Improvement of GPS Precise Point Positioning Accuracy in Urban Canyons by Using Barometric Pressure Sensor

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Abstract

In this paper, a practical method for improving GPS–PPP(Global Positioning System–Precise Point Positioning) accuracy in urban canyons is presented by using a barometric pressure sensor. Several techniques to improve PPP quality are also integrated into a PPP algorithm which is available in case that there are few (only two or three) visible satellites from automobiles moving on the street in urban canyons. Therefore, this paper verifies the usefulness to integrate barometric pressure information into these methods.

1 Introduction

In this paper, a practical method for improving GPS–PPP accuracy in urban canyons is presented by using a barometric pressure sensor.

We have already developed PPP algorithms based on GR(Gnss Regression) models [1]–[4]. Our PPP algorithm achieved the positioning accuracy in decimeter level. The algorithm does not require the real time transmitted correction information. Therefore our PPP algorithm can be easily implemented without any external online received data.

Several techniques to improve PPP quality such as using the Doppler measurement, precise modeling of the receiver clock error and the map information have been proposed and successfully integrated into a PPP algorithm which is available in case that there are few (only two or three) visible satellites from automobiles moving on the street in urban canyons. By integrating these methods, the positioning accuracy in the skyscrapers of Tokyo, Japan was considerably improved [4].

In [4], the map information functions efficiently for accuracy improvement, it is used to give a coarse height (altitude) information to keep the continuous positioning and its accuracy when the number of visible satellites decreases to less than four. The coarse altitude is obtained from the map information based on the assumption that the automobiles run on almost flat streets. Therefore, the height information was fixed to the height of the center point of the running area. With the above method, the additional height information can be taken into account in the position estimation even when the number of visible satellites greatly decreases.

However, because the height of map information is basically the height of the terrain, it is sometimes incorrect when the vehicle runs on elevated roads, overpass and so on. Therefore, in this paper, barometric pressure sensor is applied in order to observe the vertical variation of the vehicle.

2 Measurement Model

At first, based on [1, 2, 3], the measurement models for PPP are shown. Though the models shown here are for only GPS(Global Positioning System), the natural extensions for multiple frequencies and GNSS(Global Navigation Satellite Systems) systems can be similarly formulated.

We consider the following fundamental measurements of the pseudoranges \( \rho_{C,A,u}^{p}(t) \), \( \rho_{P,Y,u}^{p}(t) \) based on C/A and P(Y) codes, and \( \varphi_{L_{1},u}^{p}(t) \), \( \varphi_{L_{2},u}^{p}(t) \) as follows:

\[
\rho_{C,A,u}^{p}(t) = r_{u}^{p}(t, t - \tau_{u}^{p}) + \delta I_{p}^{A}(t) + \delta \tau_{u}^{p}(t) + \delta \tau_{u}^{p}(t) + \delta T_{u}^{p}(t) + c [\delta \tau_{u}^{p}(t) - \delta \tau_{u}^{p}(t)] + \delta b_{C,A,u} - \delta b_{C,A} + \epsilon_{C,A,u}(t), \tag{1}
\]

\[
\rho_{P,Y,u}^{p}(t) = r_{u}^{p}(t, t - \tau_{u}^{p}) + \frac{f_{2}}{f_{1}} \delta I_{p}^{Y}(t) + \delta \tau_{u}^{p}(t) + \delta \tau_{u}^{p}(t) + \delta T_{u}^{p}(t) + c [\delta \tau_{u}^{p}(t) - \delta \tau_{u}^{p}(t)] + \delta b_{P,Y,u} - \delta b_{P,Y} + \epsilon_{P,Y,u}(t), \tag{2}
\]

\[
\varphi_{L_{1},u}^{p}(t) = \lambda_{1} \varphi_{L_{1},u}^{p}(t) = r_{u}^{p}(t, t - \tau_{u}^{p}) - \delta I_{p}^{Y}(t) + \delta \tau_{u}^{p}(t) + \delta \tau_{u}^{p}(t) + \delta T_{u}^{p}(t) + c [\delta \tau_{u}^{p}(t) - \delta \tau_{u}^{p}(t)] + \delta b_{L_{1},u} - \delta b_{L_{1}} + \lambda_{1} N_{u}^{p} + \lambda_{1} \epsilon_{u}^{p}(t), \tag{3}
\]
\[
\Phi_{P,1,2}(t) = \lambda_2 \rho_{P,1,2}(t) \\
= r_{u}^p(t, t - \tau_{P}^u) - \frac{f_1^2}{f_2} \delta \tau_{P}^u(t) + \delta T_{u}^p(t) \\
+ c [\delta T_{u}(t) - \delta T_{P}(t - \tau_{P}^u)] \\
+ \delta b_{L1,2,u} - \delta b_{L1,2,P} \\
+ \lambda_2 N_{u}^p + \lambda_2 \varepsilon_{u}^p(t),
\]

where \(c\) is the speed of light (2.99792458 \times 10^8 [\text{m/s}]), and \(f_1\) and \(f_2\) are the central frequency and the wave length of the \(L_s\) carrier wave (\(f_1 = 1575.42\) [MHz], \(f_2 = 1227.60\) [MHz]). In (1)-(4), the terms \{\delta b_{C,A,u}, \delta b_{P,Y,u}, \delta b_{L1,2,u}, \delta b_{L1,2,P}\} and \{\delta \Phi_{C,A}, \delta \Phi_{P,Y}, \delta \Phi_{L1,2}, \delta \Phi_{L1,2,P}\} are the so-called receiver and satellite biases respectively, and in this paper they are ignored. Also \(r_{u}^p(t, t - \tau_{P}^u)\) is the geometric distance between the receiver \(u\) at the time \(t\) and the satellite \(p\) at the time \(t - \tau_{P}^u\) \((r_{u}^p\) denotes the travel time from the satellite \(p\) \((p = 1, \ldots, n_s)\) to the receiver \(u)\). Namely,

\[
r_{u}^p(t) \equiv r_{u}^p(t, t - \tau_{P}^u) \\
= [(x_u(t) - x_P(t - \tau_{P}^u))^2 + (y_u(t) - y_P(t - \tau_{P}^u))^2 \\
+ (z_u(t) - z_P(t - \tau_{P}^u))^2]^{1/2},
\]

where \(u \equiv [x_u, y_u, z_u]^T\) and \(s^p \equiv [x_P^p, y_P^p, z_P^p]^T\) are the user (unknown) and satellite positions, respectively. Also \(n_s\) shows the number of the observable satellites. In (1)-(4), \(\delta \tau_{P}^u\) and \(\delta T_{u}^p\) are the delay or the advance associated with the transmission of the \(L_1\) signal through the ionosphere and the troposphere, respectively. \(\delta T_{u}\) and \(\delta T_{P}\) are the clock errors of the receiver \(u\) and the satellite \(p\). \(N_{u}^p\) denotes integer ambiguity between the satellite \(p\) and the receiver \(u\), and \(\varepsilon_{u}, \varepsilon_{P}\) denote measurement errors.

Because the measurement models (1)-(4) are nonlinear due to the geometric distance term \(r_{u}^p\), it is linearized by the first order Taylor series approximation around the initial estimate \(\hat{u}\) and \(\hat{s}\) as follows:

\[
r_{u}^p \equiv \hat{r}_{u}^p + \rho_{u}^p(u - \hat{s}) \\
= ||\hat{u} - \hat{s}|| + \frac{(\hat{u} - \hat{s})T}{||\hat{u} - \hat{s}||} [u - \hat{s} - (\hat{u} - \hat{s})] \\
= \frac{(\hat{u} - \hat{s})T}{||\hat{u} - \hat{s}||} (u - \hat{s}),
\]

for \(p = 1, 2, \ldots, n_s\), where

\[
\rho_{u}^p \equiv \left[ \frac{\partial \rho_{u}^p}{\partial u} \right]_{u = \hat{u}, s^p = \hat{s}} = \frac{(\hat{u} - \hat{s})T}{||\hat{u} - \hat{s}||},
\]

Also the estimate of the satellite position \(\hat{s}\) can be obtained from the broadcast ephemeris or precise orbit information. From (1)-(4), therefore, we have the following vector regression equation:

\[
y_u^s = H_u^s \theta_u + v_u,
\]

where

\[
y_u^s \equiv \begin{bmatrix} \rho_{C,A,u}^p \\ \rho_{P,Y,u}^p \\ \Phi_{L1,2,u}^p \\ \Phi_{L1,2,P}^p \\ \lambda_1 \Delta \tau_{L1,2,u}^p \\ \lambda_2 \Delta \tau_{L1,2,P}^p \end{bmatrix}, \quad \theta_u \equiv \begin{bmatrix} u \\ \hat{u} \\ \hat{c} \delta t_u \\ \hat{c} \delta t^s \\ s \end{bmatrix}, \quad v_u \equiv \begin{bmatrix} \epsilon_{C,A,u}^p \\ \epsilon_{P,Y,u}^p \\ \epsilon_{L1,2,u}^p \\ \epsilon_{L1,2,P}^p \end{bmatrix},
\]

\[
H_u^s \equiv \begin{bmatrix} C_g^u & 1 & -I & -G_D & I & I \\ C_g^u & 1 & -I & -G_D & \frac{f_1^2}{f_2} & I \\ C_g^u & 1 & -I & -G_D & -I & I \\ C_g^u & 1 & -I & -G_D & -\frac{f_1^2}{f_2} & I \\ C_g^u & 1 & -G_D & 1 \\ C_g^u & -G_D & 1 \\ 1 & -G_D & 1 \\ 1 & -G_D & 1 \end{bmatrix}.
\]

\[
\Phi_{L1,2,u}^p \equiv \rho_{L1,2,u}^p(u - \hat{s}) \\
\Phi_{L1,2,P}^p \equiv \rho_{L1,2,P}^p(u - \hat{s}) + \delta b_{L1,2,P} + \lambda_2 N_{L1,2,P} + \lambda_2 \varepsilon_{L1,2,P},
\]

\[
\Phi_{L1,2,u}^p \equiv \rho_{L1,2,u}^p(u - \hat{s}) \\
\Phi_{L1,2,P}^p \equiv \rho_{L1,2,P}^p(u - \hat{s}) + \delta b_{L1,2,u} + \lambda_2 N_{L1,2,u} + \lambda_2 \varepsilon_{L1,2,u},
\]

By differentiation of (10) and (11), we have approximately the Doppler shift data \(\Delta \tau_{L1,2,u}^p\) and \(\Delta \tau_{L1,2,P}^p\) for \(L_1\) and \(L_2\) carrier frequencies, respectively, as follows:

\[
\lambda_1 \Delta \tau_{L1,2,u}^p \equiv \rho_{L1,2,u}^p(u - \hat{s}) + \hat{c} \delta t_u + b_{DL1,2} + \lambda_1 \varepsilon_{DL1,2,u},
\]

\[
\lambda_2 \Delta \tau_{L1,2,P}^p \equiv \rho_{L1,2,P}^p(u - \hat{s}) + \hat{c} \delta t_u + b_{DL1,2} + \lambda_2 \varepsilon_{DL1,2,P},
\]

where \(\hat{c} \delta t_u\) is receiver clock drift rate, \(b_{DL1,2}\) are biased constants, \(\varepsilon_{DL1,2,u}, \varepsilon_{DL1,2,P}\) are measurement noises.

Then from (8)-(13), we have the following vector regression equation:

\[
y_u^s = H_u^s \theta_u + v_u,
\]

where

\[
H_u^s \equiv \begin{bmatrix} C_g^u & 1 & -I & -G_D & I & I \\ C_g^u & 1 & -I & -G_D & \frac{f_1^2}{f_2} & I \\ C_g^u & 1 & -I & -G_D & -I & I \\ C_g^u & 1 & -I & -G_D & -\frac{f_1^2}{f_2} & I \\ C_g^u & 1 & -G_D & 1 \\ C_g^u & -G_D & 1 \\ 1 & -G_D & 1 \\ 1 & -G_D & 1 \end{bmatrix}.
\]
processes. From (20)-(24), we have

equation (14), we have are derived as follows.

where \( I \) denote the \( n_s \times n_s \) unit matrix and \( 1 \equiv [1, 1, \cdots, 1]^T \): \( n_s \times 1 \) vector. Also define the \( n_s \times 3 \) matrix:

Furthermore, we define a block diagonal matrix with the size \( (n_s \times 3n_s) \):

Now we assume that the information of the satellite position \( s \), the time derivative of the satellite position \( \dot{s} \), the satellite clock error \( c\delta t^* \) as well as the delay or the advance due to the ionospheric and tropospheric effects, \( \delta I_u^* \) and \( \delta T_u^* \) are provided with errors as follows

where \( 0_3 \) is a \( n_s \times 3 \) zero matrix, and the errors \( e_s, \cdots, e_{ST_u} \) are assumed to be Gaussian white noise processes. From (20)-(24), we have

Substituting the above equations (25)-(29) into the GR equation (14), we have derived as follows.

where

\[
\begin{align*}
\hat{y}_{CA,a} & = \rho_{CA,a}^s + G_{D,a}^s \delta s^* + c\delta t^* \dot{s} + \delta T_u^* - \delta T_u, \quad (31) \\
\hat{y}_{PY,a} & = \rho_{PY,a}^s + G_{D,a}^s \delta s^* + c\delta t^* \dot{s} + \frac{f_2}{f_2^2} \delta I_u - \delta T_u, \quad (32) \\
\hat{y}_{L1,a} & = \Phi_{L1,a}^s + G_{D,a}^s \delta s^* + c\delta t^* \dot{s} + \delta I_u - \delta T_u, \quad (33) \\
\hat{y}_{L2,a} & = \Phi_{L2,a}^s + G_{D,a}^s \delta s^* + c\delta t^* \dot{s} + \frac{f_2}{f_2^2} \delta I_u - \delta T_u, \quad (34) \\
\end{align*}
\]

and

\[
\begin{align*}
\hat{y}_{DL1,a} & = \lambda_1 \delta L_{1,a} + G_{D,a}^s \dot{\delta s}, \quad (35) \\
\hat{y}_{DL2,a} & = \lambda_2 \delta L_{2,a} + G_{D,a}^s \dot{\delta s}, \quad (36) \\
\end{align*}
\]

\[
C_a = \begin{bmatrix}
G_u^s & 1 \\
G_u^s & 1 \\
G_u^s & 1 & I \\
G_u^s & 1 & I \\
\end{bmatrix}
\]

3 Kalman Filter Formulation

In this section, the Kalman filtering algorithm for PPP positioning is derived. For this purpose, we derive the so-called state equation as follows.

3.1 State Equations

Let us obtain the state equation for positioning. Since the kinematic case requires mathematical models of the moving objects, we often apply one of the dynamical models which are assumed as first-order Markov processes of, the velocity of \( u \) (user position), of the acceleration of \( u \) (the so-called Singer’s moving model [5]), or of the jerk of \( u \), [6, 7], with or without the constraints [8, 9].

For the land vehicle such as automobiles, we adopt Singer’s model for the east-west (E) and north-south (N) coordinates and a first order Markov model for the velocity of the up-down (U) coordinate, in the local frame (see Fig. 1) [3]. Namely, the state vector \( \eta \) is defined as follows:

\[
\begin{align*}
\dot{y}_u & = y_u + v \\
\end{align*}
\]
\[ u_L = T_W^L (u - u_0). \] (41)

Then by the assumption of the Singer’s model, namely the accelerations; \(a_{xL}, a_{yL}\) of \(x_L, y_L\), respectively, are assumed as the first order Markov processes:

\[
\begin{align*}
\dot{a}_{xL}(t) &= -\alpha_x a_{xL}(t) + w_{a_x}(t), \\
\dot{a}_{yL}(t) &= -\alpha_y a_{yL}(t) + w_{a_y}(t).
\end{align*}
\] (42)

Also the velocity of \(v_{zL}\) of \(z_L\) is assumed as a first order Markov process:

\[
\dot{v}_{zL}(t) = -\alpha_z v_{zL}(t) + w_{v_z}(t). \] (44)

On the other hand, the receiver’s clock errors are generally modeled as follows [10, 11],

\[
\begin{bmatrix}
\dot{c}\delta t_{u,t+1} \\
\dot{c}\delta t_{u,t+1}
\end{bmatrix} = \begin{bmatrix}
1 & & \\
0 & 1
\end{bmatrix}
\begin{bmatrix}
\dot{c}\delta t_{u,t} \\
\dot{c}\delta t_{u,t}
\end{bmatrix} + \begin{bmatrix}
w_{c\delta t_{u,t}} \\
w_{c\delta t_{u,t}}
\end{bmatrix},
\] (45)

where \(\Delta_t\) denotes the sampling interval of the receiver’s clock error, and the noise \(w_{c\delta t_{u,t}}\) and \(w_{c\delta t_{u,t}}\) are assumed as white Gaussian processes with zero means and variances \(q_{c\delta t}\) and \(q_{c\delta t}\), respectively.

Then, we have the following discrete-time state equation:

\[
\eta_{L,t+1} = A_t \eta_{L,t} + v_t, \] (46)

where

\[
A_t = \begin{bmatrix}
A_{11} & 0 \\
F_{c\delta t} & I
\end{bmatrix},
\] (47)

and the \(8 \times 8\) matrix \(A_{11}\) is given in [3] and the \(2 \times 2\) matrix \(F_{c\delta t}\) is defined in (45). \(v_t\) is the Gaussian white noise process with zero mean and covariance matrix \(Q_t\).

### 3.2 Measurement Equations

Now we assume that \(n_s\) satellites are observable. Then the measurements (1)-(4), (12) and (13) are obtained from multiple satellites \(p = 1, \ldots, n_s\). Therefore, with the approximation (6), the information of (20)-(24) and the relation between the coordinate systems (41), the measurement equation can be expressed by the following vector-matrix form:

\[
y_{L,t} \equiv C_L \eta_{L,t} + v_t, \] (48)

where \(y_{L,t}\) is the \(12n_s \times 1\) measurement vector computed from C/A, P(Y) code pseudoranges, \(L_1, L_2\) carrier phases and Doppler measurements. And \(C_t\) is \(12n_s \times (2n_s + 12)\) known matrix such that

\[
C_t = \begin{bmatrix}
G_{L1, L1}^* & 0 & \ldots & 0 \\
G_{L1, L1}^* & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
G_{L1, L1}^* & 0 & \ldots & 0 \\
G_{L2, L2}^* & 0 & \ldots & 0 \\
G_{L2, L2}^* & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
G_{L2, L2}^* & 0 & \ldots & 0 \\
G_{L3, L3}^* & 0 & \ldots & 0 \\
G_{L3, L3}^* & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
G_{L3, L3}^* & 0 & \ldots & 0 \\
0 & 1 & \ldots & 1 \\
0 & 1 & \ldots & 1 \\
0 & 1 & \ldots & 1 \\
0 & 1 & \ldots & 1
\end{bmatrix},
\] (49)

where \(0_2\) is a \(n_s \times 2\) zero matrix, and

\[
G_{L1, L1}^* \equiv G_{L1, L1}^* (T_W^L)^T. \] (50)

### 4 Additional Measurement from Barometric Pressure Sensor

By applying the Kalman filter to equations (46) and (48), the position estimation can be implemented.
However, in urban canyons, the number of visible satellites often decreases to less than four due to obstacles, multi-path, etc. Then the positioning accuracy may be greatly degraded or the Kalman filter may diverge. In [4], the map information is used to give a coarse height (altitude) information to keep the continuous positioning and its accuracy when the number of visible satellites decreases to less than four. The coarse altitude obtained from the map information is added to the measurement equation (47) based on the assumption that the automobiles run on almost flat streets. However, this assumption is not sometimes appropriate because the altitude of the automobile which runs in urban canyons may frequently change due to over-passes, raised expressways and so on. Therefore, in this research, the method of [4] is improved to utilize a relatively fine altitude information by using a barometric pressure sensor.

The digital barometric pressure sensor utilized in this research is BMP085 of BOSCH which is low cost (about $5) and can provide height information with high resolution (0.03[hPa] equivalent to about 0.25[m]). In order to convert an atmospheric pressure value to altitude, the standard atmosphere model [12] can be applied such that

$$h_t = \frac{[T_0 + 273.15] \left( \frac{P_t}{P_0} \right)^{\frac{g_o}{R}} - \eta_{L,t}}{L} - (T_0 + 273.15), \quad (51)$$

where \(h_t\) is altitude of observation point [m] at time \(t\), \(P_t\) is observed barometric pressure [hPa], \(P_0\) is barometric pressure of sea level altitude, \(g_o\) is earth’s gravity, \(T_0\) is air temperature of sea level altitude[°C], \(L(-0.0065[°C/m])\) is temperature lapse rate, \(R(8.31432[\text{J/K/mol}])\) is gas constant [12].

Generally, the model of (51) should be properly calibrated with \(P_t\) and \(T_0\) to obtain the altitude above sea level. Therefore, to avoid the calibration problem, the barometric pressure sensor is utilized to provide only the vertical position variation between the successive measurement epochs by using standard pressure of \(P_0 = 1013.25\) and temperature \(T_0 = 15\). The vertical variation information can be regarded as the additional vertical velocity measurement in Kalman filter as follows.

$$y_{v,t} = (h_t - h_{t-1})/\Delta t = v_{zL,t} + \eta_{v,t}, \quad (52)$$

where \(v_{v,t}\) is the measurement noise, \(v_{zL,t}\) is the vertical velocity which is the sixth component of the state vector \(\eta_{L,t}\) and \(\Delta t\) is the interval of the measurement. Therefore, the measurement equation is extended as follows.

$$\begin{bmatrix} y_{L,t} \\ y_{v,t} \end{bmatrix} = \begin{bmatrix} C \end{bmatrix} \begin{bmatrix} \eta_{L,t} \\ v_{v,t} \end{bmatrix}, \quad \begin{bmatrix} C \end{bmatrix} = \begin{bmatrix} 1 & 1 \end{bmatrix}, \quad \begin{bmatrix} 0_{1x5} & 1 \\ 0_{1x(2n_s+6)} & 0 \end{bmatrix} \begin{bmatrix} v_{v,t} \end{bmatrix}. \quad (53)$$

In this paper, the Kalman filter is applied to the state and measurement equations (46) and (53).

5 Experimental Results

The experiment of the proposed algorithms has been carried out. In the experiment, the automobile ran in Kusatsu City area, Shiga, Japan, and the GPS data were obtained by the receiver (NovAtel OEM6) with the antenna (NovAtel GPS-600) on June 10, 2013, from 06:07:30 to 06:11:52 UTC at 1[Hz] rate (\(\Delta t = 1[\text{s}]\)). The barometric pressure recording system was built by using the pressure sensor BMP085 of BOSCH, u-blox 6 compatible GPS module E-1612-UB and the microcontroller board (Arduino). The GPS module E-1612-UB was used to add the time information to the pressure data.

Throughout the experiment, the GPS data at the reference station (YASU) of GNSS Earth Observation Network System (GEONET) is also obtained from the Geospatial Information Authority of Japan (GSI). And results of the baseline analysis, i.e. the dual frequency carrier phase differential GPS method, were used as the reference trajectory of the automobile for the evaluation of the experimental results. The averaged baseline length was about 10[km]. Fig. 2 shows the RTK (Real Time Kinematic) results of the baseline analysis, i.e. positioning in East, North and Up directions and the number of satellites used in position calculation. With applying the elevation mask angle of 20 degrees, up to 8 satellites were available during the experiment. In three figures from the top of Fig. 2, the green lines show the results of the baseline analysis, where the origine was set to the start point of the automobile.

![Fig. 2: RTK Results (regarded as the reference trajectory for evaluating PPP results); positions in east, north and up directions, and number of satellites utilized for position calculation.](image)
Fig. 3 shows the accuracy of barometric pressure sensor. The green line shows Up coordinates of the baseline analysis, so the same results of Up direction in Fig. 2. The orange line shows Up coordinates that were obtained by accumulating the vertical velocity of (52) with respect to the sampling interval $\Delta t$, where initial coordinate was set to 0[m]. From Fig. 3, it can be seen that the vertical velocity information was well obtained from (51) and (52) with the assumption of standard pressure and temperature. The standard deviation of $v_{b,t}$ in (52) was set to 0.75[m/s], which was calculated by assuming the Up coordinates of RTK as the true trajectory.

Fig. 4 shows the PPP results; positioning errors in East, North and Up directions and the number of satellites used in position calculation. With applying the elevation mask angle of 20 degrees, up to 7 satellites were available during the experiment. In the experiment, the number of satellites used in the position calculation was artificially decreased to 3 during two periods: 22060-22098 and 22220-22285 [sec]. If the number of satellites was less than 3, the Kalman filter implementation was interrupted and re-initialized as three or more satellites became available. In three figures from the top of Fig. 4, the yellow lines show the results of PPP without the Doppler and barometric pressure data, the blue lines show the results of PPP with the Doppler data, the pink lines show the results of PPP with the barometric pressure data, and the red lines show the results with the Doppler and barometric pressure data. And Table 1 shows the RMS errors in East, North and Up directions PPP results.

Also Fig. 5 shows the PPP and RTK results; the estimated trajectories of the automobile during 10 seconds of 22084-22094 [sec], and the blue line shows the result of PPP with the Doppler data, the red line shows the result with the Doppler and barometric pressure data and the green line shows the RTK result of the baseline analysis.

| Table 1: PPP Results; RMS Errors [m] |
|-------------------------------|--------|--------|--------|--------|
|                               | ppp    | with dop| with baro| with dop+baro|
| East Error                   | 8.186  | 8.112  | 3.642  | 3.632  |
| North Error                  | 1.950  | 1.929  | 1.732  | 1.729  |
| Up Error                     | 10.247 | 10.143 | 4.638  | 4.624  |

$dop=\text{doppler}, \text{baro}=\text{barometric pressure}$

Fig. 5: PPP and RTK results
From Fig. 4, Table 1 and Fig. 5, it can be seen that the Kalman filter performance without the barometric pressure data is quite degraded when the number of satellites is three. In contrast, the accurate positioning can be continuously obtained by using barometric pressure data (proposed method).

6 Conclusions

In this paper, we presented the PPP algorithm by using a barometric pressure sensor. The presented algorithm is also efficiently combined with the positioning algorithm that are applied by the Kalman filter and RTK-PPP method. The experimental results show that proposed method can provide continuous and accurate navigation even if there are only three visible satellites.

References


