GNSS Integer Ambiguity Resolution Methods Applied by Kalman Filter — The Review and Comparison

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ABSTRACT

In this paper, we investigate several methods to resolve integer ambiguities in Global Navigation Satellite Systems (GNSS) carrier phase positioning applied by Kalman filter. Especially, we focus on integration methods of Least squares AMBiguity Decorrelation Adjustment (LAMBDA) [1, 2] method and Kalman filter. They are compared from theoretical and experimental points of view, and their characteristics and performance are investigated. We conduct experiments using real receiver data, and evaluate the integer ambiguity resolution performance. Based on the results, we show a guideline to resolve ambiguities with Kalman filter.

1 INTRODUCTION

By using two or more GNSS receivers, one can obtain accurate (sub-centimeter level) positioning results as a relative position from known to unknown positions with so-called double differenced carrier phase measurement of GNSS signals [3]. Generally, measuring the phase of the incoming carrier signal from a satellite involves the ambiguous whole cycles, because a GNSS receiver cannot distinguish one carrier cycle from another. These cycles always take integers, thus they are called “integer ambiguity”, and it is constant as long as the receiver tracks the signal continuously. The data processing procedure to determine the integer ambiguity value is called “ambiguity resolution”. The ambiguity resolution is one of the most important keys to obtain highly accurate positioning results with short observation spans.

The simplified GNSS observation model of m double differenced carrier phases can be expressed with appropriate linearization as follows:

\[ y_t = H_t x_t + n + v_t \]

where \( y_t \in \mathbb{R}^m \) is the vector computed from the observed double differences, \( x_t \) is the unknown coordinates of the antenna (also if necessary velocity and acceleration), \( n \in \mathbb{Z}^m \) is the integer ambiguity, \( H_t \) is the known matrix and \( v_t \in \mathbb{R}^m \) is the measurement noise.

In the last two decades, a lot of ambiguity resolution methods have been developed and applied to actual positioning systems. Most of them, generally, consist of following three steps: (1) float solution, (2) integer solution, (3) validation of the integer solution. In the first step, the real valued integer ambiguity (so-called float estimate \( \hat{n} \)) is estimated by the least squares method or Kalman filter. Then, in the second step, the integer valued estimate is obtained under the least squares sense, namely

\[ \hat{n} = \arg \min_{n \in \mathbb{Z}^m} \| \hat{n} - n \|^2 \]

where \( P^{-1} \) is the weighting matrix computed from the estimation error covariance matrix of the least squares method or Kalman filter, and \( \hat{n} \) can be found by searching the integer points around \( \hat{n} \). In order to solve the integer least squares problem in (2), a lot of techniques have been proposed, and recently LAMBDA method is one of the most popular methods and widely utilized. In LAMBDA method, the weighting matrix \( P^{-1} \) in (2) is diagonalized as much as possible with holding the integer nature of the unknown parameter \( n \), and consequently the searching process becomes easier.

LAMBDA method is well developed and widely utilized, however there exist a lot of variations of methods applying to actual applications with Kalman filter. Because the original LAMBDA has been developed and explained based on the least squares method for the float solution, there are no standard methods or guidelines to integrate LAMBDA method and Kalman filter. In our research group, the following types of methods have been developed. The simplest integration is to utilize Kalman filter to obtain only the float solution [5]. Based on it, LAMBDA method provides the integer solution, however the integer solution has no effect on Kalman filter. This method is improved by updating Kalman filter by the integer solution. In this paper, this method is called “Kalman Filter based LAMBDA”. Also, as a variation of the integer solution, “Partial Ambiguity Resolution” [6] which is a technique to obtain the integer solution of the partial components of \( n \) has been applied. Then “Kalman filter based PAR” [7] has been developed as the method to update Kalman filter by the partial integer solution.

We compare the above described four methods integrating ambiguity estimation and Kalman filter from the theoretical and experimental points of view.
2 SYSTEM MODEL

2.1 Measurement Model

At first, based on [8–10], the measurement models for relative positioning that are utilized in this paper are shown. When two receivers observe signals from common $n_s$ satellites at time (epoch) $t$, with appropriate linearization, so-called double differenced measurement of the code pseudoranges and the carrier phases are modeled as follows:

$$\rho_{CA} = G\{u - s\} + \delta I + \delta T + \epsilon_{CA}$$
$$\rho_{PY} = G\{u - s\} + f_2^T\delta I + \delta T + \epsilon_{PY}$$
$$\Phi_{L1} = G\{u - s\} - \delta I + \delta T + \lambda_1 N_{L1} + \epsilon_{L1}$$
$$\Phi_{L2} = G\{u - s\} - f_2^T\delta I + \delta T + \lambda_2 N_{L2} + \epsilon_{L2}$$

where $(n_s - 1) \times 1$ vectors $\rho_{CA}$ and $\rho_{PY}$ are the double differenced C/A and P(Y) code pseudoranges, and $\Phi_{L1}$ and $\Phi_{L2}$ are the double differenced carrier phase observables respectively, $u$ is the three dimensional unknown receiver position coordinates, and $s$ is the three dimensional satellite position. $G$ is the known $(n_s - 1) \times 3$ matrix which consists of the double differenced direction cosines from the receivers to the satellites. $(n_s - 1) \times 1$ vectors $\delta I$ and $\delta T$ are the delay or advance associate with the ionosphere and troposphere, $N_s$ denotes integer ambiguity, $f_2$ and $\lambda_s$ are the central frequency and wave length of $L_s$ carrier wave ($f_1 = 1575.42$ [MHz], $f_2 = 1227.60$ [MHz]). $\epsilon_s$ and $\epsilon_\lambda$ are measurement errors with appropriate dimensions.

2.2 State Space Model

In Eqs. (3)–(6), unknown variables to be estimated in the positioning calculations are $u$, $\delta I$, $\delta T$, $N_{L1}$ and $N_{L2}$. By using vector-matrix forms, we consider the following discrete time linear state space model for the static environment [10]:

$$x_{t+1} = F_t x_t + w_t$$
$$y_t = H_t x_t + v_t$$

where,

$$x_t \equiv [u^T(t), \delta I^T(t), \delta T^T(t), N_{L1}^T, N_{L2}^T]^T$$
$$y_t \equiv [\rho_{CA}(t), \rho_{PY}(t), \Phi_{L1}(t), \Phi_{L2}(t)]^T$$

and the dimensions are: $u: 3 \times 1$, $\delta I$, $\delta T$, $N_{L1}$, $N_{L2}$: $(n_s - 1) \times 1$, $\rho_{CA}$, $\rho_{PY}$, $\Phi_{L1}$, $\Phi_{L2}$: $(n_s - 1) \times 1$. Therefore $x_t$ is the $(4n_s - 1) \times 1$ state vector and $y_t$ is the $(4n_s - 4) \times 1$ measurement vector. And $F_t$ and $H_t$ are the known state transition matrix and the measurement matrix with appropriate dimensions respectively. Note that $\delta I$ and $\delta T$ are negligible and excluded from the state vector $x_t$ for short baselines (e.g. less than 10[km]), and additional states such as velocity should be included into the state vector $x_t$ for the kinematic environment.

3 INTEGER AMBIGUITY ESTIMATION

In the first step of typical positioning methods, the Kalman filter is applied to the state and measurement equations (7) and (8) by regarding the integer ambiguity $N_{L1}$ and $N_{L2}$ as the real valued vectors. Then we can obtain the filtered estimate of $x_t$ as

$$\hat{x}_{t|t} = \hat{\eta}_{t|t}^T, N_{t|t}^T$$

where we define

$$\hat{\eta} = \hat{\eta} - P_{\hat{\eta}N} P_N (\hat{N} - N)$$

and

$$\hat{x}_{t|t} = [\hat{\eta}_{t|t}^T, N_{t|t}^T]^T$$

is called the “fixed solution” because the ambiguity estimate is not integer. However, the integer ambiguity is rigorously integer. Therefore we need to estimate integer solution $\hat{N}$ by searching integers around the float solution of the integer ambiguity $N$. Once we get the integer valued ambiguity $\hat{N}$, then the other states $\hat{\eta}$ is corrected based on $\hat{N}$ as follows:

$$\hat{\eta} = \hat{\eta} - P_{\hat{\eta}N} P_N (\hat{N} - N)$$

In order to obtain the integer valued estimate $\hat{N}$, LAMBDA method is applied. In LAMBDA, the estimate $\hat{N}$ is obtained as integer based on the real valued (float) estimate $\tilde{N}$ as follows:

$$\hat{N} = \arg \min_{N \in \mathbb{Z}^m} \| \tilde{N} - N \|^2_{P_N^{-1}}$$

where the weighted squared norm is defined as $\| \cdot \|^2_{W} = (\cdot)^T W (\cdot)$, $Z^m$ is the $m$–dimensional integer space. If the matrix $P_N$ is diagonal, the solution to (15) can be easily found out by rounding the each component of $\tilde{N}$ to the nearest integer. In GNSS applications, however, $P_N$ is not diagonal. Generally, the components of $N$ are highly correlated. In this case, the problem is difficult to be solved because we have to search the integer vector that yields minimum in (15) over all integer vectors. In LAMBDA method, the matrix $P_N$ is transformed into the almost diagonal matrix by
so-called $Z$-transformation [3, 11] which decorrelates $P_N$ and $\mathcal{N}$ as much as possible with holding the integer nature of the ambiguities as follows:

$$\bar{z} = Z^T \mathcal{N}, \quad P_z = Z^T P_N Z \quad (16)$$

where all the components of the matrix $Z$ are integers and $|Z| = 1$. Therefore, Eq. (15) is transformed into

$$\bar{z} = \arg \min_{z \in \mathbb{Z}^m} \|z - \bar{z}\|^2 \quad (17)$$

And the original ambiguity vector can be obtained as follows:

$$\mathcal{N} = Z^{-T} \bar{z} \quad (18)$$

By using the above $\mathcal{N}$ and Eqs. (12) and (13), we can obtain the positioning result at time $t$ based on LAMBDA method as $\bar{x}_{t|t}$.

### 3.2 KALMAN FILTER BASED LAMBDA

As stated above, LAMBDA method can provides the integer solution. However, Kalman filter is not updated by integer solution which comes from LAMBDA method. Therefore, Kalman filter based LAMBDA (KFLAMBDA) has been motivated to update Kalman filter using constraints as follows:

$$\bar{N}_{L1} = N_{L1} + \epsilon_{N_{L1}} \quad (19)$$
$$\bar{N}_{L2} = N_{L2} + \epsilon_{N_{L2}} \quad (20)$$

where $\epsilon_n$ are measurement errors with appropriate dimensions. Thereby, Eq. (10) becomes as follows:

$$y_t = [\rho_{CA}(t), \rho_{PV}(t), \Phi_{L1}^T(t), \Phi_{L2}^T(t), \bar{N}_{L1}, \bar{N}_{L2}]^T \quad (21)$$

and the dimensions are: $\bar{N}_{L1}, \bar{N}_{L2}$; $(n_a - 1) \times 1$. Kalman filter is updated by Eq. (21).

### 3.3 PAR Method

In Eq. (18), all the ambiguities (full set ambiguity) are estimated as integers. However, sometimes the full set ambiguity estimate is not reliable solution due to short observation span, geometry of satellites, atmospheric effects etc. Therefore, in recent years, the partial ambiguity resolution (PAR) method has been motivated. In PAR method, only the sub set of the ambiguities which has high probability of correct resolution is estimated as the integer vector [6, 12–14].

Hereafter the notation $\mathcal{N}_{i|t}$ stands for $i$-th ambiguity obtained through sequentially conditioned based on the previous ambiguities, i.e. we define $n = 2n_a - 2, I = n, n - 1, \cdots, i + 1$. According to [12], the probability that the conditioned $i$-th $Z$-transformed ambiguity $\bar{z}_i$, is successfully obtained, i.e. $\bar{z}_i = \bar{z}_i$, can be expressed as

$$P_{z_i|t} = P(\bar{z}_i = \bar{z}_i) = 2\Psi \left( \frac{1}{2\sigma_{\bar{z}_i}} \right) - 1 \quad (22)$$

where $\Psi$ is the cumulative normal distribution function such that $\Psi(\alpha) = \int_{-\infty}^{\alpha} \frac{1}{\sqrt{2\pi}} \exp \left[ -\frac{1}{2} \beta^2 \right] d\beta$. $\sigma_{\bar{z}_i}$ is the conditional standard deviation of de-correlated ambiguities. In other words, under the Gaussian assumption, (22) shows the probability that the estimate $\bar{z}_i$ takes the value such that

$$z_i - 0.5 \leq \bar{z}_i \leq z_i + 0.5 \quad (23)$$

The concept of PAR is to resolve a subset of the ambiguities with sufficiently high success rate. Therefore, for given minimum success rate $P_0$, the first step of PAR is to select the largest possible subset that satisfies

$$\prod_{i=1}^{n-1} \left\{ 2\Psi \left( \frac{1}{2\sigma_{\bar{z}_i}} \right) - 1 \right\} \geq P_0 \quad (24)$$

In this case, the nearest integers of the float ambiguities $\bar{z}_{ki}$ $i = n, n - 1, \cdots, n - k - 1$ are searched. And search process is started from $n$-th ambiguities, because $\sigma_{\bar{z}_i}$ is arranged in descending order by $Z$-transformation [3, 12, 15]. So one can simply start with the $n$-th decorrelated ambiguity, and check if the success rate of rounding this ambiguity is at least equal to $P_0$. If that is the case, one can continue with rounding the next conditional ambiguity $\bar{z}_{n-1|n}$, since this is now the most precise one. This procedure continues as long as Eq. (24) is satisfied. The remaining $k - 1$ ambiguities are then conditioned on the $K = k, \cdots, n$ conditionally rounded (integer valued) ambiguities, but are not sequentially rounded themselves (real valued). Therefore the “fixed” ambiguity vector, that is defined as $\bar{z}_p$, obtained by PAR becomes as follows:

$$\bar{z}_p = [\bar{z}_1^{[K]}, \cdots, \bar{z}_{k-1|K}, \bar{z}_k^{[K]}, \cdots, \bar{z}_{n-1|n}, \bar{z}_n]^T \quad (25)$$

In this case, the first $k - 1$ components $\{\bar{z}_1^{[K]}, \cdots, \bar{z}_{k-1|K}\}$ are the real valued, and the remaining $n - k + 1$ components $\{\bar{z}_k^{[K]}, \cdots, \bar{z}_{n-1|n}, \bar{z}_n\}$ are the integer valued estimates.

Then we can obtain the partially fixed ambiguity estimate $\mathcal{N}_p$ as well as the other corrected estimate $\bar{\eta}_p$ in the same fashion of Eqs. (18) and (12) as follows:

$$\mathcal{N}_p = Z^{-T} \bar{z}_p \quad (26)$$
$$\bar{\eta}_p = \bar{\eta} - P_{\eta N} P_N (\mathcal{N} - \mathcal{N}_p) \quad (27)$$

Finally, the positioning results of PAR method denoted by $\bar{x}_{p|t}$ is expressed explicitly with time $t$ as follows:

$$\bar{x}_{p|t|t} = [\bar{\eta}_{p|t|t}^T, \mathcal{N}_{p|t|t}^T]^T \quad (28)$$

### 3.4 KALMAN FILTER BASED PAR

Kalman filter based PAR (KFPAR) updates the Kalman filter estimate and its covariance matrix based on the partially fixed solution $\bar{x}_p$, because PAR has no effect on the Kalman filter (float solution). The PAR result $\bar{x}_{p|t|t}$ in Eq. (28) is obtained based on the Kalman filter float solution $\bar{x}_{f|t}$ Eq. (11) at time $t$. By focusing on the ambiguity vector $\mathcal{N}$,
the new information on the ambiguity $N$ is obtained as the PAR result $\hat{N}_p$. Therefore, this method regard $\hat{N}_p$ as the new (pseudo) measurement of $N$. The pseudo measurement equation can be expressed as follows:

$$\hat{N}_p = N + v_p$$  \hspace{1cm} (29)

where $v_p$ is Gaussian white noise such that $v_p \sim N(0, R_p)$.

On the other hand, by Bayes’ rule, the conditional probability density function (CPDF) of the state vector $x_t$ can be expressed as follows:

$$p(x_t|Y^t, \hat{N}_p) = \frac{p(x_t, Y^t, \hat{N}_p) p(\hat{N}_p)}{p(Y^t, \hat{N}_p)} = \frac{p(\hat{N}_p|x_t, Y^t) p(x_t|Y^t) p(Y^t)}{p(Y^t, \hat{N}_p)} = K_0(Y^t, \hat{N}_p) p(x_t|Y^t) p(\hat{N}_p|x_t)$$  \hspace{1cm} (30)

where $K_0$ is the constant factor and $Y^t$ means the set of measurements up to time $t$ such that $Y^t = \{y_0, y_1, \ldots, y_t\}$. Then we have the relations:

$$p(x_t|Y^t) = \frac{1}{(2\pi)^{n_x/2}|P_{t|t}|^{1/2}} \times \exp \left\{-\frac{1}{2}(x_t - \hat{x}_{t|t})^T P_{t|t}^{-1} (x_t - \hat{x}_{t|t}) \right\}$$  \hspace{1cm} (31)

$$p(\hat{N}|x_t) = \frac{1}{(2\pi)^{n_N/2}|R_p|^{1/2}} \times \exp \left\{-\frac{1}{2}(\hat{N}_p - C x_t)^T R_p^{-1} (\hat{N}_p - C x_t) \right\}$$  \hspace{1cm} (32)

where $n_x \equiv 4n_s - 1$ is the dimension of the state vector $x_t$. Also we define $n_x$ and $n_y$, i.e. the dimensions of $N$ and $\eta$ as $n_x \equiv 2(n_s - 1)$ and $n_y \equiv 2n_s + 1$, and define the matrix $C$ as follows:

$$C = \begin{bmatrix} \frac{0_{n_y \times n_x}}{0_{n_y \times n_y}} \end{bmatrix}$$  \hspace{1cm} (33)

Therefore, $p(x_t|Y^t, \hat{N}_p)$ in Eq. (30) is expressed as follows:

$$p(x_t|Y^t, \hat{N}_p) = K_0(Y^t, \hat{N}_p) \times \frac{1}{(2\pi)^{n_x/2}|P_{t|t}|^{1/2}} \times \exp \left\{-\frac{1}{2}(x_t - \hat{x}_{t|t})^T P_{t|t}^{-1} (x_t - \hat{x}_{t|t}) \right\} \times \frac{1}{(2\pi)^{n_N/2}|R_p|^{1/2}} \times \exp \left\{-\frac{1}{2}(\hat{N}_p - C x_t)^T R_p^{-1} (\hat{N}_p - C x_t) \right\}$$  \hspace{1cm} (34)

Then, with some calculations that is completing the square of the power term of the CPDF in Eq. (34), we have the following updating algorithm:

$$\hat{x}_{u,t|t} \equiv [\hat{y}_{u,t|t}, \hat{N}_{u,t|t}]^T = \hat{P}_{u,t|t}(P_{t|t}^{-1} \hat{x} + CR_p \hat{N}_p)$$  \hspace{1cm} (35)

$$\hat{P}_{u,t|t} = (P_{t|t}^{-1} + CT R_p^{-1} C)^{-1}$$  \hspace{1cm} (36)

In this method, the estimate of the Kalman filter $\hat{x}_{t|t}$ and its covariance matrix $\hat{P}_{t|t}$ are substituted by the above $\hat{x}_{u,t|t}$ and $\hat{P}_{u,t|t}$ respectively.

Then, with long observation span, sometimes $\hat{P}_{u,t|t}$ may become too small and, in this case, the estimate $\hat{x}$ will be too conservative. Therefore, in case that the full set of ambiguities is estimated as integers, i.e. Eq. (24) is satisfied for $k = 1$, KFPAR does not update kalman filter by using Eqs. (29) to (36).

### 4 EXPERIMENTAL RESULTS

In experiments, four ambiguity estimation methods of LAMBDA, KFLAMBDA, PAR and KFPAR were performed for the static relative positioning, and the ambiguity estimation accuracy as well as the positioning accuracy were compared for short baseline. The GPS data were collected and provided by the GEONET (GNSS Earth Observation Network System) of Geospatial Information Authority of Japan (GSI).

Table 1 details the environments of the experiments. In the experiments, ten data sets were collected every day from 14 to 15 o’clock during the period of August 1 to 10, 2016 were processed. The atmospheric effects $\delta I$ and $\delta T$ were neglected because the baseline length was short, therefore $\delta I$ and $\delta T$ were excluded from the equations in the previous sections. Generally, the estimated integer-valued ambiguity needs to be validated in order to judge whether it is acceptable or not. This procedure is called validation, and one of the most popular and easiest method is so-called the ratio test [12]. In this experiment, the ratio test (threshold is 3.0) was also carried out to check the performance in LAMBDA. In addition, the threshold $P_0$ in PAR method which is the minimum success rate of the ambiguity estimation was set to 0.9999. Prior to the experiments, we obtained the integer ambiguity estimates for every data set by LAMBDA method. And we checked that the highly acculate position estimates were obtained based on those ambiguities. Therefore, in this study, we regarded those ambiguities as the true ambiguities, and the integer estimates of four methods were examined whether they were correct or not. The positioning accuracy of the rover station was evaluated by using its coordinates provided by GSI that came from the baseline analyses of the GEONET.
Table 1: Experimental Conditions

| Date       | August 1-10, 2016 |
|------------|-------------------|
| Time (JST) | 14:00:00~15:00:00 |
| Reference station: | TARUI            |
| Name       |                   |
| Receiver   | NET-G3 (Topcon)   |
| Antenna    | TPSCR.G5 (Topcon) |
| Rover station: | SEKIGAHARA     |
| Name       |                   |
| Receiver   | DELTA-G3T (Javad) |
| Antenna    | TPSCR.G5 (Topcon) |
| Baseline length | 7.3[km]        |
| Epoch interval | 30 [s]            |
| Elevation angle mask | 15 [deg.]  |
| Measurement Data | L1, L2 carrier-phase, C/A, P/Y code |

As a result, Figs. 1 and 2 show the RMS (Root Mean Square) values of the horizontal and upper positioning errors respectively. In addition, their values are listed in Tables 2 and 3. Fig. 3 shows the number of epochs required to obtain the correct ambiguity. And Fig. 4 shows the total number of correctly fixed ambiguity. The “correctly fixed ambiguity” means the ambiguity estimate that passes the validation procedure mentioned above.

From Fig. 3, we can see that LAMBDA and KFLAMBDA methods show the same performance for the speed of accurate ambiguity estimation. Then, PAR and KFPAR have same results too. However, PAR and KFPAR can find correct integer ambiguities faster than KFLAMBDA and LAMBDA. Further, from Fig. 4, we can see that KFLAMBDA was easy to pass the ambiguity validation than LAMBDA and, PAR and KFPAR was more easy to pass the validation. Also, comparing Figs. 1, 2 with 3, 4, we can see that the positioning accuracy is improved as the ambiguity is correctly and rapidly resolved.

Table 2: Horizontal RMS error [m]

| DATE | LAMBDA | KFLAMBDA | PAR | KFPAR |
|------|--------|----------|-----|-------|
| Aug. 1 | 0.2860 | 0.2811 | 0.1782 | 0.1782 |
| Aug. 2 | 0.0738 | 0.0738 | 0.0738 | 0.0738 |
| Aug. 3 | 0.0144 | 0.0145 | 0.0153 | 0.0201 |
| Aug. 4 | 0.0402 | 0.0402 | 0.0402 | 0.0402 |
| Aug. 5 | 0.0439 | 0.0439 | 0.0445 | 0.0440 |
| Aug. 6 | 0.1581 | 0.0944 | 0.0864 | 0.0864 |
| Aug. 7 | 0.1308 | 0.0595 | 0.0595 | 0.0595 |
| Aug. 8 | 0.5234 | 0.1226 | 0.1096 | 0.0722 |
| Aug. 9 | 0.1639 | 0.1639 | 0.0216 | 0.0216 |
| Aug. 10 | 0.0766 | 0.0765 | 0.0650 | 0.0746 |

Table 3: Upper RMS error [m]

| DATE | LAMBDA | KFLAMBDA | PAR | KFPAR |
|------|--------|----------|-----|-------|
| Aug. 1 | 0.3382 | 0.3364 | 0.3452 | 0.3452 |
| Aug. 2 | 0.1271 | 0.1272 | 0.1272 | 0.1272 |
| Aug. 3 | 0.0355 | 0.0354 | 0.0364 | 0.0373 |
| Aug. 4 | 0.0481 | 0.0481 | 0.0481 | 0.0481 |
| Aug. 5 | 0.0632 | 0.0633 | 0.0227 | 0.0532 |
| Aug. 6 | 0.0827 | 0.0823 | 0.0660 | 0.0660 |
| Aug. 7 | 0.1067 | 0.0884 | 0.0884 | 0.0884 |
| Aug. 8 | 0.1563 | 0.1446 | 0.1556 | 0.1008 |
| Aug. 9 | 0.1494 | 0.1494 | 0.0342 | 0.0342 |
| Aug. 10 | 0.0226 | 0.0227 | 0.0086 | 0.0198 |
5 CONCLUSIONS

In this paper, four methods, LAMBDA, KFLAMBDA, PAR and KFPAR that are the methods to integrate the ambiguity estimation and Kalman filter, were briefly reviewed and their characteristics as well as performances were examined by using dual frequency GPS data collected in the short baseline circumstances. The experiments were conducted for ten times. As a result, we can conclude that KFLAMBDA, PAR and KFPAR can provide better ambiguity estimation and positioning accuracy than LAMBDA for short baseline cases.

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