3D Building Model-Assisted Multipath Signal Parameter Estimation

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Abstract—Multipath remains a dominant source of error in satellite-based navigation, despite a great deal of effort by researchers and receiver manufacturers to reduce it. Mitigation of multipath errors is especially difficult when the Doppler shift between the direct and secondary propagation paths is very small (approximately 1-2 Hz) and this is usually the case in urban canyons where the reflectors are almost parallel to the direction of motion of the receiver. Multipath parameter estimation is one option; however, the method needs the number of secondary paths in order to estimate the multipath parameters. Moreover, in weak signal environments, the problem becomes more challenging. In this paper we present multipath parameter estimation assisted with a 3D building model to provide the number of secondary paths as well as initial estimates for the relevant delays. The estimation is based on a Least Squares estimation technique using a grid of correlators. The concept is proven using simulated data and tested using real data. Result shows that the accuracy of estimated parameters improves significantly if the estimator is aided with 3D building model information.

Keywords—Multipath, 3D building model, NLOS Signals, Parameter Estimation, Least Squares, MEDLL, Assisted-MEDLL

I. INTRODUCTION

Global Navigation Satellite System (GNSS) based technology has proven to be a viable low-cost standalone solution for several outdoor positioning and navigation applications. However, urban environments pose significant challenges in terms of signal quality and hence limit their use as a standalone system in such scenarios. Specifically, poor satellite visibility, poor Dilution Of Precision (DOP) and signal reflections from nearby buildings severely affect positioning accuracy. The reflected signals, also known as Non-Line-of-Sight (NLOS) signals, when combined with the direct Line of Sight (LOS) signals, create unwanted multipath effects that remain the dominant source of errors [1-3]. The fact that multipath cannot be removed by differential techniques, limits positioning accuracy in multipath prone areas like urban canyons [4-6].

Several techniques have been proposed for characterization and mitigation of multipath signals either at the antenna level or signal processing level [6-11]. At the signal processing level parametric approaches such as the Multipath Estimating Delay Lock Loop (MEDLL) [12-13] have been used for modeling multipath and then estimating the nuisance parameters. However, these methods try to minimize the mean squared error for a specific multipath model, without any a-priori knowledge of the number of reflected signals. Furthermore, the estimated parameter accuracies are affected in case of weaker signal scenarios, which is usually the case in urban canyon environments. With this in mind this research expands the concept proposed in [12] by aiding information from 3D building models.

Objectives of this research are twofold: first, to use information that could be extracted from 3D building models to improve the accuracy of estimated signal parameters; and second, to analyze the performance of the proposed methodology on frontends with different bandwidths. The methodology is tested in different simulated multipath environments with different NLOS signal characteristics. Furthermore, the efficacy of the algorithm is analyzed in different urban environments using real data collected in Downtown Calgary. Results show significant improvement in accuracy of estimated parameters with the methodology proposed in this research. It is worth mentioning here that although the results presented in this paper are based on urban canyon data, the proposed concept holds good even for indoor environments, knowing approximate user location and aiding information from 3D building model.

II. SIGNAL MODEL AND EFFECT OF MULTIPATH

In traditional GNSS receivers the received signal is down-converted and correlated with a locally generated signal to provide signal measurements [14]. The measurements generated using correlator outputs, are used as input to a navigation processor [4, 14]. It is evident that any error at the measurement level propagates to the navigation output and hence affects the navigational performance. With this in mind, the in-phase, S(I), and quadrature phase, S(Q), signal model at the correlator output in the presence of ‘M’ NLOS signals can be expressed as:

$$S(I) = A_k R(\Delta T_k) \text{sinc}(\pi T_c \Delta f_L) \cos(\pi T_c \Delta f_L + \Delta \theta_L) + \frac{M}{k=1} (A_{N_k} R(\Delta T_{N_k}) \text{sinc}(\pi T_c \Delta f_{N_k}) \cos(\pi T_c \Delta f_{N_k} + \Delta \theta_{N_k})) + \eta_I$$

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\[ S(Q) = A_L R(\Delta \tau_L) \text{sinc}(\pi T_c \Delta f^L_1) \sin(\pi T_c \Delta f^L_1 + \Delta \theta_L) + \sum_{k=1}^{M} (A_{N_k} R(\Delta \tau_{N_k}) \text{sinc}(\pi T_c \Delta f_{N_k}^L) \sin(\pi T_c \Delta f_{N_k}^L + \Delta \theta_{N_k})) + \eta_Q \] 

where, \( A \) is the signal amplitude after correlation; \( \Delta \tau \), \( \Delta f \) and \( \Delta \theta \) are the code, frequency and phase mismatch between incoming and locally generated signals; \( T_c \) is coherent integration time; \( R(\Delta \tau) \) is the autocorrelation function of the ranging code; \( \eta_I \) and \( \eta_Q \) are Gaussian noise present at in-phase and quadrature phase channels [4, 14]. Subscripts \( L \) and \( N_k \) represent the LOS and \( k \)-th NLOS signal respectively. To best deal with reflected signals, the receiver has to estimate all relevant parameters in (1) and (2). It follows that if the number of NLOS signals is unknown (or an incorrect number of NLOS signal is assumed) that the resulting measurements, and thus position, would be degraded. Fortunately, as described below, a 3D building model can provide the number of reflections and, optionally, initial estimates of the associated code phase delay that may improve a receiver’s ability to estimate the desired parameters.

### III. METHODOLOGY

The overall methodology of this research is based on constructive use of the extracted information from a 3D building model, for improving accuracy of estimated signal parameters. At a high level, the methodology can be depicted by Fig. 1. For this research, Least Squares (LSQ) is used to estimate the parameters, however the methodology holds good for any other estimator. Information about the number of reflectors and excess path delay corresponding to each reflector can be obtained for each satellite using a 3D building model and a ray-tracer [15]. This information is used as input for the LSQ estimator, as described below.

**A. Least Squares Method**

Least Squares is one of the most commonly used methods for parameter estimation. The measurement model (\( Z \)) and states (\( X \)) to be estimated depends on the number of NLOS signals. For this research a maximum of two NLOS signals is considered, however, the concept can be extended for any number of NLOS signals. The measurement model is based on the power of the correlators output given by \( S(I)^2 + S(Q)^2 \).

Using (1) and (2), and assuming the frequency mismatch (\( \Delta f \)) is negligible, the measurement model for a single NLOS signal (\( M=1 \)) is

\[ Z = A_L^2 R^2(\Delta \tau_L) + A_{N_1}^2 R^2(\Delta \tau_{N_1}) + 2A_L A_{N_1} R(\Delta \tau_L) R(\Delta \tau_{N_1}) \cos(\delta_{LN_1}) + \zeta \]  

(3)

where, \( \delta_{LN_1} \) is phase difference between LOS and NLOS signal;

\[ Z = A_L^2 R^2(\Delta \tau_L) + A_{N_1}^2 R^2(\Delta \tau_{N_1}) + 2A_L A_{N_1} R(\Delta \tau_L) R(\Delta \tau_{N_1}) \cos(\delta_{LN_1}) + \zeta \]

\[ \zeta = 2A_L A_{N_1} R(\Delta \tau_L) R(\Delta \tau_{N_1}) \cos(\delta_{LN_1}) + \eta_Q \]

where, \( \delta_{LN_1} \) is phase offset of \( k \)-th NLOS signal with respect to LOS signal and \( \delta_{N_1} \) is phase offset between the two NLOS signals. The corresponding state vector is

\[ X = \begin{bmatrix} A_L & \tau_L & A_{N_1} & \tau_{N_1} & \delta_{LN_1} \end{bmatrix} \]

(4)

One of the benefits of using measurement model based on the correlators power is that the states to be estimated are free from absolute phase of LOS and NLOS signals. Rather, only the relative phase offset of the NLOS signal with respect to LOS signal is needed.

The measurement model for a two NLOS signal (\( M=2 \)) case, can be expressed as:

\[ Z = A_L^2 R^2(\Delta \tau_L) + A_{N_1}^2 R^2(\Delta \tau_{N_1}) + A_{N_2}^2 R^2(\Delta \tau_{N_2}) + 2A_L A_{N_1} R(\Delta \tau_L) R(\Delta \tau_{N_1}) \cos(\delta_{LN_1}) + \zeta \]

(5)

\[ \zeta = 2A_L A_{N_1} R(\Delta \tau_L) R(\Delta \tau_{N_1}) \cos(\delta_{LN_1}) + \eta_Q \]

\[ \delta_{LN_1} = \text{phase offset of } k \text{th NLOS signal with respect to LOS signal} \]

\[ \delta_{N_1} = \text{phase offset between the two NLOS signals} \]

where, \( \delta_{LN_1} \) is phase offset of \( k \)-th NLOS signal with respect to LOS signal and \( \delta_{N_1} \) is phase offset between the two NLOS signals. The corresponding state vector is

\[ X = \begin{bmatrix} A_L & \tau_L & \delta_{LN_1} & A_{N_1} & \tau_{N_1} & \delta_{N_1} & A_{N_2} & \tau_{N_2} & \delta_{LN_2} \end{bmatrix} \]

(6)
Since (3) and (5) are non-linear equations, the linearized LSQ estimate of the corrections to the current state estimates is

$$\Delta \mathbf{x} = (H^T R^{-1} H + P_0^{-1})^{-1} H^T R^{-1} \Delta \mathbf{z} \tag{7}$$

where, $\Delta \mathbf{x}$ is error in current state estimates, $H$ is Jacobian matrix, $R$ is measurement noise covariance matrix, $\Delta \mathbf{z}$ is misclosure vector and $P_0$ is covariance matrix of a-priori information. In case there is no a-priori information provided to LSQ, $P_0$ term is infinity.

The autocorrelation function $R(\Delta t)$ used in this research is based on the hyperbolic model proposed by Sharp [16], taking into account the effect of frontend bandwidth. The accuracy of the hyperbolic correlator model was confirmed by comparing it to the correlator outputs obtained when using a Spirent hardware simulator as input. Comparing the correlators outputs against the model yielded correlation coefficients of approximately 0.99, which is considered to be more than good enough.

B. Apriori Information from 3D city model for LSQ

This sub-section elucidates the approach for incorporating the information from 3D city models for LSQ aiding. As shown in [15], the 3D city model can provide information about the number of NLOS signals and their associated delay, with the help of a ray-tracer. In this research, this information is provided to LSQ as aiding information, in two aspects. In the first aspect, the number of reflections is provided to select the correct measurement model for LSQ. As can be inferred from (3) and (5) that in case of wrong information about the number of NLOS signals, the estimated states of LSQ would be suboptimal because of wrong measurement model.

In the second aspect, code phase delay of each NLOS signal with respect to LOS signal (here on referred as delta delay), is used for point of expansion for LSQ. It can be observed from (3) and (5) that the LSQ model used here is non-linear and hence the initial estimate of states becomes an important factor for convergence of LSQ towards the (hopefully) true values. With this in mind, the delta delay information is provided to LSQ in two ways. First, by providing the NLOS delay information obtained using 3D city model, as the initial point of expansion with infinite covariance. In the second method, the delta delay information is provided along with its uncertainty information as determined from the quality of the 3D city model and ray-tracer. The following section shows the results and analysis comparing results with and without the information from the 3D model.

IV. Analysis Using Simulated Data

A. Test Scenario and Data processing

The results presented in this section were obtained using simulated data. The primary reason for this was to prove the concept by having control of the desired parameters, especially the delta phase.

B. Result Analysis and Summary

The results presented in this section are based on two scenarios. The first scenario is based on presence of only one NLOS case. The different simulated multipath scenarios for single NLOS case are shown in TABLE I. For the two NLOS case, the MDR and delta phase of second NLOS signal were set be same as that of first NLOS signal. However, the delta delay of second NLOS signal was provided with offset of 0.1 chips with respect to the first NLOS signal. Finally, the results and analysis presented here were done using parameters of Global Positioning System (GPS) L1 C/A signal, however it is expected that key findings will translate to other GNSS signals as well. In case there is no assistance, the initial estimate of states were assumed to be 0.5, 60 m and 60 degrees, for Multipath to direct ratio (MDR) $\frac{A_{NLOS}}{A_L}$, delta delay and phase delay of NLOS signal with respect to LOS signal’s phase (here on referred as delta phase) respectively. The LSQ measurement model was assumed to be single NLOS case, unless assistance regarding the number of reflections was provided. These values replicate the most likely scenario in any urban canyon [17]. It is worth mentioning that for the simulated scenario presented here, the code phase delay of LOS signal was set to zero, hence NLOS delay and delta delay were the same in this case.

Different scenarios considered for analyzing the single NLOS case are shown in TABLE I. For the two NLOS case, the MDR and delta phase of second NLOS signal were set be same as that of first NLOS signal. However, the delta delay of second NLOS signal was provided with offset of 0.1 chips with respect to the first NLOS signal. Finally, the results and analysis presented here were done using parameters of Global Positioning System (GPS) L1 C/A signal, however it is expected that key findings will translate to other GNSS signals as well. Frontend bandwidths of 2 MHz, 5 MHz and 10 MHz were considered for the analysis, which together, capture a wide spectrum of GNSS applications.

In order to analyze the 210 different scenarios in TABLE I (i.e., 5, 6 and 7 different scenarios for MDR, delta delay and delta phase respectively) in presence of noise (which is normally distributed in this case), each scenario presented in TABLE I was run 100 times, each with a different set of simulated noise sequence. Furthermore, in order to analyze the effect of frontend bandwidth on accuracy of estimated parameters, the error statistics are provided separately for each of the three bandwidths considered. More precisely, statistics for each bandwidth presented are based on 21,000 runs (using all combination of values from TABLE I, each for 100 noise sets).

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Unit</th>
<th>Range</th>
<th>Step</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDR</td>
<td>N/A</td>
<td>0.1 to 0.5</td>
<td>0.1</td>
</tr>
<tr>
<td>Delta Delay</td>
<td>Metre</td>
<td>15 to 90</td>
<td>15</td>
</tr>
<tr>
<td>Delta Phase</td>
<td>Degree</td>
<td>0 to 180</td>
<td>30</td>
</tr>
<tr>
<td>Frontend Bandwidth</td>
<td>MHz</td>
<td>2, 5 and 10</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Results from real data are presented and analyzed in following sections.

For simulated data, the assistance data provided here in terms of the number of NLOS signals and NLOS signals’ delta delay were assumed to be available from the 3D city model. Furthermore, the uncertainty (a-priori covariance) involved with the available delta delay was considered to be 3 metres.

In case of no assistance, the initial estimate of states were assumed to be 0.5, 60 m and 60 degrees, for Multipath to direct ratio (MDR) $\frac{A_{NLOS}}{A_L}$, delta delay and phase delay of NLOS signal with respect to LOS signal’s phase (here on referred as delta phase) respectively. The LSQ measurement model was assumed to be single NLOS case, unless assistance regarding the number of reflections was provided. These values replicate the most likely scenario in any urban canyon [17]. It is worth mentioning that for the simulated scenario presented here, the code phase delay of LOS signal was set to zero, hence NLOS delay and delta delay were the same in this case.

B. Result Analysis and Summary

The results presented in this section are based on two scenarios. The first scenario is based on presence of only one
NLOS signal. For this scenario, the assistance data was used only in terms of delta delay (i.e., not the number of NLOS paths), since the LSQ was assumed to be based on the one-NLOS model if no assistance data was provided. Furthermore, in this case the assistance data of delta delay was used in two ways: for the point of expansion for delta delay state without covariance information (\( P_0 \) is infinity), and for the point of expansion for the delta delay state with covariance (\( P_0 = 9 \text{ m}^2 \)). The second scenario is based on presence of two NLOS signals. In this case the aiding information was provided in terms of number of reflections and in terms of delta delay with and without covariance information (as for the first scenario).

The statistical performance of the estimated delta delay for the single NLOS signal scenario and two NLOS signal scenario is presented in Fig. 2 and Fig. 3 respectively. As can be inferred from the two figures, the assistance data improves the accuracy of the estimated states. Moreover, the inclusion of covariance information improves the estimated states’ accuracy as compared to when using delta delay information alone for aiding.

For the 2-path scenario (LOS and 1 NLOS signals), the Root Mean Squared (RMS) accuracy of the estimated delta delay improved by 32%, 14% and 2% for 10 MHz, 5 MHz and 2 MHz bandwidth respectively, using only delta delay information from 3D model. However, using the a-priori variance information along with delta delay information from the 3D city model, the accuracy improved by 74%, 58% and 45% respectively. Furthermore, the median of error samples, using a-priori information, was 1 metre for all the three bandwidths. This is important since it suggests that lower-cost, lower bandwidth and thus less power consuming receivers could be used without loss of estimation accuracy.

For the 3-path scenario (LOS and 2 NLOS signals) improvements were more profound, since the aiding information was done in two way; number of reflections and delta delay. The error without aiding information was more as compared to single NLOS case, since the LSQ was based on one NLOS signal if no aiding information was available (indeed, the results are much worse that in Fig. 2). The improvement in estimated accuracy of delta delay was observed by 80%, 77% and 70% respectively for 10 MHz, 5 MHz and 2 MHz bandwidth when the aiding information was provided in terms of delta delay only. Furthermore, the improvement was approximately 90% when aiding was provided in terms of delta delay and the variance matrix (\( P_0 \)), for all the three bandwidths case.

V. DATA PROCESSING AND ANALYSIS FOR REAL DATA COLLECTED IN DOWNTOWN CALGARY

In order to test and analyze the feasibility and performance of the proposed algorithm in real scenarios, two different datasets collected in downtown Calgary were used. The first dataset was collected on 15th May 2015 (here on referred as the first dataset) primarily to analyze the algorithm in relatively mild urban, environments using a frontend with bandwidth of 8 MHz. The second dataset was collected on 14th January 2014 (here on referred as the second dataset) in deep urban canyon using a frontend with bandwidth of 20 MHz. The primary objective of analyzing the two datasets was to see the performance in these two different environments and secondly to see the frontend bandwidth effect on overall performance.

The data collection setup for the Downtown first dataset consisted of a NovAtel SPAN-LCI reference system, a Leap Frog frontend for Intermediate Frequency (IF) sample collection, a NovAtel antenna and a base station. The reference trajectory was obtained using Inertial Explorer software using a tightly coupled forward and backward smoothing configuration, and is shown in Fig. 4, for the first dataset. The base station was set up nearby and was used for differential processing of the reference solution and for extracting navigation message data bits for bit wipe-off as required for longer coherent integration. The IF data was collected using a Leapfrog frontend with an external stable Oven Controlled Crystal Oscillator (OCXO), which enabled longer coherent integration. The IF samples were collected at sampling rate of 10 Mega Samples Per Second (MSPS). All the equipments were mounted on a test van (except for the base station) and the vehicle was driven through downtown Calgary.
with a maximum speed of about 15 m/s. The Downtown second dataset was collected using similar setup as the first dataset except instead of Leapfrog frontend, a National Instrument (NI) frontend was used with 20 MHz bandwidth. Also, the oscillator onboard the frontend was used instead of an external oscillator. The reference trajectory was obtained similar way as for the first dataset and is shown in Fig. 5.

A. Data Processing for the first and second dataset

The IF data for both the datasets were processed to generate the observations for the LSQ with the help of University of Calgary’s GSNRx™ software receiver as described in [18]. More precisely, the correlator output from the software receiver was used as measurements (Z in (3) and (5)) for LSQ. The version of GSNRx™ used was based on a block processing strategy that was suitable for longer coherent integration time. The parameter configuration for the block processing is summarized in TABLE II. In order to enable longer coherent integration, the base station data was used for bit wipe off.

![Reference trajectory for data collected on 15th May 2015. The black rectangles are regions where at least one of the PRNs (PRN 2 or PRN 5) has exactly one NLOS signal. The blue oval is the region where the PRN 5 has two NLOS signals.](image1)

![Reference trajectory for data collected on 14th January 2014. The black oval is region where density of building was more as compared to other regions of trajectory highlighted in orange oval.](image2)

<table>
<thead>
<tr>
<th>TABLE II. BLOCK PROCESSING STRATEGY</th>
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<tbody>
<tr>
<td><strong>Search Space</strong></td>
</tr>
<tr>
<td>Code Phase Domain</td>
</tr>
<tr>
<td><strong>Search Step</strong></td>
</tr>
<tr>
<td>Code Phase Domain</td>
</tr>
<tr>
<td><strong>Integration Time</strong></td>
</tr>
</tbody>
</table>

The data processing strategy used for the real data is shown in Fig. 6. The correlator outputs from the software receiver are used as observations for the LSQ to estimate the unknown states, including NLOS signal delay(s). Furthermore, validation of the estimated NLOS signal’s delay is also done using reference position and ray-tracing. Details of delay generation using reference position, ray-tracing and 3D building model is provided in [15]. It is worth mentioning here that the delay obtained using ray tracer with reference (true) position can be treated as reference (true) delay of NLOS signal for a given satellite, since the NLOS signal’s delay is a function of user position, which is well known in this case [15].

Since LSQ estimation is sensitive to the initial point of expansion, and because a 3D model can only provide information about the number of paths and the delay along each path, initial amplitude of NLOS signal(s) was provided as a vector of MDR with values ranging from 0.1 to 0.9 with step of 0.1. Similarly, the initial point of expansion for delta phase was provided as a vector with values ranging from −180 degrees to +180 degrees with a step of 30 degrees. Based on all these initial values, the final estimate was selected as the one that produced the smallest residuals. More precisely, the estimated delay corresponding to the MDR and delta phase with the small sum-squared residuals was declared as final estimated delay.

For the first dataset, PRN 5 was selected for analyzing the estimated delay accuracy since that satellite had reflections for most of the epochs along the trajectory. PRN 2 was selected for analyzing the effect of frontend bandwidth since PRN 2 had smaller extra path delays, which are of primary concern for smaller frontend bandwidths. Epochs considered for results and analysis was between GPS time of 529390 to 529360.

As mentioned earlier, the primary reason for using the second dataset was to analyze the performance of algorithm in dense urban environments and the second objective was to analyze the effect of frontend bandwidth. In order to do so three PRNs were selected for which at least one reflection was present. PRN 1 (Azimuth: 296 degrees, elevation: 43 degrees), PRN 31 (Azimuth: 167 degrees, elevation: 35 degrees) and PRN 32 (Azimuth: 290 degrees, elevation: 47 degrees) were considered primarily because of available reflections from these PRNs and secondly because of two of the PRN’s having different geometry (in terms of Azimuth), which would enable the analysis for effect of PRNs being in different orientation (relative to the user). Finally, the epochs considered for analysis were selected between GPS time of 251390 to 251720 where the NLOS signals were present for above PRNs.
B. Result Analysis and Summary for Downtown first dataset

All the results presented here were obtained using the a-priori information from 3D building model, however in order to show the effect of aiding, the error statistics are compared with and without aiding. Fig. 7 and Fig. 8 depict the estimated delays and their comparison with corresponding true delay for PRN 5 and PRN 2 respectively. PRN 5 was having azimuth of 160 degrees and elevation of 11 degrees approximately, throughout the epochs considered here. PRN 2 had azimuth of 190 degrees and elevation of 68 degrees approximately, for all of the epochs considered here.

Fig. 7 depicts the comparison of true delay and estimated delay for epochs having only one NLOS signal along with LOS signal (2-path signals) and two NLOS signals along with LOS signal (3-path signals) separately and presented in two different subplots, subplot 1 (top) and subplot 2 (bottom) respectively, of Fig. 7. The epochs selected for this analysis belongs to the portion of the trajectory which is parallel to the buildings (refectors). Since the delay is function of perpendicular distance of receiver from the reflector, the delay does not change drastically between all epochs.

Results depicted in Fig. 7 allude towards two important inferences. Firstly, the lower elevation satellites (PRN 5 in this case, with elevation of 11 degrees) are the ones responsible for larger NLOS signal delays. Also, these lower elevation satellites are also most likely candidates for multiple reflections (2 NLOS in this case). This fact can be corroborated by the possibility of having more visible candidates’ reflectors in view for lower elevation satellites as opposed to that for higher elevation satellites. Secondly, as indicated by TABLE III, the LSQ estimated delay matches with true delay with Root Mean Squared (RMS) error of 5 metres for 2-path signals and 4.8 metres for 3-path signals. It can be inferred further that the LSQ performance for 3-path signal is slightly better than 2-path signal. However, it must be noted carefully that the epochs for 3-path signals are lesser as compared to 2-path signals’ presence. Given the fact that the accuracy of 3D models is considered as 3 metres the results still are reasonable, however similar analysis for 3D building models with better accuracy is left for future analysis.

Result for PRN 2 is depicted in Fig. 8. The NLOS delay for PRN 2 is shorter as compared to PRN 5. This is probably because the candidate reflectors for PRN 2 are closer to the receiver for the epochs considered here. Furthermore, since the bandwidth of the frontend (Leapfrog) considered here is 8 MHz, this limits the smallest NLOS delay that can be estimated using the LSQ. This can be corroborated by the relatively poor results, in terms of matching of estimated and true delay.
The effect of aiding (number of signal paths and NLOS signals’ delay) from 3D building model can be observed from TABLE III. An improvement of approximately 68% and 90% in the RMS error is observed for the 2-path scenario and 3-path scenarios respectively. The more profound effect of aiding for 3-path scenario can be corroborated by the fact that in absence of aiding information, the LSQ model was assumed to be a 2-path signal model.

C. Results for Downtown second dataset

Comparison of true delay and estimated delays for PRN1, PRN 31 and PRN 32 are shown in Fig. 9, Fig. 10 and Fig. 11 respectively. For all the three figures, subplot 1 corresponds to high density building region and subplot 2 corresponds to the lesser building density region. It is evident that PRN 1 had more occurrences of reflection in high density building region as compared to PRN 31 and PRN 32.

Result for PRN 1 is depicted in Fig. 9. The top subplot corresponds to the region with higher density buildings (black oval region in Fig. 5). The bottom subplot corresponds to the remaining region (orange oval region in Fig. 5). As can be inferred the estimated NLOS delay matches to true delay with better accuracy in lesser density building region. Error statistics for PRN 1 (with and without aiding) are shown in TABLE IV. The LSQ estimated delay matches with true delay with RMS error of 3 metres approximately for the region with lesser density buildings. On the other hand for higher density building regions (black oval region in Fig. 5) the LSQ estimated delay matches with true delay with Root Mean Squared (RMS) error of 13.7 metres and 16.2 metres for 2-path and 3-path signals respectively.

Furthermore, the effect of aiding can be observed from TABLE IV in terms of an improvement of about 60% and 74% in the RMS error for the 2-path and 3-path signal scenarios respectively, in higher density region. For low building density region, the improvement in RMS error due to aiding (from 3D city building model) was around 80%.

<table>
<thead>
<tr>
<th>Error Statistics (metres)</th>
<th>PRN 5</th>
<th>PRN 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Aiding Mean</td>
<td>4.3</td>
<td>4.4</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.8</td>
<td>1.6</td>
</tr>
<tr>
<td>Without Aiding Mean</td>
<td>12.4</td>
<td>16.6</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>9.6</td>
<td>11.7</td>
</tr>
</tbody>
</table>

TABLE IV. ERROR STATISTICS FOR DATA COLLECTED ON 14TH JAN 2014: PRN1

<table>
<thead>
<tr>
<th>Error Statistics (metres)</th>
<th>Higher density region</th>
<th>Remaining region</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Aiding Mean</td>
<td>9.9</td>
<td>12.1</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>9.4</td>
<td>10.8</td>
</tr>
<tr>
<td>Without Aiding Mean</td>
<td>26.9</td>
<td>56.9</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>20.4</td>
<td>30.4</td>
</tr>
</tbody>
</table>

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TABLE V. ERROR STATISTICS FOR SECOND DATASET: PRN 31

<table>
<thead>
<tr>
<th>Error Statistics (metres)</th>
<th>Higher density region</th>
<th>Remaining region</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Aiding</td>
<td>Mean</td>
<td>9.3</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>6.2</td>
</tr>
<tr>
<td>Without Aiding</td>
<td>Mean</td>
<td>21.1</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>12.7</td>
</tr>
</tbody>
</table>

Result for PRN 31 and PRN 32 are depicted in Fig. 10 and Fig. 11 respectively. It can be inferred that the RMS error for higher building density region and remaining region is 11.2 metres and 12.4 metres respectively for PRN 31. Error statistics for PRN 31 is shown in TABLE V. The improvement in RMS error due to aiding from 3D building model was observed to be approximately 55% and 72% in higher building density and lower building density regions respectively.

It can be inferred from the table that unlike PRN 1 the estimated delay’s accuracy looks worse in lesser building region as compared to denser building region. However with careful analysis it can be observed that the two epochs (last 2 epochs) for PRN 31, with 2 NLOS signals have larger errors and can be treated as outliers. Ignoring these two epochs the RMS error for the remaining region changes to 7.7 metres for PRN 31. Now the accuracy of estimated delay looks better however, still the performance is worse as compared to that for PRN 1. This is an interesting finding and indicates that in order to improve the performance of the proposed algorithm one criteria for identifying outliers need to be obtained. At this stage there is no solid conclusion on why there is a larger error in these two epochs; however, one of the possible candidates could be in terms of error in building model, specially the structure creating that particular reflection. Another possible reason could be the presence of multiple reflections along a single path (i.e., “multi-bounce” reflections) that are currently not captured by the ray-tracer. With this in mind it is worth analyzing the correlator outputs at these epochs and compare with that from other epochs. However, these activities/analysis are left as future work.

Fig. 11 corresponds to comparison results for PRN 32. It can be inferred that the RMS error for higher density building region and remaining region is 14.9 metres and 5.6 metres respectively. The error statistics for PRN 32 is shown in TABLE VI. As can be inferred the estimated NLOS delay matches to true delay with better accuracy in lesser density building region. Furthermore, there is an improvement of approximately 63% and 84% in RMS error in high and low building density regions respectively due to aiding information from 3D building model.

PRN 1 and PRN 32 are located on the same side with respect to user since the azimuth of PRN 1 and PRN 32 are 296 degrees and 290 degrees with similar elevation. The azimuth for PRN 31 is 166 degrees. This further implies that PRN 1 and PRN 32 performance should be similar for a given urban scenario. With careful analysis from TABLE IV and TABLE VI results follow previous statement and indicate consistent performance of the algorithm.

Based on the results and analysis presented above for the first objective (effect of building densities), it can be summarized that the performance of the proposed algorithm is expected to be better in lower density building environments (e.g. first dataset) as compared to dense urban canyon environments (e.g. black oval region for second dataset). This does not mean that the proposed algorithm will not be useful at all in dense urban environments. However, further analysis is required in order to tune the LSQ parameters and/or modify the ray-tracer for dense urban environments. Moreover, the measurements (correlator outputs) in dense urban environments need to be analyzed and compared with those obtained in lesser dense building environments. At this stage these analysis are not done and is proposed as future work of this paper.

With the second objective in mind (effect of frontend bandwidth), all the epochs where NLOS signal delay was smaller (< 12 metres) were considered for PRN 1. The result is depicted in Fig. 12 and can be inferred that RMS error is 2.2 metres.

![Fig. 12. Results for PRN 1 for epochs where NLOS signal delays were smaller. Mean error is 2 metres and standard deviation is 1 metre.](image-url)
The RMS error is less (for NI frontend with BW of 20 MHz) compared to that for first dataset (frontend BW of 8 MHz). Hence it can be inferred that with larger bandwidth the smaller delays can be better estimated by LSQ with better accuracy. It is worth mentioning here the two datasets (dataset 1 and dataset 2) are collected in different regions of Downtown Calgary and hence one to one comparison of bandwidth effect might not seem reasonable. However, given the fact that the Downtown 2nd dataset has relatively harsh environment and the algorithm still provides better results with higher frontend BW, indicates that if the same NI frontend is used in dataset 1, the results would be much better in terms of estimated delay accuracy for smaller NLOS signal delays.

VI. CONCLUSION

A novel methodology for estimating multipath signal parameter, assisted with 3D building model, is presented in this work. Effect of assistance information on 2-path and 3-path signal models are analyzed for three different frontend bandwidths of 2, 5 and 10 MHz using simulated data. The effect of aiding is observed to be more profound in case of a 3-path signal scenario, where the improvement in estimated accuracy of delta delay is observed as 90% for all the three bandwidths case considered. Considering a mass market of 2 MHz bandwidth, results using the proposed methodology allude towards a great improvement in multipath parameter estimation and hence positioning accuracy, using GNSS systems in multipath environments. Furthermore results using real data were analyzed in two different scenarios with higher building densities and lower building densities. It was observed that most of epochs the estimated NLOS delay was more accurate in lesser building density environment as compared to that of higher building density environment. Furthermore using real data it was shown that with larger frontend bandwidth the estimated smaller NLOS delays can be more accurate as compared to that of lower bandwidth frontend data. Nevertheless, the accuracy of estimated NLOS signal delay using the proposed methodology being in range of 6 metres in deep urban canyons, even with 8 MHz bandwidth frontends, alludes towards the huge potential of the proposed methodology.

REFERENCES


