Adaptive Estimation of Measurement Noise to Improve the Performance of GNSS Single Point Positioning in Dense Urban Environment

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Abstract This paper argues that an adaptive extended Kalman filter (EKF) improves performance of Global Navigation Satellite System (GNSS) position, velocity, and timing (PVT) by single point positioning without sensor aiding or coupling in dense urban environments. The one of the most important and difficult problems is the negative impact of non-line-of-sight (NLOS) due to large buildings that shade line-of-sight (LOS) signals and create NLOS signals by reflection and/or diffraction. The GNSS receiver eventually tracks the NLOS signal only, which causes significant and unexpected measurement errors that degrade the PVT performance of conventional positioning methods. To reduce this negative impact, an adaptive EKF is implemented for single point positioning. Six laps of test drives prove that the adaptive EKF drastically reduces position and velocity errors and removes outliers compared to conventional EKF. Regarding the horizontal position, for example, the adaptive EKF produces 16.1 m of cumulative probability in the one-sigma error range (68.27%), while the conventional EKF results in 48.0 m. Mean error is also minimized, from 12.90 m to 2.74 m. Similar improvements are present in vertical position and 3-D velocity. The only difference between the EKFs in this paper is the adaptive estimation of the covariance matrix of the measurement noise. Detailed analysis confirms that the adaptive covariance matrix of the measurement noise matched the actual measurement error, as all correlation coefficients exceed 0.95, which highlights significant improvement in positioning performance. The adaptive estimation of the covariance matrix has a simple formulation and the process is not expensive, which means it can run on a low-cost receiver in real-time. Thus, the adaptive EKF could be proposed as a simple and effective technique to reduce the negative impact of NLOS and to improve the GNSS PVT performance in heavy NLOS environments for any type of GNSS receiver.

Keyword EKF, Adaptive EKF, NLOS, Urban environment

1. Introduction

Because the Global Navigation Satellite System (GNSS) is utilized for various applications such as pedestrian, marine, and automotive navigation, it is a de facto standard for position sensors involving outdoor navigation. In particular, there is high demand for precise and robust GNSS navigation in the urban market for applications such as autonomous driving and advanced driver assistance systems [1] [2].

Non-line-of-sight (NLOS) signals are interrupted by large buildings and NLOS signals are created by reflection and/or diffraction so that GNSS receivers eventually track NLOS signals only. Measurements from NLOS-only tracking contain significant and unexpected errors which lead conventional GNSS positioning algorithms to produce many position outliers. Therefore, recent studies have been conducted to eliminate NLOS, such as detecting NLOS by fish-eye images and orientation estimation [3], or removing bias caused by NLOS from measurements using 3D models [4]. However, it has proven difficult to run such expensive processing on low-cost receivers in real-time to date.

On the other hand, some studies have applied an adaptive extended Kalman filter (EKF) to reduce the number of positioning errors [5] [6]. The adaptive Kalman filter considers the case in which the true values of the covariance matrices of process noise and measurement noise are “unknown” [7]. The authors consider the NLOS biases on GNSS measurements to be exactly “unknown” due to a complicated propagation path. Moreover, it is possible to apply the adaptive EKF on low-cost receivers in real-time, because the adaptive tuning is quite simple and inexpensive.

This paper examines the performance of the adaptive EKF in urban canyons involving dense NLOS environments. Note that the GNSS positioning method in this paper does not utilize any sensor aiding or coupling, although it is popular to integrate GNSS and some sensors [5] [6]. Test data are collected based on a total of six laps in the Nishi-Shinjuku area, which is one of the densest urban canyons in Japan. Analysis of the performance is carried out by comparing the position and velocity of the adaptive EKF with those of the conventional EKF. The analysis also verifies the relationship between the covariance matrices of measurement noise with actual measurement errors.

2. Kalman Filtering

This section introduces EKF and adaptive tuning applied to GNSS position, velocity, and timing (PVT) estimation.
2.1 EKF for GNSS single point positioning

An EKF measurement update of a state vector $x$ and its covariance matrix $P$ are represented by a measurement vector $z_k$ at epoch $k$ [8] [9] as

$$
\tilde{x}_k = \tilde{x}_{k-1} + K_k(z_k - h(\tilde{x}_k))
$$

$$
P_k = P_{k-1}K_k^T H(\tilde{x}_k)P_k + R_k^{-1}
$$

where $\tilde{x}_k$ and $P_k$ are the state vector and its covariance matrix after the measurement update at epoch $k$. $\tilde{x}_{k-1}$ and $P_{k-1}$ are the state vector and its covariance matrix before the measurement update. $h(x)$, $H(x)$, and $R$ are the measurement model vector, the matrix of partial derivatives, and the covariance matrix of the measurement noise, respectively. Assuming the system model is linear, the time update of the state vector and its covariance matrix are

$$
\dot{\tilde{x}}_k = \dot{\tilde{x}}_{k-1} + \dot{\tilde{u}}_k
$$

$$
\dot{P}_k = F_kP_{k-1}F_k^T + Q_k
$$

where $F_k$ and $Q_k$ are the transition matrix and the covariance matrix of the state error from epoch $k-1$ to $k$. $\dot{\tilde{x}}_k$ relates the optional control input $\dot{u}_k$ to the state vector.

GNSS single point positioning defines the measurement equations as follows:

$$
\rho^i = \gamma^i + \delta t + \epsilon^i
$$

$$
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$$

where $\rho^i$ and $\rho^i$ are pseudo-range in meters and Doppler shift in meters per second of satellite $i$, respectively. Note that the measurements here have already been corrected for satellite clock errors, ionospheric and tropospheric propagation delays, and inter-system biases in an alternate manner. $\gamma^i$ and $\gamma^i$ are the geometric range and its rate between satellite $i$ and the user, $\delta t$ and $\delta t$ are the receiver clock bias and drift, and $\epsilon$ is the measurement noise.

The unknown state vector can be defined as

$$
x = (g_u \delta t, g_u \delta t)^T
$$

$$
y_u = (x_u, y_u, z_u)
$$

$$
y_u = (x_u, y_u, z_u)
$$

where $(x_u, y_u, z_u)$ and $(\dot{x}_u, \dot{y}_u, \dot{z}_u)$ are the user position in meters and velocity in meters per second in an earth-centered, earth-fixed (ECEF) coordinates frame, respectively.

According to (3) and (4), the measurement vector $z$, the measurement model vector $h(x)$, and the matrix of partial derivatives $H(x)$ are defined as follows [8] [10]:

$$
z = (\rho, \dot{\rho})^T
$$

$$
\rho = (\rho^1, \rho^2, ..., \rho^m)^T
$$

$$
\dot{\rho} = (\dot{\rho}^1, \dot{\rho}^2, ..., \dot{\rho}^m)^T
$$

$$
h(x) = (y, y)^T
$$

$$
\gamma = (\gamma^1 + \delta t, \gamma^2 + \delta t, ..., \gamma^m + \delta t)
$$

$$
\dot{\gamma} = (\gamma^1 + \delta t, \gamma^2 + \delta t, ..., \gamma^m + \delta t)
$$

$$
y^i = \|g - y_u\|_2 = a_u^i(y^i - y_u)^T
$$

$$
a_u^i = \frac{g^i - y_u}{\|g^i - y_u\|}
$$

$$
H(x) = \frac{\partial h(z)}{\partial x} \bigg|_{x=x^i}
$$

$$
= \begin{bmatrix}
a^1_u & 1 \\
\vdots & \vdots \\
a^m_u & 1
\end{bmatrix}
$$

where $(x^i, y^i, z^i)$ and $(\dot{x}^i, \dot{y}^i, \dot{z}^i)$ are the position in meters and velocity in meters per second of satellite $i$ in the ECEF coordinates frame, respectively.

The covariance matrix of measurement errors can be written as

$$
R = \begin{bmatrix} R_p & 0 \\
0 & R_p \end{bmatrix}
$$

$$
R_p = \begin{bmatrix} \sigma_{p1}^2 & \sigma_{p2} & \sigma_{p3} & \sigma_{p4} & \sigma_{p5} \\
\sigma_{p2} & \sigma_{p2}^2 & \sigma_{p3} & \sigma_{p4} & \sigma_{p5} \\
\sigma_{p3} & \sigma_{p3} & \sigma_{p4}^2 & \sigma_{p4} & \sigma_{p5} \\
\sigma_{p4} & \sigma_{p4} & \sigma_{p4} & \sigma_{p5} & \sigma_{p5} \\
\sigma_{p5} & \sigma_{p5} & \sigma_{p5} & \sigma_{p5} & \sigma_{p5}
\end{bmatrix}
$$

where $\sigma_{p1}$ and $\sigma_{p1}$ are the standard deviation of measurement noise of the pseudo-range and Doppler shift from satellite $i$.

The time update of (2) is expressed as

$$
F = I, D_k = I \cdot \Delta t_k
$$

$$
u_k = (\dot{x}_{uk-1}, \dot{y}_{uk-1}, \dot{z}_{uk-1}, \delta t_{k-1}, 0, 0, 0)^T
$$

$$
Q = \begin{bmatrix} Q_{\dot{\rho}u} & \sigma_{\dot{\rho}t}^2 \\
\sigma_{\dot{\rho}t}^2 & Q_{\dot{\rho}u} \end{bmatrix}
$$

$$
Q_{\dot{\rho}u} = \text{diag}(\sigma_{\dot{\rho}u}^2, \sigma_{\dot{\rho}u}^2, \sigma_{\dot{\rho}u}^2)
$$

$$
Q_{\dot{\rho}t} = \text{diag}(\sigma_{\dot{\rho}t}^2, \sigma_{\dot{\rho}t}^2, \sigma_{\dot{\rho}t}^2)
$$

where $\Delta t_k$ is the elapsed time from epoch $k-1$ to $k$, and $\sigma_{\dot{\rho}u}$ and $\sigma_{\dot{\rho}u}$ are standard deviations of the process noise of elements $n$ and $n$, respectively.

The process state and measurement equation for GNSS single point positioning can be given by the two simple expressions:

$$
\tilde{x}_k = \tilde{x}_{k-1} + D_k \cdot \nu_{k-1} + w_k
$$

$$
z_k = h(\tilde{x}_k) + H(\tilde{x}_k)(\tilde{x}_k - \tilde{x}_k) + v_k
$$

where $w_k$ and $v_k$ represent the process and measurement noise, respectively. They are independent of each other and are independent from the white Gaussian noise sequence. Thus,

$$
E(w_k) = 0, E(v_k) = 0
$$

$$
E(w_k v_k^T) = 0
$$

$$
E(w_k v_k^T) = 1
$$

$$
E(v_k v_k^T) = 1
$$

where $E(\cdot)$ denotes the expectation function.

The GNSS PVT by single point positioning is derived by solving (1) and (2) with equations (4) through (9). The present paper defines the EKF introduced here as the conventional EKF to distinguish it from the adaptive EKF that will be described in the following subsection.

2.2 Adaptive estimation of the covariance matrix

An adaptive Kalman filter provides real-time estimation of the covariance matrices of process and measurement noise.
One of the most important techniques of the adaptive estimation is its innovation-based algorithm used to adapt the covariance matrix \( R \). Based on (1), the innovation sequence \( d_k \) is defined as [5] [7] [11]
\[
d_k = z_k - h(\hat{x}_k) \tag{12}
\]
Substituting \( z_k \) of (10) into (12), the innovation can be transformed to
\[
d_k = H(\hat{x}_k)(\hat{x}_k - x_k) + v_k \tag{13}
\]
When the filter is in optimal mode, the innovation sequences \( d_k \) are white Gaussian. Taking the variance of both sides, theoretical covariances are defined as follows [11]:
\[
C_{d_k} = H(\hat{x}_k)P_kH(\hat{x}_k)^T + E\{v_kv_k^T\} \tag{14}
\]
Based on (14), the measurement noise covariance matrix \( R \) can be adapted as [7] [11]
\[
\hat{R}_k = \frac{C_{d_k}}{N} - H(\hat{x}_k)P_kH(\hat{x}_k)^T \tag{15}
\]
where \( \hat{C}_{d_k} \) is the estimated variance-covariance matrix of the innovation and is computed by averaging within a moving estimation window of size \( N \).

Substituting \( \hat{R}_k \) for \( R_k \) in (1) enables the implementation of the adaptive EKF that adapts the innovation to the covariance matrix of the measurement noise.

Another adaptive estimation of covariance matrix \( R \) employs a residual-based algorithm that is obtained by replacing \( h(\hat{x}_k) \) in (12) with \( h(\hat{x}_k) \) [5]. The residual can be exploited for not only adaptive estimation, but also for the practical purposes of system failure detection or reasonableness checking of measurement data [12]. The adaptive estimation of the covariance matrix of process noise, \( Q \), introduced in [5] is a scaling technique based on either the innovation or the residual.

3. Experimental results

The following subsections describe configurations and results of a driving test carried out to assess adaptive EKF in a dense urban environment.

3.1 Driving test configuration

Fig. 1 shows the test path and 3D view of the area around the path. As seen in the figures, the test path is surrounded by large buildings that should interrupt LOS and create NLOS signals. Both EKFs are implemented in post-processing with raw measurement data corrected by Furuno Multi-GNSS receiver, GN-8720 [13]. As described previously, the raw data does not include any sensor data, but only the GNSS measurement. The driving test data are summarized in Table 1. The accuracy of the true position and velocity are centimeters and centimeters per second, respectively, which should be more accurate than the requirements for the evaluation of this paper [16].

Table 1 Driving test configurations

| Date & Time       | Nov.09.2015 10:00-18:00 (JST) |
|-------------------|--------------------------------|
| Test Area         | Nishi-shinjuku, Tokyo          |
| Total Laps        | 6 laps                        |
| Antenna Type      | Taoglas AA.171.301111 [15]    |
| Antenna Placement | Car roof                      |
| Raw Measurement   | Furuno GN-8720 [13]           |
| GNSS System Usage | GPS/QZSS L1CA, GLONASS L1OF   |
| Masks             | Elevation: 5° | SNR: 33(dBHz)(GPS/QZSS) | 34(dBHz)(GLONASS) |
| Sampling Rate     | 1 Hz                          |
| True Position/Vel. | Applanix POSLV 520(Post Proc.) [16] |

Fig. 2 Process flow diagram of the adaptive tuning

The present study empirically determines the initial value of the covariance matrices of the process noise in (2) and of the state vector in (9) as follows:
\[
\sigma_{p_n} = 2, \sigma_{p_n} = 1 \tag{16}
\]
For the standard deviation of the measurement noise of the conventional EKF in (8), an exponential approximation is utilized according to the signal-to-noise ratio (SNR). The approximations are derived by referencing [17] [18]:
\[
\sigma_R(SNR) = 0.64 + 784 \times e^{-0.142\times SNR} \tag{17}
\]
\[
\sigma_R(SNR) = 0.0125 + 6767 \times e^{-0.267\times SNR} \tag{17}
\]

The covariance matrix of the measurement noise of the conventional EKF consists of the squared values of equation (17) only. On the other hand, the matrix of the adaptive EKF is not derived only from equation (17). The following describes how the adaptive covariance matrix of the measurement noise is derived.

In this paper, the adaptive estimation in (15) is computed with the simplest window size, \( N = 1 \). One of the reasons for utilizing this value is responsiveness, as measurement errors caused by NLOS can change very quickly. Another reason is easy real-time estimation, although the evaluation is carried out in post-processing. This adaptive estimation would not challenge even low-cost receivers.
This study also establishes two restrictions: the estimated standard deviation of the measurement noise has a lower band threshold [the value in (17)], and the estimated covariance matrix of the measurement noise is adapted after the conventional EKF has converged sufficiently. Both of these restrictions aim to detect NLOS signals correctly and then to recognize the measurement noise as unknown. In other words, the adaptive estimation is not implemented for LOS measurements. Fig. 2 presents the process flow of the adaptive tuning described here.

On the other hand, this study does not adapt the covariance matrix of the process noise, $Q$, and instead sets it to be constant. This is because the benefits of adaptive estimation of the matrix $Q$ require a large number of window sizes [5], which may not be suitable for real-time estimation.

### 3.3 Comparison of position and velocity error

Fig. 3 and Fig. 4 compare horizontal and vertical position errors between the adaptive EKF and the conventional EKF. The origin of the axes of Fig. 3 denotes the starting position of the test path. Note that both results are not reported by the GN-8720 receiver, but by the results of the EKFs introduced in this paper. These figures show six laps (all the driving tests).

From the comparison, the adaptive estimation obviously contributes to reducing the position errors. The conventional EKF creates many position jumps, excursions, and oscillations (seen on the right sides of Fig. 3 and Fig. 4), while there are no large outliers, simply smooth plots, for the adaptive EKF (seen on the left sides of Fig. 3 and Fig. 4).

The statistics displayed in Fig. 5 and Table 2 also indicate an apparent improvement in the adaptive filtering ability. Regarding the horizontal error, the cumulative probability of...
the adaptive EKF at one-sigma error range (68.27%) is 16.1 m and at two-sigma range (95.45%) is 33.6 m, while those of the conventional EKF are 47.9 m and 140.8 m, respectively. The mean error is also reduced, from 12.87 m for conventional EKF to 2.71 m for adaptive EKF. The vertical error shows similar results, as the cumulative probability of the adaptive EKF at one-sigma range is 24.8 m and at two-sigma range is 95.5 m, while those of the conventional EKF are 115.4 m and 271.7 m, respectively. The mean error is also reduced, from 93.98 m (conventional EKF) to 26.29 m (adaptive EKF).

The adaptive covariance matrix of the measurement noise also contributes to improving the performance of the velocity estimation, as seen in Fig. 6. The adaptive EKF removes obvious outliers that are present in the conventional EKF results. The statistics summarized in Fig. 7 and Table 3 indicate that the performance in terms of the 3D-velocity measurements is obviously enhanced by the adaptive EKF, as are the position results.

These comparisons demonstrate that the adaptive EKF achieves highly accurate and precise GNSS navigation in a dense urban environment. More detailed analysis and discussions of these improvements will be presented in the following Section.

| Table 2 Statistical summary of position errors |
|-----------------|-----------|-----------|-----------|
|                | Mean error[m] | Error at 68.27%[m] | Error at 95.45%[m] | Error at 100%[m] |
| Horizontal     |            |                        |                        |                |
| Adaptive EKF   | 2.71       | 16.1                   | 33.6                   | 102.5          |
| Conventional EKF | 12.87     | 47.9                   | 140.8                  | 290.7          |
| Vertical       |            |                        |                        |                |
| Adaptive EKF   | 26.29      | 24.8                   | 95.5                   | 167.8          |
| Conventional EKF | 93.98     | 115.4                  | 271.7                  | 409.7          |

| Table 3 Statistical summary of velocity errors |
|-----------------|-----------|-----------|-----------|
|                | Mean error[m/s] | Error at 68.27%[m/s] | Error at 95.45%[m/s] | Error at 100%[m/s] |
| Horizontal     |            |                        |                        |                |
| Adaptive EKF   | 0.007      | 0.12                   | 0.78                   | 6.94           |
| Conventional EKF | 0.022     | 0.17                   | 1.55                   | 15.80          |
| Vertical       |            |                        |                        |                |
| Adaptive EKF   | 0.039      | 0.16                   | 1.10                   | 11.67          |
| Conventional EKF | 0.182     | 0.24                   | 2.26                   | 16.79          |

4. Deep analysis of the improvement

4.1 Actual measurement errors

The following technique considers the actual measurement errors (particularly by NLOS-only tracking) that represent an important factor when considering position and velocity improvements.

The residuals of the single difference of the pseudo-range and Doppler shift between QZSS and satellite \( i \) can be determined from (3), so that:

\[
\Delta \rho_{\text{QZSS},i} = (\rho_{\text{true}} - \rho_{\text{QZSS},i}) - (\rho_{\text{true}} - \rho_{\text{QZSS},i})
\]

\[
\Delta \dot{\rho}_{\text{QZSS},i} = (\dot{\rho}_{\text{true}} - \dot{\rho}_{\text{QZSS},i}) - (\dot{\rho}_{\text{true}} - \dot{\rho}_{\text{QZSS},i})
\]

where \( \rho_{\text{QZSS}} \) and \( \dot{\rho}_{\text{QZSS}} \) are the pseudo-range and Doppler shift of QZSS, and \( \rho_{\text{true}} \) and \( \dot{\rho}_{\text{true}} \) are the true values of geometric distance and its rate computed from the reference position and velocity obtained from POSLV [16] and the satellite position and velocity derived from the broadcasted ephemeris. At this time, using the measurement errors of NLOS, \( \delta_{\text{NLOS}} \) and \( \dot{\delta}_{\text{NLOS}} \), (3) can be slightly modified to

![Fig. 8 Residuals of single difference of pseudo-ranges at lap04](image1)

![Fig. 9 Residuals of single difference of Doppler shift at lap04](image2)
\[
\rho^i = \gamma^i + \delta t + \delta^i_{\text{LOS}} + \epsilon_{\rho^i}
\]
\[
\rho_{\text{QZSS}} = \gamma_{\text{QZSS}} + \delta t + \delta^i_{\text{NLLOS}} + \epsilon_{\rho_{\text{QZSS}}}
\]
\[
\dot{\rho}^i = \dot{\gamma}^i + \delta \dot{t} + \delta^i_{\text{NLLOS}} + \epsilon_{\dot{\rho}^i}
\]
\[
\dot{\rho}_{\text{QZSS}} = \dot{\gamma}_{\text{QZSS}} + \delta \dot{t} + \delta^i_{\text{NLLOS}} + \epsilon_{\dot{\rho}_{\text{QZSS}}}
\]  

When the elevation angle of QZSS is high enough during the test drive, there should not be large NLOS errors either for the QZSS pseudo-range or for Doppler shift. Thus, assuming \(\delta^i_{\text{NLLOS}} \equiv 0\) and \(\delta^i_{\text{NLLOS}} \equiv 0\), (18) can be transformed by substituting (19) into it so that:

\[
\Delta \rho_{\text{(residual)}}^{\text{QZSS},i} = \delta^i_{\text{NLLOS}} + \epsilon_{\Delta \rho_{\text{QZSS},i}}
\]

\[
\Delta \dot{\rho}_{\text{(residual)}}^{\text{QZSS},i} = \delta^i_{\text{NLLOS}} + \epsilon_{\Delta \dot{\rho}_{\text{QZSS},i}}
\]  

Using (20) enables direct viewing of the measurement errors, especially those caused by NLOS-only tracking. This provides a large benefit when computing the residual of the single difference of the pseudo-range and Doppler shift between QZSS and satellite \(i\).

Fig. 8 and Fig. 9 depict the measurement errors derived from (20) at lap04 of the driving test. The reason for selecting this lap is that the QZSS satellite has the highest elevation angle of all the laps (~86°). This implies that there are no NLOS errors on the QZSS measurements but there are very large NLOS errors on the measurements from the other satellites. As shown in Fig. 8, errors on the single difference of the pseudo-range frequently exceed 100 m and can exceed 500 m in worst-case conditions. Such large and random errors present an unexpected situation to conventional EKF that manifests as degraded PVT performance. Moreover, the large measurement errors have a generally positive sign, which indicates that the time of NLOS signal arrival always lags the LOS signal.

The errors in Doppler shift are also unexpected for conventional EKF, as they measure a few m/s and reach up to 15 m/s or more. This also explains why the position and velocity estimates of conventional EKF are degraded. In this case, the large measurement errors have both positive and negative sign because the Doppler shift represents the relative change of the geometric distance between the user and the satellite’s position.

4.2 Correlations between the actual errors and innovation, and the actual errors and SNR

This subsection considers the considerable improvement in the performance of the position and velocity errors by examining the relationship between the actual measurement errors and the errors measured by the innovation adaptation, and between the actual errors and SNR.

Correlations between the actual measurement error and the innovation at lap 04 are shown in Fig. 10 and Fig. 11. Because

\[
r = 0.956
\]

\[
r = 0.963
\]
of the positive and negative signs of the measurement errors, the figures represent absolute values. As can be observed, there is an obvious and strong correlation between the innovation and the actual measurement errors. The innovation value increases as the error becomes large. Correlation coefficients, $r$ in Fig. 10 and Fig. 11, also indicate high coherence, as all values exceed 0.95. These results indicate that the tuning observed in Fig. 2 detects NLOS signals correctly and the innovation-based adaptive estimation of the covariance matrix of the measurement noise fairly matches the actual measurement noise. This is the principal reason for the improvement of the position and velocity estimates obtained by adaptive EKF.

However, it is difficult to determine a noticeable correlation between the SNR and the actual measurement errors as shown in Fig. 12 and Fig. 13. Regarding the pseudo-range errors, there are errors greater than 100 m in either low or high SNR cases. The Doppler shift errors also exhibit similar behavior. Correlation coefficients shown in the figures also indicate low coherence, as they are far less than those of adaptive EKF. The SNR approximation of the measurement noise is the standard technique, but in a dense urban environment it is very difficult to predict the NLOS errors based on this technique.

Again, the only difference between adaptive EKF and conventional EKF in this study is the covariance matrix of the measurement noise. Thus, it is obvious that the adaptive estimation of the covariance matrix produces a large improvement regarding the accuracy and precision of the position and velocity in harsh urban canyons. Since it seems very difficult, or even impossible for conventional EKF to expect the measurement errors resulting from NLOS-only tracking, adaptive EKF has a clear advantage over conventional EKF.

5. Conclusion

The performance of an adaptive EKF in a dense NLOS environment has been presented. The innovation-based adaptive estimation of a covariance matrix of measurement noise contributes to significantly improving accuracy and precision of both position and velocity compared with conventional EKF. Although it was beyond the scope of this study, timing should also be improved by the adaptive estimation. That is because the state vector of the EKF introduced in this paper consisted of the position, velocity, and bias and drift of the receiver clock, which implies that the adaptive EKF must contribute to enhancing the overall performance of GNSS PVT in dense urban environments.

The principal reason for the measurement enhancements is that the adaptive covariance matrix of the measurement noise fairly matches actual measurement errors. Correlation coefficients indicating coherency were quite high, as all...
coherence values were more than 0.95. These high values lead the authors to conclude that the adaptive tuning presented in this paper detects NLOS signals correctly and then adapts the innovation to the covariance matrix as intended. On the other hand, a similar estimation appears to be very difficult for the SNR-based approximation. The correlation coefficients between SNR and the actual measurement errors were far less than those of adaptive EKF. This result indicates that the errors by NLOS–only tracking are beyond prediction by the SNR approximation applied.

Finally, the authors propose the adaptive EKF as one of the most effective solutions to improve the PVT performance of GNSS single point positioning in dense urban environments. It is a very simple formulation that should run smoothly even on low-cost receivers in real-time. Furthermore, coupling with some sensors or image processing would enable further enhanced PVT performance in most types of GNSS receivers.

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