Accuracy Assessment of a High Sensitivity GPS Based Pedestrian Navigation System Aided by Low-Cost Sensors

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Abstract

Using long total dwell times, acquisition and weak GPS signal tracking in degraded signal environments are possible. A technology utilizing such long integration methods is called High Sensitivity GPS (HSGPS). A previous hardware-in-the-loop GPS signal simulator test has demonstrated that, for a stand-alone HSGPS implementation provided by SiRF Technologies Inc., signals as weak as -186 dBW could be tracked by the receiver (MacGougan et al., 2002). This corresponds to 25-30 dB weaker signals than the typical outdoor line-of-sight GPS signals. However, measurement noise increases as signal power decreases and the receiver tracking loops become susceptible to possible tracking of cross-correlation or echo-only signals that can lead to severe position and velocity estimation errors.

This paper presents the results of the accuracy analysis of the sensor aided HSGPS receiver for pedestrian navigation in signal-degraded environments. Description of the downtown test and the equipment used is given. Analysis of the stand-alone HSGPS results with Receiver Autonomous Integrity Monitoring (RAIM) techniques is presented. Brief analysis of gyro bias estimation problems with GPS is presented. Kalman filter integration methodology is presented and the results are analyzed.

Introduction

Recently, significant research results have taken place in the area of pedestrian navigation. Most of the work so far has concentrated on the design, implementation and integration aspects of inertial sensors with conventional GPS. In most indoor environments and urban canyons, conventional GPS barely provides any position/velocity fixes due to poor observation availability. Thus, such systems mostly navigate in a pure inertial or Pedestrian Dead Reckoning (PDR) mode (e.g., Levi et al., 1999) once a GPS solution is unavailable. If an HSGPS receiver is used as part of the system, availability improves but new challenges arise. The availability of the HSGPS solution becomes truly remarkable considering the environment, but poor statistical estimates of the measurement errors present a challenge for a conventional Kalman filter (MacGougan et al., 2003).

The aforementioned challenges associated with HSGPS require special processing and integration techniques. Receiver Autonomous Integrity Monitoring (RAIM) algorithms applied to HSGPS data can help to successfully detect an inconsistent navigation situation and identify and potentially exclude faults present in the measurements on the presumption that redundant measurements are available (Lachapelle et al., 2003). However, RAIM methods are not optimal if multiple faults are present at a single epoch. In a reliable pedestrian navigation system, HSGPS and inertial sensors should complement each other to further aid in the reliability and quality assessment of HSGPS data. Essentially, the dead reckoning sensors should help in verifying HSGPS accuracy and HSGPS should correct long-term drift of the PDR sensor unit.

It has been shown in previous research (Collin et al., 2003a) that if HSGPS errors are estimated erroneously in a signal-degraded environment, the use of a Kalman Filter can lead to fatal solution. An Adaptive Kalman Filter (AKF) that utilizes stored innovation sequences can be used to adapt the measurement accuracy estimates. However, this requires a good knowledge of the system dynamics. This leads to a problem of the PDR sensor unit initialization, or, in other words, convergence of the PDR filter states. In this work, aforementioned problems are studied in detail and the results are presented.

The testing of the system has been performed in the Calgary downtown environment, which is typical of an average North American urban canyon with mask angles of up to 80 degrees. Several tests of long-term walking (up to an
hour) have been performed. In each test the system is turned on in an area where GPS signals are obviously degraded. This is done to investigate how poor initial conditions affect different filters being analyzed, as it is typical for a personal navigation user. To assess the accuracy of the system, the solutions at manually time-tagged traverse points are compared to the pre-surveyed reference points.

**Urban Canyon Test and Test Equipment**

To assess the accuracy of the stand-alone and aided HSGPS/MEMS pedestrian navigation system, a downtown test has been conducted. The tests carried out in the previous research on HSGPS navigation (Mezentsev et al., 2003; Collin et al., 2003a) had the HSGPS receiver initialized in the area with good GPS coverage allowing the receiver to acquire the full ephemerides and the internal Kalman filter to be initialized. In this work, an original test has been conducted: the equipment has been started in the very urban canyon leaving almost no initialization time. The motivation for such test is quite obvious – a person leaving a downtown building (office/mall/parking) and starting to use a handheld navigation device is in the same situation.

The HS GPS receiver used in the testing is HS SiRF X-trac receiver. The sensitivity of this receiver goes as low as -186 dBW, which corresponds to 25-30 dB fading of nominal Earth level line-of-sight GPS signal power. The PDR unit consists of 3 gyros and 3 accelerometers built in a classical perpendicular triad scheme that represents a full 6 Degrees-Of-Freedom (DOF) low-cost Inertial Measurement Unit (IMU) and is shown in Figure 1. The gyros used are Analog Devices ADXRS150: ±150°/s single chip rate gyro (A of Figure 4), a recently released new line of MEMS gyros that are well suited to pedestrian navigation needs due to their small size (7 mm × 7 mm × 3 mm) and low power consumption (< 50 mWatt). The MEMS accelerometers used are VTI SCA 610 series (B of Figure 1). The total unit volume including a power regulation circuit is less than 100 cm³. In industrial commercial product, the volume of such unit with similar components may be minimized to 1 cm³. The unit has been worn on the test person’s belt.

The test trajectory, the photos of the test person and the urban canyon environment are shown in Figure 2. Several walking tests were conducted and a statistically representative one was selected for the analysis. The testing loop is around 1.5 km long and was walked in approximately 30 minutes. The digital map of Calgary (metre level accuracy), provided by the city of Calgary, is used for plotting the results and for cross-track accuracy analysis. In all intersections (shown in Figure 2 as black markers), the data was manually time-marked for a 2D accuracy assessment.
Accuracy Analysis of Stand-Alone HSGPS Receiver

One of the most successful methods for statistical accuracy analysis of stand-alone GPS results is RAIM (Kaplan, 1996). In recent research (Lachapelle et al., 2003b), RAIM methods have been applied to HSGPS data in a very challenging indoor environment and it was concluded that in presence of multiple blunders RAIM identification of faults may fail. Obviously, RAIM techniques cannot be applied when no redundant observations are made. The mentioned above, i.e. presence of multiple blunders at a single epoch and/or no redundant observations, is very characteristic to urban canyon GPS data. The following briefly summarizes the RAIM procedures that will be applied to the HSGPS data.

RAIM Overview

The linearized pseudorange measurement equations in least-squares epoch-by-epoch GPS positioning can be expressed as follows (Kaplan, 1996; Parkinson et al., 1996)

$$\Delta p = H\Delta x + \varepsilon$$

where, \(\Delta p\) is the misclosure vector, that is the difference between the predicted and measured pseudorange measurements, \(\varepsilon\) is the vector containing pseudorange measurement errors assumed to be normally distributed with zero-mean, and the matrix \(H\) is the design matrix. The incremental component from the linearization point, \(\Delta x = [\Delta v_x, \Delta v_y, \Delta v_z, -c\Delta t_x]^{T}\), can be estimated as follows

$$\Delta x = (H^{T}C_i^{-1}H)^{-1}H^{T}C_i^{-1}\Delta p$$

where, the matrix \(C_i\) is the covariance matrix of the pseudorange measurements and is assumed here to be diagonal.

If redundant observations have been made, least-squares residuals (Ryan, 2002; Wieser, 2001) of pseudorange measurements can be obtained from the least-squares estimation as follows

$$\Delta p = H\Delta x - \Delta p$$

The resulting residual vector \(\tilde{\Delta p}\) can be used to test the internal consistency (Kuang, 1996) among the pseudorange measurements. The residuals can be standardized/studentized (Ryan, 2002; Kelly, 1998) as follows

$$w_i = \frac{|\tilde{\Delta p}|}{\sqrt{C_i}}$$

where, \(n\) denotes the number of observations and the matrix \(C_i\) denotes the covariance matrix of the residuals presented as follows

$$C_i = C_0 - H(H^{T}C_i^{-1}H)^{-1}H^{T}$$

To detect a measurement error in the position solution computation, least-squares range residuals can be statistically tested. The errors in the functional models in the solution computations are assumed Gaussian zero-mean in the unbiased cases, but this assumption does unfortunately not hold in degraded signal environments. Thus, the reliability testing theory in the FDE schemes does not necessarily hold for poor signal conditions with multiple errors, and special attention should be given to the design of a FDE scheme and to the interpretation of the results.

Global Test

A global test for detecting an erroneous and inconsistent position solution includes testing whether or not an ‘a posteriori’ variance factor, \(\hat{\sigma}^2_0\), multiplied by the degrees of freedom \((n-p)\) is centrally chi-squared distributed with a significance level of \(\alpha\) and degrees of freedom of \((n-p)\) as presented in the following

$$\hat{\sigma}^2_0 = \frac{x^T C_i^{-1} x}{n-p}$$

and

$$H_0 : \hat{\sigma}^2_0 \leq \hat{\sigma}^2_{0, \text{threshold}} \quad (\text{No integrity failure})$$

$$H_1 : \hat{\sigma}^2_0 > \hat{\sigma}^2_{0, \text{threshold}} \quad (\text{Integrity failure})$$

The parameter \(n\) denotes the number of satellites in view and the parameter \(p\) denotes the number of parameters to be estimated. The value \(\alpha\) represents the false alarm rate of the global test, the value \(\beta\) represents the probability of missed detection (Caspary, 1988; Kuang, 1996; Gertler, 1998), and the value \(\lambda\) is the non-centrality parameter of the biased chi-squared distribution (Kaplan, 1996). The chi-squared threshold \(\chi^2_{n-p, \alpha, \text{threshold}}\) determines whether the fault-free hypothesis of the global test is accepted or rejected. If the global test fails, inconsistency is detected in the assessed observations, and some action should be taken in terms of attempting to identify the measurement errors.
Local Test

In case the global test fails, an attempt to correct the inconsistent position solution may be performed if there is enough redundancy. With the assumption that only one blunder exists at a time, each standardized residual \( w_i \) can be statistically tested with a fault-free hypothesis \( H_{0,i} \) against an alternative hypothesis \( H_{a,i} \). The underlying assumption include that the standardized residuals are normally distributed (Ryan, 2002) with zero expectation in the unbiased case (Kuang, 1996). The local testing of the standardized residuals against the normal distribution is conducted as follows

\[
H_{0,i} : w_i \leq n_{1-\alpha /2} \\
H_{a,i} : w_i > n_{1-\alpha /2}
\]

In the local test, the measurement with the largest standardized residual exceeding the threshold is regarded as an outlier and that measurement is excluded from the solution computation (Kelly, 1998; Teunissen, 1998). The \( k^{th} \) observation is suspected to be erroneous when

\[
w_k \geq w_i \forall i \land w_k > n_{1-\alpha /2}
\]

As an approximation for a testing procedure to detect multiple observation errors using the local fault identification test, the single-fault local test may recursively be applied whenever a fault is detected. Thus, if an outlier is found and excluded, the test is repeated on the sub-sample remaining after deletion of the outlier (Hawkins, 1980; Petovello, 2003) assuming that there is enough redundancy to perform multiple exclusions. The identification and exclusion of measurements with the local test is performed sequentially until no more outliers are found in the navigation situation.

Figure 3 shows the HSGPS results of the downtown pedestrian test when RAIM has been applied. Only the global test has been performed. No observations have been rejected based on the local testing. The elevation cut-off angle is 0°; no height constraining is applied. As can be seen from the figure, many position fixes did not pass the global test. Some epochs pass the global test, but the errors for some of those epochs reach hundreds of metres. Figure 3 shows the internal receiver solution, Kalman filtered inside the receiver. The error in such solution also reaches almost a kilometer level value.

![Figure 3: Single point HSGPS results (RAIM, no exclusions)](image)

Figure 4 shows the HSGPS results of the downtown pedestrian test when the sequential global-local testing procedure has been applied. The elevation cut-off angle is 0°; no height constraining is applied. Sequential global and local tests are applied until no more outliers are detected or no redundancy in the observation matrix is reached. As can be seen from Figure 4, the solution at points where the global test failed (red points on Figure 3) is recomputed by iteratively rejecting observations that do not pass the local test criteria. In some epochs, after performing such sequential local testing, the solution accuracy actually degrades. In many epochs (~50% of all epochs), observations have been rejected until no redundancy is reached (4 observations for a 3D fix), and thus, after, those points are treated as “no redundancy” on Figure 4.
It can be seen from Figure 4 that after applying sequential global-local test RAIM to HSGPS results in downtown, position solution is still far from being accurate. In many epochs, multiple observation rejections have been performed until no redundancy condition is reached, and yet errors reach hundreds of metres for many (frequently consecutive) epochs. In a few epochs, a global test failure is detected, but no rejections are performed because the observations pass the local test. On a contrary, several position fixes are treated as accepted (no global test failure), but the across track position errors are close to several hundred metres.

Such analysis of the stand-alone HSGPS results show that for reliable pedestrian navigation system based on the HSGPS receiver, some form of aiding and enhanced filtering techniques are required.

**PDR Mechanization**

In this work, to aid the HSGPS data, sensors data have been processed in pedestrian mechanization mode (Levi and Judd, 1999). The method exploits the acceleration pattern to detect and count foot steps. In such mechanization, the position error depends on the heading error and the step length estimation error and is proportional to distance traveled rather than time as in the classical inertial navigation systems. To propagate the solution at the moment of a detected step, the following equations can be used:

\[
E_i = E_{i-1} + \hat{s} \cdot \sin(\hat{\alpha}) \\
N_i = N_{i-1} + \hat{s} \cdot \cos(\hat{\alpha})
\]

where, E and N are Easting and Northing coordinates respectively; \( \hat{s} \) is the estimated step length; \( \hat{\alpha} \) is the estimated heading. Static state of a user can reliably be detected through the analysis of the variance of the accelerometer signals. Steps occurred can either be directly detected from the raw data assuming the step frequencies are between 0.5 Hz and 3 Hz or after de-noising the acceleration pattern using wavelets. Heading is usually obtained using only one vertical gyro (if the unit is worn on the belt) “leveled” with horizontal accelerometers. A thorough description of sensor data handling for 3D-PDR mechanization can be found in Collin et al (2003b).

**Aspects of Handling Low-Cost Sensors**

In any DR system, accurate estimation of heading is crucial for a good performance. In the following section behaviour of MEMS-quality gyros and bias estimation with HSGPS is briefly discussed. During many research projects carried out by the authors, small Murata’s ENC-03J gyros have been tested in real environments, and their behaviour shows many problematic points that need to be taken into account when integrating the PDR system with GPS (the gyros used in the current system are expected to exhibit slightly better performance, but no extensive database for the new line of ADRX150 is available for analysis yet). The biggest problem for such gyros is the temperature-caused drifts that once integrated cause very large errors in the heading domain. Even after well-performed temperature correction, remaining errors are noticeable. Another issue in the real implementation is the sensitivity to input voltage, which has not been studied extensively in this paper. In the test system the used voltage regulators were of high quality.

**Estimating MEMS Gyro Biases**

In a particular test the Murata gyros were carried along with accurate Ring Laser Gyros (RLG) (1°/hour accurate) by a pedestrian so the gyro error analysis could be performed. In Figure 5 the errors of low-cost gyros (with respect to the...
RLG reference) are plotted with respect to time. The whole test lasted 30 minutes. In this figure the high-amplitude errors are caused by the scale factor errors, and during the static test parts the low frequency drift can be seen. The scale factor errors are not very critical due to following integration, but the low frequency changes in bias cause real problems. During the test temperature of gyros changed only few degrees, but yet the changes in biases are very significant. One clear problem that can be seen from this plot is that the temperature sensitivity of bias is individual for each sensor, so each gyro needs to be calibrated separately.

![Gyro Errors](image)

**Figure 5: MEMS-grade gyro errors**

For the z-axis gyro, a linear temperature compensation of the output has been applied, and result is shown in Figure 6 (raw signal in blue, low-pass filtered in red). In this case, the correction works quite well, and the resulting errors are varying around zero. In this case the bias could be modelled as a first-order Gauss-Markov process. Estimation of scale factor error might be useless or even harmful when using code-based GPS, due to high GPS measurement noise. However, this statement has not been proven by the authors because RLG reference has been carried along only in few tests. But after the temperature compensation the total error of MEMS gyros over this 30 minute test period was 300 degrees, in which the scale factor-caused part was less than 5 degrees. This strengthens the idea of estimating only the low-frequency bias in PDR/GPS filtering.

![Figure 6: MEMS gyro errors – raw data (blue) and low-pass filtered (red) bias](image)

Figure 7 shows one generated realization of 1st order Gauss-Markov process ($\beta=0.0001$ and $w$ with $(10^{-6})$ (rad/s)$^2$) overlaid with the real z-axis bias after temperature compensation.
The heading rate that can be obtained from GPS measurements assuming various signal environments can be simulated. Assuming walking speed of 5km/h = 1.4 m/s and GPS velocity accuracy of 3cm/s STD (clear sky, Petovello et al., 2003), PDOP of 2, one could expect the GPS heading rate to be as shown in Figure 8. It should be noted, that GPS is not directly measuring the turn-rate of the PDR unit. Thus, a very strong assumption here is that the unit is fixed to the pedestrian body rigidly (on the belt, for example). Using a Kalman filter the prediction of the error with given values is plotted in Figure 9.
The theoretical state error variance converges to a value of 0.006 (deg/s)² in about 100 seconds. The convergence time is quite long, but the bigger problem in practical implementation is that the chosen GM-model seems to be actually wrong in the first place. This is shown clearly in Figure 10, where gyro biases are collected from the real data over a period of one year. The picture clearly shows a major problem: temperature effects are very hard to compensate, and even after the compensation the run-to-run biases would become a major problem.

Another important example of gyro bias estimation problems is the effect of sudden change in bias that would be fatal for a GM-based estimator with non-zero beta, as simulation in Figure 11 shows. The estimator would provide biased estimates, as the filter tries to ‘push’ the estimate towards zero. Two conclusions can be drawn from this brief analysis:

- The gyro bias should be estimated directly as random walk rather than a Gauss-Markov process with small beta;
- The long convergence time, even with good GPS measurements, is a big problem, especially if a GPS receiver is not kept on continuously;

Even in the case of no sudden changes in the bias, the GM-model is not at all superior to the random walk model, as shown in Figure 12. This figure clearly shows the long delay of the filter. It should again be noted that the GPS errors were taken from the clear sky example.

The conclusion of this brief analysis is that, currently, the estimation of low-cost gyro biases with GPS is very problematic. If the better MEMS gyros (with smaller variance of run-to-run biases and more linear temperature functionality) will be available on the market in the near future, a more successful estimation modelling can be applied to such sensors.
Kalman Filtering

In the view of the previous section analysis, a Kalman filter integration analysis is presented in this section. The state vector for kinematic pedestrian modeling can be chosen to be \{Easting, Northing, Speed, Heading, Heading rate\}, that later will be referred as \{x_1, x_2, x_3, x_4, x_5\}. For these states, the dynamic equations can be written as the following:

\[
\begin{bmatrix}
    x_1 \\
    x_2 \\
    x_3 \\
    x_4 \\
    x_5
\end{bmatrix} = \begin{bmatrix}
    x_1 \cdot \sin(x_4) \\
    x_1 \cdot \cos(x_4) \\
    \beta \cdot x_3 + \sigma_s \\
    x_4 \\
    0
\end{bmatrix} + \begin{bmatrix}
    0 \\
    0 \\
    \sigma_s \\
    0 \\
    \sigma_s
\end{bmatrix}
\]

where, speed is treated as Gauss-Markov model and heading rate state (gyro bias) is modeled as a pure random walk.

This system of equations is non-linear with respect to the state variables, and, therefore, the linearized Kalman filter equations have to be used. After the linearization, \( F \) matrix can be obtained:

\[
F = \begin{bmatrix}
    \frac{\partial f}{\partial x_1} & \cdots & \frac{\partial f}{\partial x_5} \\
    \frac{\partial g}{\partial x_1} & \cdots & \frac{\partial g}{\partial x_5}
\end{bmatrix} = \begin{bmatrix}
    0 & 0 & \sin(x_4) & x_1 \cos(x_4)x_3 & 0 \\
    0 & 0 & \cos(x_4) & -x_1 \sin(x_4)x_3 & 0 \\
    0 & 0 & 0 & \beta & 0 \\
    0 & 0 & 0 & 0 & 1 \\
    0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]

The \( F \) matrix has to be evaluated at every filter epoch at the linearizing point, which is chosen as an optimal estimate of the previous filter epoch. State transition matrix, \( \Phi \), as well as the process noise matrix, \( Q \), are also to be calculated every filter epoch. The measurement vector is formed as \{GPS Easting, GPS Northing, PDR Speed, GPS heading – PDR Heading, GPS Heading Rate – PDR Heading Rate\}. Then, the standard linearized Kalman filter procedure can be applied (Gelb, 1974).

The fact that the test has been performed without any initialization makes the convergence of Kalman filter an issue. Thus, the choice of the process noise and measurement covariance matrices is very important for the filter performance. Essentially, the process covariance matrix depends on the knowledge of the system dynamics, i.e., modeling of the walking behavior and the sensor noise behavior and the measurement covariance matrix has to be adaptive for the case of HSGPS. The later is very hard to adjust properly taken into account the harsh test environment. HSGPS data is frequently biased, or, in other words, HSGPS errors correlate over time. In this case, the measurement covariance matrix was a function of the a posteriori variance factor obtained in the least-squares GPS solution. The result of Kalman filtering of HSGPS (no RAIM exclusion) and PDR is shown in Figure 13.
As can be seen from Figure 13, visually, the accuracy of the filtered solution is quite poor with respect to the true trajectory. Numerically, the accuracy of the filtered solution is computed at the time-tagged traverse points, coordinates of which are known from the digital map and expected to have sub-5 metres accuracy. There are a few obvious outliers in the filtered solution due to strong effects from the HSGPS updates that are huge blunders in reality that have very small a posteriori variance factors due to possible presence of multiple measurement blunders at a single epoch or no a posteriori variance factor at all due to lack of redundancy. In the case of no redundancy, the variance of the measurement in the filter is set to a certain number that may not be representative of the actual solution accuracy. Detection of such outliers in the integrated solution (as well as in the stand-alone solution) is a real challenge due to the considered case of no system initialization. Therefore, no constraints on the position “jumps” can essentially be placed (both sides of the “jump” can be considered as possible truth). Considering the overall 2D solution accuracy with respect to the marked traverse points, the average 2D error is 507 metres. Without considering obvious filter outliers, the average accuracy of the solution with respect to the marked traverse points is 193 metres along the trajectory.

**Position/Velocity Correlation Analysis in Kalman Filtering**

In the previous research (Mezentsev et al., 2003), it was discussed that position/velocity correlation of HSGPS data along with other statistical analysis is beneficial in harsh signal environments. If the velocity vector agrees well with the position solution during the linear motion of the user then both the position and the velocity results can be treated as reliable, i.e., meaning in this case that both passed the position/velocity correlation check. With the PDR data available, it is rather easy to check for the linearity of motion of a user, therefore, the position/velocity check can also be easily performed:

\[
\sum_{k=1}^{W} \left| \bar{e}_{k} \right|^2
\]

where, \(e_k\) is a prediction misclosure vector at time epoch \(k\); \(p_k\) is the LSQ GPS position estimate at time epoch \(k\); \(v_k\) is the LSQ GPS Doppler derived velocity estimate at time epoch \(k\); \(W\) is the window length to deal with the possible GPS position/velocity error correlation in time to some extend. For a pedestrian navigation case, \(W\) should be kept quite small 2-3 seconds.

Figure 14 shows the results of Kalman filtering HSGPS/PDR data with the position/velocity correlation testing applied. If the correlation value between the velocity vector and the position solution is too large (more than 10 metres in this case) then this position solution is not used in the filter update. The filter state vector is propagated to a next epoch through the dynamic model only. As can be seen from Figure 14, visually, the result is more accurate than the results in Figure 13. Numerically, due to still remaining HSGPS outliers with good accuracy estimates (that demonstrates the presence of multiple consecutive position/velocity correlated epochs in HSGPS data), improvement is not very significant. The overall 2D solution accuracy (average) with respect to the marked traverse points is 490 metres. Without considering the obvious filter outliers, the average accuracy of the solution with respect to the marked traverse points is 153 metres along the trajectory.
Conclusions

The following conclusions can be drawn:

- HSGPS significantly increases the availability of GPS measurements even in very challenging environments such as urban canyons for a pedestrian navigation case under analysis.
- Frequent lack of redundancy and/or presence of multiple measurement blunders at a single epoch does not permit successful RAIM testing of stand-alone HSGPS results. Some form of sensor aiding is required for a reliable pedestrian downtown navigation.
- Temperature dependent bias drift is the biggest source of error in low-cost gyros. Estimation of the bias even after temperature compensation with GPS (even with accurate GPS measurements) is problematic due to the difficulty of proper bias modeling and long-time convergence of the estimation.
- Poor estimation of HSGPS solution accuracy makes the proper modeling of measurement covariance matrix in Kalman filter very difficult. Also, the measurement and process noise covariance values for sensor states should be adaptively adjusted with the temperature data if such available.
- The results of Kalman filtering show that considering environment and no initialization time, Kalman filter is perhaps not the optimal integration solution of HSGPS data and low-cost PDR. In future work, different integration schemes for the pedestrian downtown navigation, such as the use of batch processing of HSGPS data (more than one epoch of observations processed at a time) for better accuracy assessment are to be developed.

References


