Multipath Mitigation by Voting Channel Impulse Response in Navigation Domain with High-sensitivity GNSS Receivers

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BIOGRAPHY

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ABSTRACT

High sensitivity GNSS receivers have proven to be of great potential in vast applications, such as location based services, vehicular and pedestrian purposes. When it comes to challenged environments, the signal tracking and navigation solution may encounter many difficulties and get degraded results. Vector tracking receivers that take advantages of mutual information among satellites are usually used, and sometimes can improve performance. However, it generally requires other operations, such as filtering along time, smoothing by using Doppler or even extending coherent integration using data bit wipe-off. In certain scenarios, multipath and cross correlation may still significantly affect the performance, and it is difficult to assess whether or not the bottleneck is due to signal tracking and/or navigation solution.

This paper focuses on evaluating the performance of code phase tracking in some challenged environments. No extended coherent integration, no filtering or smoothing is applied. Navigation domain multipath mitigation methods that use maximum likelihood vector tracking architecture and maximum likelihood navigation solution are introduced. Both foliage and downtown data show more robust code phase tracking and more reliable positioning can be achieved by using the algorithm proposed herein.

INTRODUCTION

With the emergence of multiple constellation capability in GNSS receivers, there is an increasing demand for more accurate location based services (LBS). However, multipath induced errors are still one of the most significant error sources for many positioning applications and hinder accurate LBS for either pedestrian or vehicular users.

Multipath mitigation problems have been studied for decades and can be tackled in several aspects. Among them, the most popular ones are the use of special multipath-resistant antennas such as chokering antenna, and post-processing techniques that are based on correlator outputs. For example, a standard GNSS receiver commonly uses an early-minus-late (EML) discriminator to estimate the path delay of the incoming signal (Misra & Enge 2011). In order to improve the resolvability of the direct and multipath signal delays, well-known narrow correlator can enhance the receiver’s resolvability of multipath given a suitable front-end bandwidth (Van Dierendonck et al 1992). Variants of narrow correlator techniques are the so-called double-delta technique that uses more than early, prompt and late correlators to estimate the delay, strobe correlator technique (Garin & Rousseau 1997), pulse aperture correlator (PAC), multipath estimating delay lock loop (MEDLL) (van Nee et al 1994), and vision correlator (Fenton & Jones 2005) to name a few.
Regarding high-sensitivity receivers, multiple correlators can be used. In the meantime, the shape of the filtered correlation function is still limited by the signal modulation scheme – such as bi-phase shift keying (BPSK) and binary offset carrier (BOC) – transmitter/receiver front-end filtering, and local oscillator quality etc. One way to resolve the multipath in the code phase domain is the inverse filter or inverse correlation methods discussed in Do et al (2005), which has proven to be effective. The basic problem is actually a 'de-convolution' process. The observed correlator outputs are the convolution sum of the filtered correlation function with the propagation channel impulse response (CIR) plus the noise. By using de-convolution, multipath can usually be better resolved. Researchers have also compared the performance of the de-convolution algorithms such as least squares (LSQ), minimum mean square error (MMSE), Teager-Kaiser (TK) algorithm and projection on convex set (POCS) as discussed in Lohan et al (2006).

On the other hand, the benefits of a navigation domain receiver (also called maximum likelihood position receivers), which shares all mutual information among channels (i.e., it operates spatially) has been investigated recently. Closas et al (2007) has analytically assessed the positioning performance. Weill (2010) discussed the potential benefits for ground mobile use, and Lin et al (2011) reported some pedestrian results in indoors.

In recognizing that current multipath mitigation methods are all based on single channel/satellite processing (i.e., they operate temporally), it is inevitable that either the low signal signal-to-noise ratio (SNR), the dominance of multipath, or cross correlation will cause difficulties to reliably track the signal. This paper investigates the benefits of the standalone position domain/navigation domain (ND) receiver architecture in challenged environments. In order to clearly justify the code phase tracking and positioning performance in challenged environment considered herein, there should be no filtering of code phase or Doppler smoothing in time. Here Doppler frequency and velocity are tracked independently by using similar navigation domain approaches.

In this paper, the receiver architectures used for comparison are first introduced. Then temporal and spatial de-convolution algorithms are summarized. Two data sets (foliage and downtown) are used to assess the performance. The comparison of the performance with different receiver architectures is made. The improvement of code phase tracking in both scenarios is observed as compared to the conventional block process vector tracking receiver.

This section introduces the architectures used for the high sensitivity GNSS receivers in the paper. The temporal and spatial de-convolution algorithms implemented herein are discussed. The former aims at resolving multipath in the time-delay axis, while the latter tries to resolve the multipath directly in the position domain.

**Receiver Architectures**

The diagram of the receiver implemented in this paper is shown in Figure 1. In a high sensitivity receiver, the intermediate frequency samples are first fed to the local tracking loops. As in this figure, an open loop tracking scheme is used, which evaluates the correlation values within pre-defined grids of candidate Doppler and code phase bins. The Doppler and code phase offsets are then estimated by finding the maximum power among these candidate grids. Conventional observations like pseudorange and Doppler can also be built. In a block processing vector receiver, the searching centres of such grids are only controlled by the navigation feedback (not shown in the figure). It is called centralized vector tracking (CVT) and detailed discussion can be found in Lin et al (2011). In that case, the navigation solution is computed by using a standard Kalman filter.

![Figure 1: Receiver Architectures. Block processing, Navigation domain, Navigation domain plus LSQ, Navigation domain plus TD, Navigation domain plus SD](image)

Regarding the navigation domain receiver used in this paper, the same sizes of grids are used in the open loop

**METHODOLOGIES**
tracking in all cases. Code phase spacing is 0.02 chips and Doppler spacing is 2 Hz. However, instead of using only one correlator to build the measurement, the whole correlator output arrays are used and projected onto navigation domain, i.e., position search space and velocity search space. The search point that has the maximum power is considered as the maximum likelihood (ML) navigation solution. The ML navigation solution actually reflects the position velocity and timing (PVT) residuals. These residuals can be filtered in order to get smoother solutions, and in turn to control the channel numerical controlled oscillators (NCOs). In this paper, we want to evaluate the code phase tracking performance alone, which requires that we isolate the filtering effects or smoothing effects on code phase tracking in difficult environments. Thus no filtering or smoothing is used. The ML navigation residuals are directly used to control the channel NCO, and the receiver is essentially running in the ML vector tracking (MLVT) mode.

Five kinds of processing used in this paper are illustrated in Figure 1:
1. Block processing (BP) vector receiver which uses Kalman filtered navigation solution to feedback control. Its navigation solution shown in the figures below uses LSQ with pseudorange measurements.
2. Navigation domain (ND) receiver wherein the correlators are projected in the position solution and the ML position is obtained.
3. ND receiver but the navigation solution is built based on LSQ. This approach is denoted ND-LSQ (i.e., navigation domain receiver using least-squares). By comparing BP with ND-LSQ, we can assess the tracking improvement of MLVT over CVT (if any). Similarly, by comparing the ND with ND-LSQ, we are able to see the ML navigation solution benefits over conventional navigation solution (LSQ).
4. ND receiver wherein the temporal de-convolution is used before projecting the correlator outputs to the position domain to compute the ML solution. This implementation is called ND-TD (i.e., navigation domain receiver with temporal de-convolution).
5. ND receiver projecting conventional correlator outputs onto position domain, but navigation solution is based on spatial de-convolved results. This is denoted ND-SD (i.e., navigation domain receiver with spatial de-convolution).

All of the above approaches were implemented in a modified version of the University of Calgary’s GSNRx™ software GNSS receiver (O’Driscoll et al 2009).

Temporal and spatial de-convolution

If assuming that the incoming signal is corrupted by the multipath, the CIR is thus composed of both line-of-sight (LOS) and non-line-of-sight (NLOS) propagation, and it has passed the front-end filter. The actual correlation outputs are the ideal correlation convolved with the impulse response of the propagation channel and the front-end filter.

In case of GPS and GLONASS signal, the ideal correlation will be a triangle. The receiver front-end filter has limited bandwidth, and makes the actual correlation shape to be rounded in the peak region. The focus of the paper is trying to mitigate the multipath, whose information is only contained in $h_p(t, \tau)$, which is the CIR. Assuming that the propagation channel is frequency selective and slow fading, then the CIR can be expressed as

$$h_p(t, \tau) = \sum_j \alpha_j \delta(t - \tau_j)$$  \hspace{1cm} (1)

With this model, the parametric de-convolution can be used to estimate the CIR magnitude coefficients $\alpha_i$. In turn, the actual correlation outputs will be

$$c_i(\tau) = R(\tau) * h_p(t, \tau) + n(t)$$  \hspace{1cm} (2)

The problem is given correlation outputs, $c_i(\tau)$, and the autocorrelation function, $R(\tau)$, how to resolve the CIR coefficients in $h_p(t, \tau)$?

During the integration time interval (including coherent and any non-coherent integration), it is assumed that the signal $s(t)$ is known except for the unknown delays, $\tau_i$. The frequency is assumed locked within a small range of the reciprocal of the integration time being used. The convolved signal is then given by

$$s(t) * h(t, \tau) = \sum \alpha_j s(t - \tau_j)$$  \hspace{1cm} (3)

If there are $L$ code phase offsets during the observation interval, CIR coefficients can be estimated by using

$$\min \sum_i \left| r(t + t_i) - \sum_j \alpha_j s(t + t_i - \tau_j) \right|^2$$  \hspace{1cm} (4)

Or be expressed in matrix form $\min \| r - Sa \|^2$. In this case, the vector $r$ is the received data samples and can be expressed as $r(t + t_0), r(t + t_1), \ldots r(t + t_{L-1})$, and $a$ is the CIR coefficients. The matrix $S$ can be expressed as

$$s(t + t_0 - \tau_0) \quad s(t + t_0 - \tau_1) \quad \cdots \quad s(t + t_0 - \tau_{L-1})$$

$$s(t + t_{L-1} - \tau_0) \quad s(t + t_{L-1} - \tau_1) \quad \cdots \quad s(t + t_{L-1} - \tau_{L-2})$$

The CIR coefficients can be estimated as

$$\hat{a} = (S^H S)^{-1} S^H r = Q^{-1} c$$  \hspace{1cm} (5)

If considering the above formula during the observation time, the matrix $S^H S$ becomes a matrix composed of autocorrelation values, and is denoted as $Q$. 

\[
\begin{pmatrix}
R(0) & R(t_1 - t_0) & \cdots & R(t_{L-1} - t_0) \\
\vdots & \ddots & & \vdots \\
R(t_0 - t_{L-1}) & R(t_1 - t_{L-1}) & \cdots & R(0)
\end{pmatrix},
\]

and the term \( \mathbf{S}\mathbf{r} \) becomes actual correlation array \( \mathbf{c} \),
\[
\int_{t_0}^{t_0+L-1} r(t) s(t - t_0) dt \approx c_t(t_0)
\]

The subscript “\( e \)” here implies the temporal correlation values. This least square de-convolution algorithm is easy to implement, but sometimes suffers from noise amplification. In order to reduce the chances of noise amplification, one choice is to use regularized least square de-convolution, by including a least norm constrain term in the cost function (Press et al 2007)

\[
\min \| \mathbf{r} - \mathbf{S}\alpha \|^2 + \mu \| \Gamma\alpha \|^2
\]

Here, the regulation parameter \( \mu \) can weigh the estimation to be less affected by noise. Larger \( \mu \) will make the estimation more smooth while smaller \( \mu \) will fit data better. The matrix \( \Gamma \) is called Tikhonov matrix. The modified estimator would be

\[
\hat{\alpha} = (\mathbf{Q} + \mu \Gamma^T\Gamma)^{-1}\mathbf{c}
\]

Similar to above, the spatial impulse response is defined as

\[
h_s(t, \Delta\mathbf{p}) = \sum \alpha_\ell, j \delta_\ell (\mathbf{p} - \Delta\mathbf{p})
\]

The correlation powers in code phase axis can be also projected onto position domains, such as east, north, vertical and clock bias axes. Define the spatial correlation at the position offset relative to the current position estimate as \( \Delta\mathbf{p} = (\Delta E, \Delta N, \Delta U, \Delta Clk) \) as

\[
c_s(t, \Delta\mathbf{p}) = \sum_m \| c^m_t(\tau(\Delta\mathbf{p})) \|
\]

The subscript “\( s \)” here implies the spatial de-convolution. The script “\( m \)” stands for the index of satellites. The spatial integration here is non-coherently combining among satellites. By definition, this spatial correlation is of higher dimension, i.e., 4D with east, north, vertical and clock bias unknowns. For simplicity, each dimension is treated separately. The ideal spatial auto correlation values can be pre-computed by using the same formula

\[
R_s(t, \Delta\mathbf{p}) = \sum_m \| R^m(\tau(\Delta\mathbf{p})) \|
\]

In such case, the spatial \( \mathbf{Q}_s \) will be

\[
\begin{pmatrix}
\sum \| R^m(\Delta p) \| & \sum \| R^m(\tau(\Delta p_1 - \Delta p)) \| & \cdots & \sum \| R^m(\tau(\Delta p_{L-1} - \Delta p)) \| \\
\sum \| R^m(\tau(\Delta p_0 - \Delta p_{L-1})) \| & \sum \| R^m(\tau(\Delta p_1 - \Delta p_{L-1})) \| & \cdots & \sum \| R^m(\tau(\Delta p)) \|
\end{pmatrix}
\]

The general relationship between spatial correlation and spatial response is

\[
c_s(t, \Delta\mathbf{p}) = R_s(t, \Delta\mathbf{p}) * h_s(t, \Delta\mathbf{p}) + n_s(t, \Delta\mathbf{p})
\]

Analogously, the least square based de-convolution algorithms are implemented. Spatial response (SR) coefficients are computed via

\[
\hat{\alpha}_s = \mathbf{Q}_s^{-1}\mathbf{c}_s
\]

As mentioned above, each dimension is treated separately for simplicity. In our case, the front-end is bandwidth limited. The CIR is not an impulse any more, and it needs be reconstructed by using specified front-end filtering bandwidth (Yang & Porter 2005).

**REAL DATA PROCESSING & FIELD TEST**

To test the different processing strategies, two real data sets were collected in Calgary. The primary pieces of equipment for the data collection were a National Instruments (NI) front-end, a NovAtel SPAN receiver and a LCI IMU (Novatel 2010). The raw IF data was collected with the NI front-end at 10 and 12.5 MHz as complex samples. The first scenario is foliage as shown in the top picture in Figure 2. The second data set was in the urban environment shown in the lower picture of Figure 2.
Since in this paper, no carrier phase tracking is enabled, only code phase and Doppler are tracked independently in a non-coherent manner. In the foliage scenario, it is expected to see minor disturbances in code phase tracking or positioning results. In the second data set, multipath, blockage, and cross correlation are expected to be quite common, and will affect the code phase tracking and navigation solution more severely. In such scenario, GPS plus GLONASS are used in order to improve the signal availability in downtown as reported in O’Driscoll et al (2011).

Temporal de-convolution

As shown in equation (5), the temporal de-convolution is implemented with a LSQ approach. The propagation channel responses in open sky and in multipath environments are shown in Figure 3 and Figure 4 respectively. In Figure 3, it clearly shows there is only one dominant propagation path, which indicates the fact that at this epoch the receiver is operating in near open sky.

However, in Figure 4 the correlation does not have a single peak anymore, and we could approximately see two major propagation paths. After the de-convolution, the CIR plots prove our justification. By de-convolution, the powers distributed among different paths or components are more separated. In this sense, it is expecting to see the improved multipath resolvability when projecting or voting these propagation responses instead of correlation outputs.

Foliage Scenario (GPS)

In the foliage scenario, only the GPS constellation is used. If looking at the \(C/N_0\) profiles in Figure 5, it can be seen that most satellites still have relatively strong powers for the entire data set. \(C/N_0\) values of certain satellites only drop to about 35dB-Hz during certain epochs.
The trajectories of various navigation solutions are shown in Figure 6. It can be seen that for most of the time, BP solution is good enough. However at certain epochs, there are some extremely large outliers (red lines away from the trajectory). Regarding all the other ND solutions, they are more robust, even though the ND-SD and ND-TD appear to be much noisy.

The error percentiles of east, north and vertical errors are shown in Figure 7, Figure 8, and Figure 9 respectively. By inspecting the Figure 7 and Figure 8, we can see that the ND-LSQ curve is more convex than all the other four. This indicates the MLVT tracking slightly outperforms the CVT (i.e., the BP curve). It also shows that the east and north positioning errors in ND-TD and ND-SD are poorer than ND approach. These errors might due to LSQ de-convolution process. Temporal de-convolution outperforms spatial de-convolution results in east and north axes.

The other thing need to be mentioned is for BP tracking, if navigation solution is built with LSQ then there are some huge outliers that are reflected in the trajectories. As for ND, ND-SD, and ND-TD, none of these occurs, which proves the measurement quality of the MLVT.

In Figure 9, it can be seen that ND-SD outperforms ND-TD and ND approaches in vertical axis. In the meantime, ND-LSQ still is slightly better than BP, which denotes the improvement of MLVT over CVT.
Above figures shows the error percentiles of east, north, and vertical axes. The RMS errors in foliage are also summarized here in Table 1.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>East (m)</th>
<th>North (m)</th>
<th>Up (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP</td>
<td>2015.1</td>
<td>1070.5</td>
<td>12516.9</td>
</tr>
<tr>
<td>ND-LSQ</td>
<td>1.1</td>
<td>1.6</td>
<td>7.9</td>
</tr>
<tr>
<td>ND</td>
<td>3.1</td>
<td>2.1</td>
<td>18.6</td>
</tr>
<tr>
<td>ND-TD</td>
<td>7.5</td>
<td>6.2</td>
<td>17.4</td>
</tr>
<tr>
<td>ND-SD</td>
<td>15.1</td>
<td>15.9</td>
<td>11.5</td>
</tr>
</tbody>
</table>

Huge RMS errors shown in BP are due the occasionally large outliers. We also observe that the ML navigation solutions do not show any benefits over conventional LSQ approach if comparing ND-LSQ to ND, ND-TD, and ND-SD. Only the improvement of the code phase tracking can be observed when comparing the ND-LSQ to BP solution, since the measurements being built by using ND have no huge outliers thus ND-LSQ performs much better than BP solution. It is quite possible that in these foliage scenarios when the code phase can be reliably tracked, the conventional navigation solution is robust enough.

**Urban Canyon Scenario (GPS+GLONASS)**

The following results are based on downtown data set which includes both GPS and GLONASS constellation. In this case, multipath, blockage and cross correlation will affect the code phase tracking and navigation solution much more significantly than under foliage. The C/N₀ and sky plots are shown in Figure 10. From the C/N₀ plots, we could see once the vehicle enters downtown, many C/N₀ values begin to fluctuate very frequently. This kind of fluctuation may due to the blockage, multipath, and/or fading effects.

The trajectories of various navigation solutions are plotted in Figure 11. It can be seen that the BP trajectory just runs away from the truth once it enters urban canyon. This indicates that both the BP tracking breaks in these epochs, and the observations built with this receiver architecture are not good enough for Kalman based navigation solution. For the ND approaches, even though the trajectory looks very noisy, it still keeps tracking of the signal. This means the ND approaches has better code phase tracking of the incoming signals than BP approach.

The east error percentiles in downtown scenario are shown in Figure 12. All ND approaches obviously are more robust...
than the CVT. It can also be observed that when east positioning errors are less than 20 m, ND-LSQ outperforms other ND methods. However, ND-LSQ still has large outliers. When the errors are larger than 30 m, ND-SD outperforms ND and ND-TD.

**Figure 12: East error percentile - downtown**

In Figure 13 and Figure 14, north and vertical error percentiles are shown. With scrutiny of the north error percentile, the ND-TD and ND-SD are almost the same and ND-only solution outperforms both of them. Overall, all three approach are still able to track the signal. Regarding the vertical axis, all the ND approaches are very similar when errors are smaller than 15 m and larger than 40 m. The ND-LSQ in the vertical also has poorer performance as compared to ND, ND-SD and ND-TD. This validates the benefits of ML navigation solution over conventional navigation solution.

**Figure 13: North error percentile - downtown**

**Figure 14: Vertical error percentile - downtown**

The RMS errors in the downtown scenario are summarized in Table 2. The RMS errors for BP and ND-LSQ are very huge. The poor BP results are due to the loss of lock of the incoming signal. For the ND-LSQ, this is because at certain epochs there are very large outliers. Even though at most of the other epochs, it performs better than the ML navigation solution.

**Table 2 Position RMS errors in downtown**

<table>
<thead>
<tr>
<th>Strategy</th>
<th>East (m)</th>
<th>North (m)</th>
<th>Up (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP</td>
<td>8814.4</td>
<td>3479.8</td>
<td>3710.3</td>
</tr>
<tr>
<td>ND-LSQ</td>
<td>78.7</td>
<td>1216.3</td>
<td>1412.5</td>
</tr>
<tr>
<td>ND</td>
<td>20.1</td>
<td>24.1</td>
<td>34.9</td>
</tr>
<tr>
<td>ND-TD</td>
<td>20.5</td>
<td>29.5</td>
<td>35.6</td>
</tr>
<tr>
<td>ND-SD</td>
<td>18.1</td>
<td>28.2</td>
<td>49.1</td>
</tr>
</tbody>
</table>

From the downtown data processed here, it is apparent that code phase tracking using MLVT is more robust than CVT. Furthermore, with same tracking scheme, the ML navigation solution was more robust and reliable than the conventional LSQ solution. The outliers occurred in ND-LSQ solutions are very likely due to poor measurement quality in some channels, where strong multipath and cross correlation between satellites occurs.

**CONCLUSIONS AND FUTURE WORK**

In this paper, position/navigation domain receiver architecture is proposed and used to mitigate multipath effects on code phase tracking and positioning. In order to clearly justify the code phase tracking and positioning performance, no filtering or smoothing is used. Doppler and code phase are tracked in an open loop manner. With the ND receiver architecture, the temporal and spatial deconvolution algorithms are then introduced and implemented with a LSQ method.
Two real data sets collected in foliage and downtown scenarios are processed with various processing methods. It is shown that:

- In foliage scenario, code phase tracking using block processing vector receiver is very robust and accurate for most epochs. Very occasionally, measurements may have large outliers if with a LSQ navigation solution.
- In foliage scenario, ND receiver not only provides accurate and robust code phase tracking but also better measurements. The benefits of ML navigation solution in such scenario are not obvious. Temporal and spatial de-convolution performance only shows improvement in vertical axis.
- In downtown scenario, block processing vector receiver code phase tracking is very fragile, and produce poor pseudorange measurements.
- In downtown scenario, ND approaches could maintain robust code phase tracking, and build better measurements. The ML navigation solution is proven to be more reliable than LSQ. Temporal and spatial de-convolution algorithm only shows improvements in east axis.

Currently, the de-convolution algorithm employed here is implemented done using LSQ. There are other options which may have less systematic errors, such as TK-algorithm, POCs, and MMSE; these will be investigated in future work. The results here are based on unfiltered and unsmoothed data. In the near future, we will try to compare the filtered and smoothed results in various environments.

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