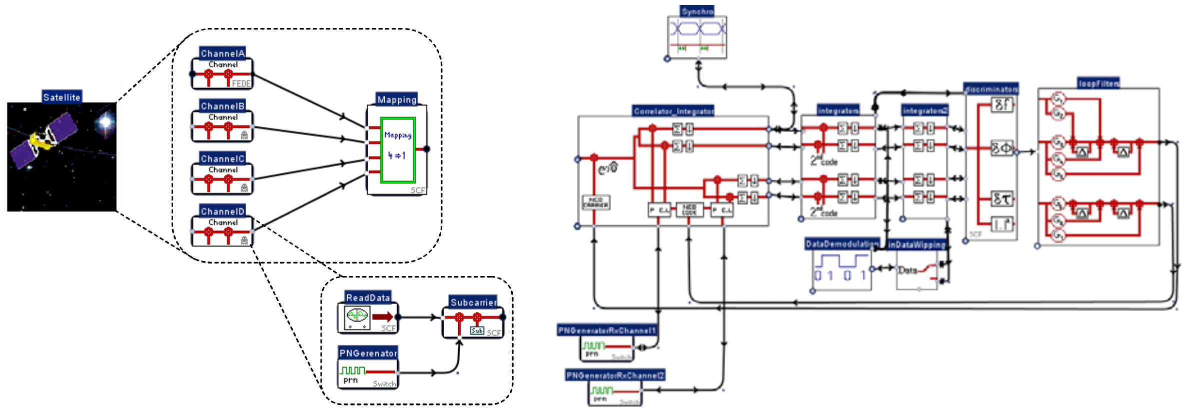

Figure 7: Satellite model and tracking architecture of GNSS SW receiver.

The simulations were performed at a sampling frequency of 36 MHz. The software receiver provides pseudorange and carrier phase as well as the C/N0 evolution as outputs. In order to be interfaced with the ML and MMSE multipath mitigation algorithms the receiver provides additionally the correlation functions sampled at 35 points.

Parameters

The tracking consists of a 3rd order PLL aided by a 2nd order FLL carrier tracking loops with a noise bandwidth of 5 Hz, and a 2nd order dot product discriminator DLL that is Doppler aided by the carrier loops. The integration time was chosen equal to 1ms. As illustrated in Figure 8 an assessment of the DLL parameters has lead to an optimum bandwidth of 1 Hz for the given receiver dynamics.

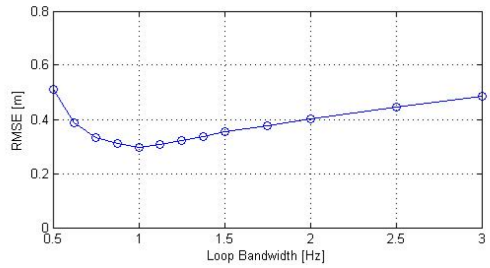

Figure 8: Code tracking error depending on DLL bandwidth

The chip-spacing between early and late correlator equals 0.125 chip, corresponding to a narrow correlator case. The C/N0, without degradation by the propagation channel, is set equal to 50 dB-Hz, which is a classical value for a high elevation satellite. To adjust the mitigation algorithms to the time-variant channel scenario, an observation period of 100 ms was selected for the ML estimator and the MMSE estimator, thus resulting in a filter rate of 10 Hz for the Bayesian MMSE estimator. The ML and MMSE estimator assume the maximum number of multipath signals to be N=1. Hence only a single additional replica is detectable by the multipath mitigation algorithms. The transition probabilities of the Bayesian estimator [18] were matched empirically to the channel statistics.

SIMULATION RESULTS

The aim of the simulations was to assess signals performances in the selected realistic multipath scenario. The behavior of the receivers was observed in the LOS and non LOS environments and in static and dynamic conditions. Statistics were calculated on the whole 400 s of the simulations to obtain cumulative error probability function, bias and root mean square error. The simulation results shown are the following: receiver performances with regard to the signal waveform, receiver performances with regard to the mitigation algorithm implemented and influence of the propagation channel simplification on the receiver behavior.

Signal Performance

The results with respect to the performance of the considered signals are illustrated in Figure 9. For the DLL receiver the BOC(1,1) outperforms the BPSK(1), whereas the CBOC is clearly superior to both. Interestingly for the ML receiver the BPSK(1) performance is degraded in the region of larger error only. For the MMSE the difference in performance with respect to the signal waveform is less distinct but still given.

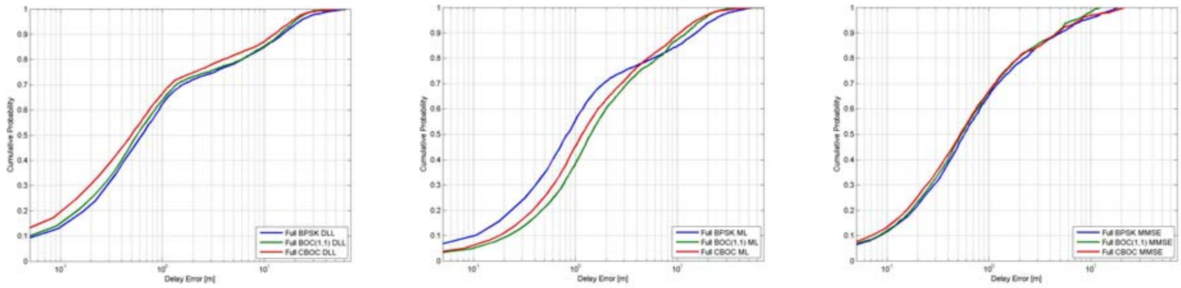

Figure 9: Cumulative error distributions for BPSK, BOC(1,1) and CBOC signals

Reduction

The results with respect to the applied reduction techniques are shown in Figure 10, Figure 11, and Figure 12. In particular for the DLL and ML receiver (Figure 10 and Figure 11) the aggregation method gives good results compared to the selection method, which tends to be optimistic with respect to the tracking errors. Unlike the DLL and ML receiver the reduction leads to rather pessimistic errors for the MMSE receiver (Figure 12).

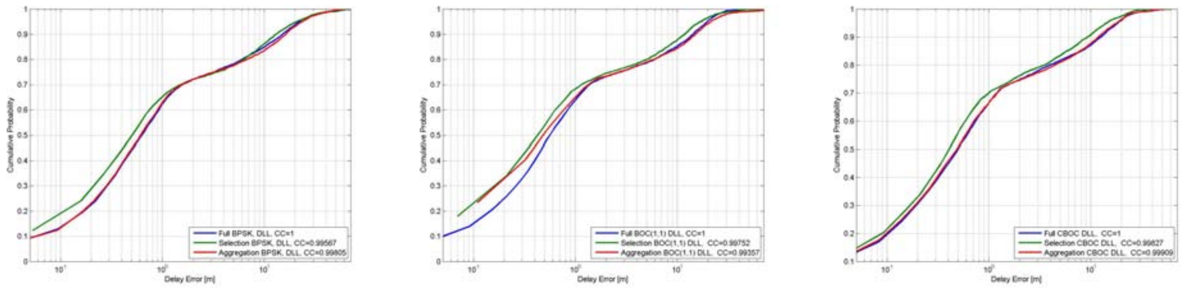

Figure 10: Cumulative error distributions depending on reduction technique using the DLL

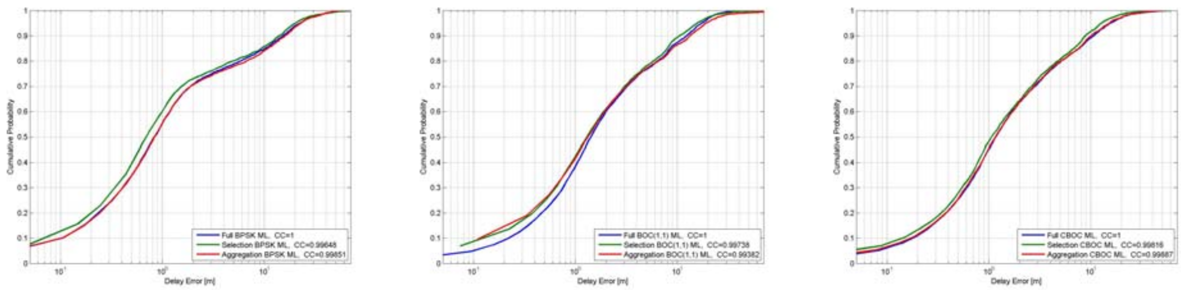

Figure 11: Cumulative error distributions depending on reduction technique using the ML estimator

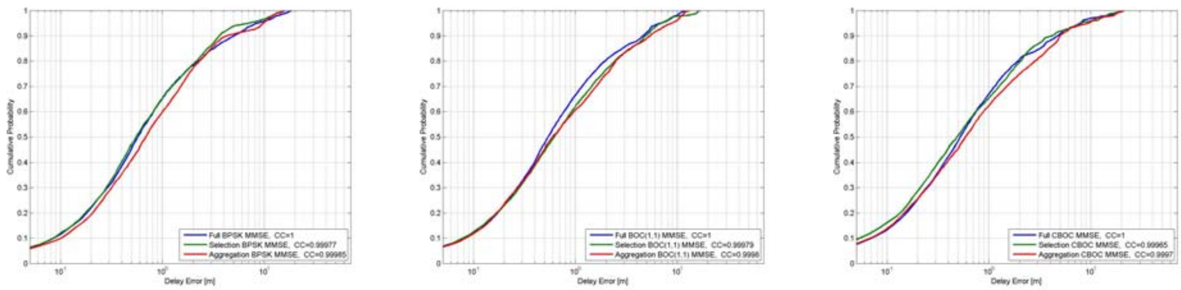

Figure 12: Cumulative error distributions depending on reduction technique using the MMSE estimator

Figure 10, Figure 11, Figure 12 and Table 2 tend to show that the cumulative error distributions and the statistics for the simplified methods are close to the complete channel model when they are computed for the complete simulation scenario. The cross-correlation coefficients (CC) between full and reduced channel LOS estimates are indeed high (over 0.99) and the cumulative error distributions for the aggregation method are close to the full model at least for the DLL and ML case.

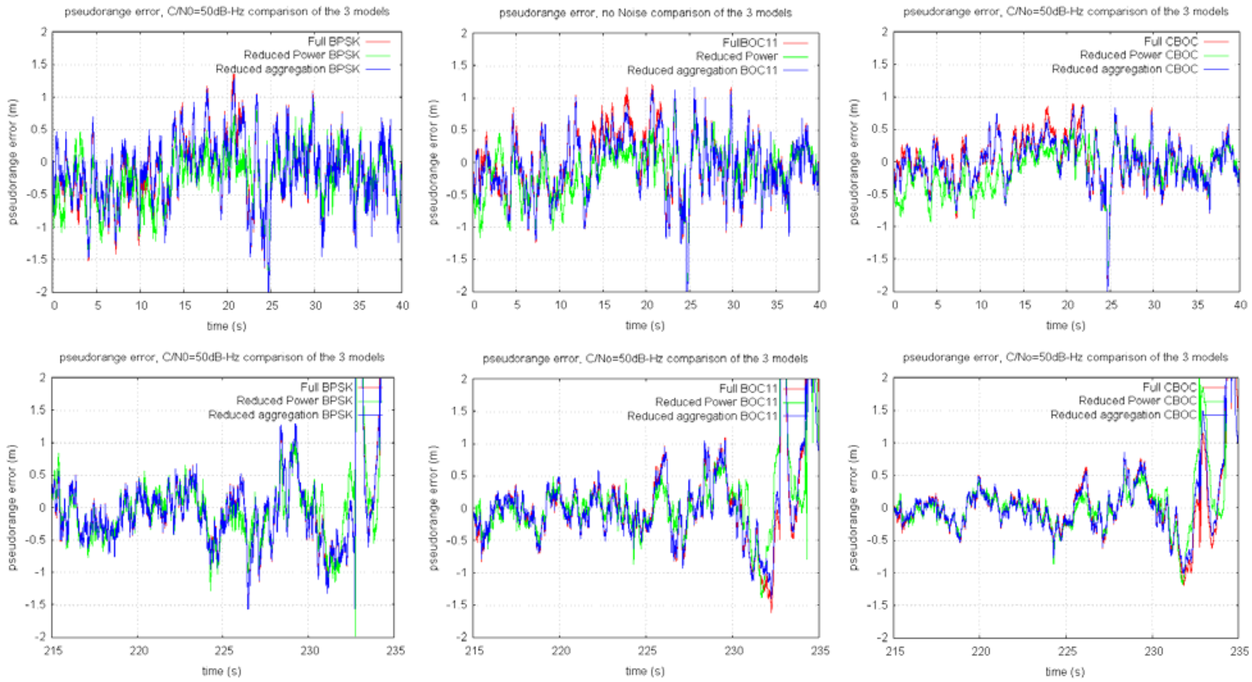

Figure 13: temporal evolution of the pseudorange error for a DLL receiver in 2 LOS cases

In particular for the LOS case, which occurs most of the time during the scenario, both simplification methods provide good results. As it can be seen in Figure 13 the receiver behavior for a DLL architecture is preserved for both reduction methods, whereas the aggregation method produces similar errors compared to the full model and the selection method tends to underestimate them. The large percentage of occurrence of LOS case compared to non LOS case weights the statistics such that they don't reflect the lack of representativeness of the simplification methods during non LOS conditions properly. As it can be seen in Figure 14, during blockage the behavior of the receiver is quite different between the full channel model and the simplified ones. During loss of the direct path the receiver tracks the superposition of a variety of echoes, and thus even small differences in the channel can make it react differently. Even if the order of magnitude of the error is kept, the behavior is changed and further analysis shall be performed to define better simplification methods suitable to these specific cases.

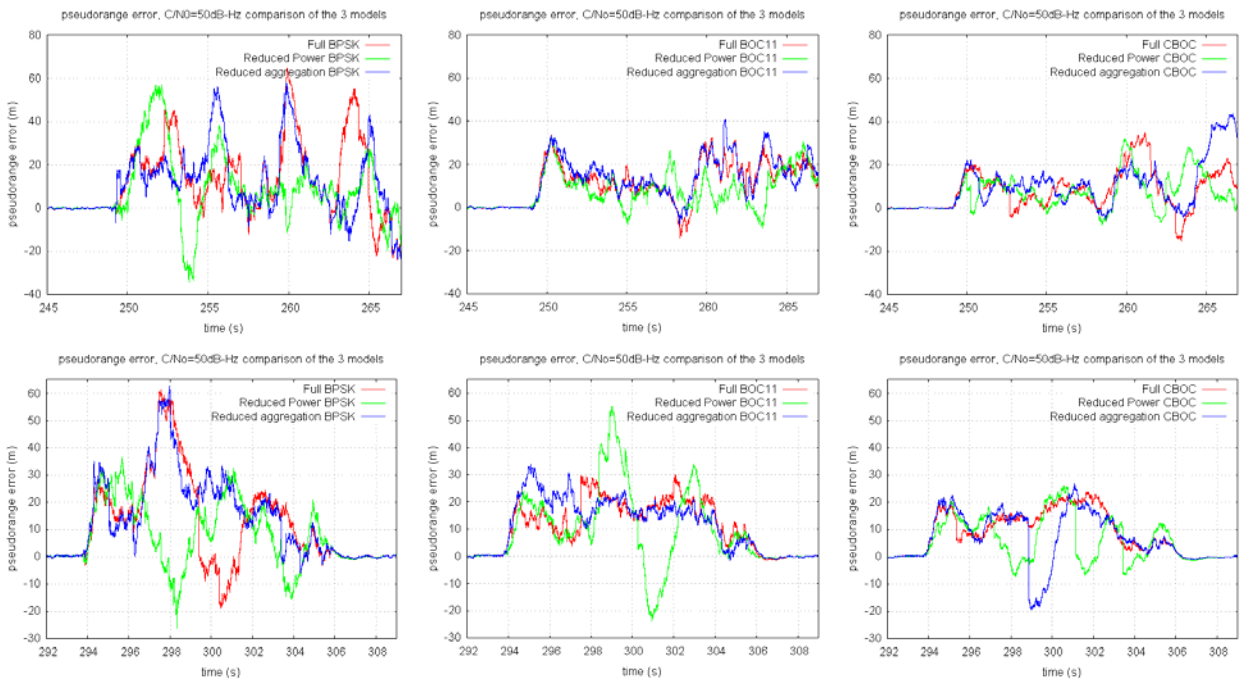

Figure 14: temporal evolution of the pseudorange error for a DLL receiver in 2 non LOS cases

Based on the simulation results presented in Table 2 a conclusion on the influence of channel reduction is difficult to draw. Though the cross correlations between the pseudorange errors for the full model and the reduced ones are indeed high, still the reduction RMSE is not satisfactory.

Mitigation

The results shown in Figure 15 reveal the benefit of the advanced mitigation algorithms. Since the observation period of the ML estimator is 100 ms and thus small compared to the equivalent averaging period of the 1 Hz DLL, the ML estimator performs worse than the DLL for small errors due to the higher noise. Nevertheless it can be observed that the ML approach outperforms the DLL in the region of larger errors. The MMSE estimator shows significantly improved multipath robustness, in particular for large errors, which are much less likely.

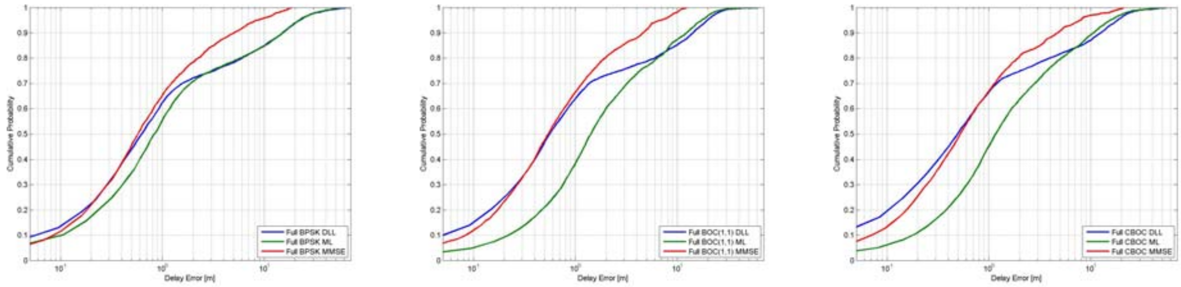

Figure 15: Cumulative error distributions depending on mitigation technique with BPSK (left), BOC(1,1) (middle), and CBOC (right) signal.

Figure 16 shows a section of the simulations comparing the temporal evolution of the pseudorange errors of the DLL and the MMSE estimator. As illustrated the DLL estimate has large errors during three successive periods of LOS blockage between 40 s and 70 s. In these sections the MMSE estimator takes advantage of its prior knowledge and shows significantly reduced errors. Furthermore the small bias due to multipath, which occurs in the DLL tracking after 90 s is successfully mitigated by the MMSE estimator, in particular for the CBOC signal.

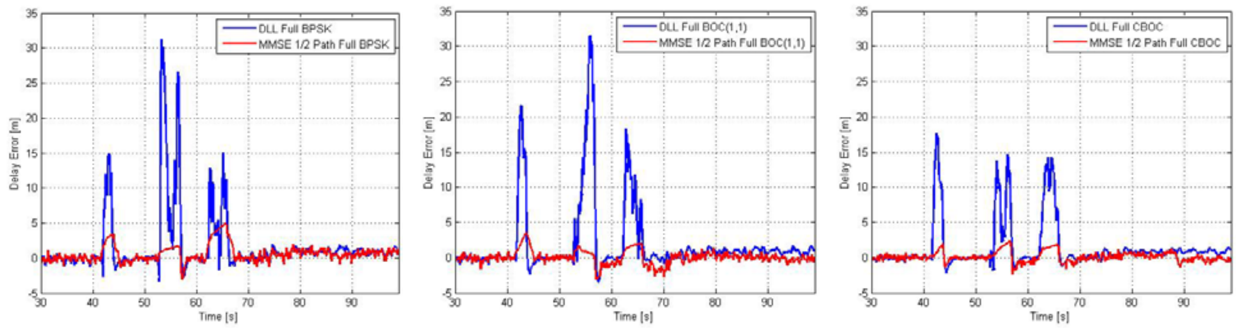

Figure 16: Temporal evolution of pseudorange errors for DLL and MMSE estimator

CONCLUSIONS

In this paper we have assessed the performance of navigation signals in a realistic multipath environment, which was generated from DLR's land mobile channel model [1]. The assessment has been done taking into account several signal modulations and for different multipath mitigation algorithms. The results, which were obtained for BPSK(1), BOC(1,1) and CBOC modulated navigation signals, confirm the benefits of novel navigation signals such as the CBOC. Furthermore it was observed that the use of advanced mitigation algorithms can lead to significant improvement compared to the classical mitigation techniques, in particular during periods of strongly attenuated LOS conditions. In addition a first attempt to evaluate the feasibility and representativeness of propagation channel simplification was made. The reduction of the number of taps of the channel model in order to make it synthesizable by hardware simulators seems to be feasible at least in LOS cases, where it can produce comparable errors for the classical receiver tracking architectures, at least when an elaborated simplification method such as the aggregation method is used. But this conclusion may not be true for any new type of receivers implementing completely different reception algorithms. For further investigations and future work it could may be more appropriate to compute result statistics for different cases: on the one hand LOS conditions that produce low errors and for which the time series show that the reduction methods provide good results; and on the other hand non LOS conditions, which produce errors of several tenths of meters and for which a simplification of the channel is less obvious. The approach followed in this study was based on observing the channel "through the receiver eyes" and to evaluate the channel simplification accuracy by looking at the receiver's tracking behavior. It was based on the simplistic assumption that the simplification of the propagation channel is appropriate if the errors at receiver level are equivalent. The aim of this study was to obtain preliminary results assessing the feasibility and representativeness of propagation channel simplification. For future work greater effort shall be made on the definition of simplification methods and regarding the preservation of further characteristic channel properties, in particular with respect to the frequency domain.

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APPENDIX

Table 2 below summarizes the simulation results in terms of RMSE and mean of LOS estimation errors, the cross-correlation coefficient (CC) between full and reduced channel LOS estimates

$$CC_{xy} = \frac{N \cdot \sum xy - \sum x \sum y}{\sqrt{N \cdot \sum xx - \left(\sum x\right)^2} \cdot \sqrt{N \cdot \sum yy - \left(\sum y\right)^2}},$$

and the resulting RMSE and mean of the reduction errors, which are calculated from the difference of the full and the reduced channel results

Signal	Channel	Receiver	RMSE [m]	Bias [m]	Reduction CC	Reduction RMSE [m]	Reduction Bias [m]
BPSK	Full	DLL	9,0	3,4	-	-	-
		ML	8,7	3,4	-	-	-
		MMSE	3.5	0,8	-	-	-
	Selection	DLL	9,5	3,0	0.9957	9,6	-0,4
		ML	9,0	3,0	0.9965	8,7	-0,5
		MMSE	3,0	0,4	0.9998	2,2	-0,5
	Aggregation	DLL	9,3	3,6	0.9981	6,4	0,2
		ML	8,9	3,6	0.9985	5,6	0,1
		MMSE	3,4	0,5	0.9999	1,8	-0,3
BOC(1,1)	Full	DLL	7,3	3,3	-	-	-
		ML	6,9	2,3	-	-	-
		MMSE	2.7	0,5	-	-	-
	Selection	DLL	8,6	3,0	0.9975	7,2	-0,4
		ML	8,5	2,0	0.9974	7,5	-0,3
		MMSE	3,1	0,7	0.9998	2,1	0,2
	Aggregation	DLL	13,2	2,7	0.9936	11,7	-0,5
		ML	12,9	1,8	0.9938	11,4	-0,5
		MMSE	3,1	0,8	0.9998	2,0	0,2
CBOC	Full	DLL	7,1	2,9	-	-	-
		ML	6,7	2,0	-	-	-
		MMSE	3.6	0,4	-	-	-
	Selection	DLL	5,9	1,8	0.9983	6,0	-1,1
		ML	5,9	1,1	0.9982	6,2	-0,9
		MMSE	3,5	0,7	0.9997	2,7	0,4
	Aggregation	DLL	7,0	2,7	0.9991	4,4	-0,2
		ML	6,6	1,8	0.9989	4,9	-0,2
		MMSE	3,8	1,1	0.9997	2,5	0,7

Table 2: Overview of simulation results