Analysis of ambiguity resolution in precise pseudolite positioning

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***Abstract*—Global Navigation Satellite Systems (GNSS) positioning technology is vulnerable in a wide range of environments such as indoors or in urban canyons. Even with high sensitivity GNSS receivers, the positioning results are far from being reliable. Therefore, pseudolite positioning technology can be useful as a complement in such environments. Many studies have been carried out for pseudolite positioning in various applications, but for precise pseudolite positioning, the carrier phase measurements must be taken into consideration. Consequently, integer ambiguity resolution issues need to be dealt with.**

In this contribution, by processing double differenced static and kinematic pseudolite data, ambiguity resolution and validation issues for pseudolite positioning are analyzed. An introduction to pseudolite positioning technologies is presented at first, and then mathematical models for double differenced pseudolites positioning are introduced. Subsequently the parameter estimation procedures by least-squares and integer least-squares are presented. To search for the integer candidate, the efficient LAMBDA method, which is based on the integer least-squares, is utilized. Providing the integer candidates in hand, ambiguity validation procedures are conducted to validate the resolved integer ambiguities. With the validated integer ambiguities, an online stochastic model is implemented to improve the performance of ambiguity resolution in the static and kinematic cases. It has been shown that the integer least-squares is more reliable for ambiguity resolution and validation than integer rounding, and the ambiguity resolution and validation are highly affected by the pseudo-range measurements, the geometry of the pseudolites and the realistic stochastic model used. Moreover, the introduced online stochastic model is very effective for ambiguity resolution and validation in static and kinematic positioning in case of the signal block out occurs.

Keywords-component; pseudolite positioning, ambiguity resolution, ambiguity validation, on-line stochastic model

I. INTRODUCTION

The development of Global Navigation Satellite Systems (GNSS) has revolutionized the traditional surveying, geodesy and navigation for the past decades, and it has been widely applied nowadays to achieve reliable and accurate positioning results. However, when the GNSS signals transmit through a distance of 20, 000 km to the surface of the Earth, the strength of the signal is fairly weak to penetrate into the obstructions, such as indoors, urban canyons, which then results in an insufficient number of available satellites and a very poor geometry to conduct the reliable positioning.

To overcome the problem of poor geometry and the insufficient of available satellite, ground-based pseudo-satellites (pseudolites) have been designed to augment GNSS for both indoor and outdoor positioning. Theoretically, GNSS can be replaced by pseudolites completely for positioning, even though it is not practically applicable [9].

Pseudolites have been widely used to augment GNSS positioning. Considerable work has proved that even augmented with one pseudolite, the geometry of satellites can be dramatically improved [12]. As a matter of fact, the integration of pseudolites, GNSS and/ or INS can fully exert the flexibility of pseudolites to achieve good geometry and thus reliable results. Apart from augmenting other sensors, pseudolites can work independently and successfully in the areas where GNSS satellites signals are too weak to be tracked, such as indoors, underground car park, long tunnels, etc [1].

Similar to GNSS positioning, there are also some challenging issues in pseudolite positioning. For instance, multipath effects, mathematical modeling of the pseudolite measurements, hardware, effects of linearization and troposphere delay [1], [12]. All these aspects more or less contribute to the performance of pseudolites positioning. As a consequence, the double differenced float solutions from the least-squares estimation are somehow biased, which then may lead to an unsuccessful integer ambiguity resolution.

The problem of resolving the integer number of wavelengths in pseudolite positioning is similar as in the GNSS field. Traditionally, the integer ambiguities in pseudolite positioning are resolved by placing the rover on a known point to initialize, from which the integer ambiguity can be obtained by simply rounding the float solution to its nearest integer, the so-called integer rounding (IR) technique. However, there are no integer ambiguity validation procedures for IR, and it has been proved that the integer least-squares (ILS) is the best in terms of maximizing the success-rate [7]. So in this paper, instead of IR, we perform the integer ambiguity resolution by ILS, e.g. by the LAMBDA method [8], and by using ILS, integer ambiguity results can be more reliable and it is then more convenient to performance the ambiguity validation.

When the integer ambiguities have been correctly identified, they can be used to study the stochastic property of the measurements, such as the measurement quality. Providing this information, it is possible to predict the stochastic model for the coming epoch, especially for re-tracking a signal which has been obstructed in a short time, the performance of ambiguity resolution and validation can be greatly improved.

Therefore, the contribution of this paper aims at researching the mathematical modeling for pseudolite positioning in terms of reliable ambiguity resolution and validation. The rest of this paper is organized as follows. In Section II, the double differenced functional and stochastic models for pseudolite positioning in static and kinematic modes have been presented. Section III analyzes the ambiguity resolution and validation techniques; in addition, the online stochastic modeling method is introduced. Section IV shows the experimental analysis by analyzing static and kinematic pseudolite data. The last section summarizes this contribution.

II. MATHEMATICAL MODELING

A. Mathematical modeling

Pseudolite clocks and pseudolite related receiver clocks use inexpensive crystal oscillators and operate independently, which results in clock errors that are not negligible [9]. The pseudolite location in our experiment has been precisely determined so that there are no pseudolite location errors. To eliminate the other errors, the double differencing technique is utilized in the following [4]:

$$\Delta\nabla\Phi = \frac{1}{\lambda}\Delta\nabla\rho + \Delta\nabla N + \varepsilon_{\Phi} \quad (1)$$

$$\Delta\nabla P = \Delta\nabla\rho + \varepsilon_{P} \quad (2)$$

where $\Delta\nabla$ is the double differencing operator between pseudolites and receivers. Φ and P are the carrier phase and pseudo-range measurements respectively. λ is the carrier phase wavelength, and ρ is the geometric distance between pseudolites and receivers. N is the integer ambiguity vector. ε represents the measurement error. The multipath error is also a major concern for indoor positioning. Despite the multipath errors appear to be constant in static mode, it is fairly hard to deal with these errors in kinematic mode [1]. So the multipath errors have been assumed to be randomized into the measurement errors instead and the measurement noises are enlarged accordingly.

After linearization with an initial rover position, model (1) and (2) can be expressed as:

$$y = Ax + v \quad (3)$$

where y is the vector of 'observed-computed' distance. x denotes the baseline components x_r and the integer ambiguity N , and A includes the relevant design matrices. v is the measurement noise. Equation (3) is referred here as the functional model.

Meanwhile, an appropriate stochastic model is required. As shown in the following equation.

$$D = \sigma_0^2 Q = \sigma_0^2 P^{-1} \quad (4)$$

D is the measurement variance matrix. σ_0^2 is the a priori variance. Q and P are the covariance matrix and weight matrix respectively.

A stochastic model describes the quality of the measurements. In practice, it is extremely difficult to capture the stochastic property of the measurements, especially in the case of pseudolite positioning, where the multipath is severe. As pointed out in [12], 'the effect of multipath on the pseudo-range observation is two orders of magnitude larger than on the carrier phase measurements'; this should be taken into consideration when constructing the stochastic model.

In GNSS positioning, the stochastic model popularly used is the elevation dependent model. This model, however, is not suitable to be applied in pseudolite positioning. Instead, an empirical-value based model, which is assign the measurement accuracy based on empirical values, is often preferred. For reliable ambiguity resolution and validation, the empirical model is not sufficient, and as an alternative, an online stochastic model can be generated when the correct integer ambiguities have been resolved [3]. With this online stochastic model, which appropriately reflects the measurements quality and the condition scenarios of the receiver, the ambiguity resolution and validation in the coming epochs, particularly for the re-tracked satellites, can be greatly improved.

B. Static and kinematic pseudolite positioning

In GNSS positioning, the coordinates of the satellites are changing all the time, so that the satellite geometry in each epoch is different. However, for indoor pseudolite positioning, the pseudolites are fixed. Therefore, in case of the static pseudolite positioning, there is no changing in the pseudolite geometry with the time, and the design matrix A_i in each epoch is the same, which can be expressed as follows:

$$A = \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_i \end{bmatrix}, \qquad A_i = \begin{bmatrix} a_i/\lambda & 0 \\ a_i & I \end{bmatrix} \quad (5)$$

where A is the design matrix for a session data processing in static positioning, and a_i is the line of sight vector. A_i in each epoch is the same because of the stability of pseudolites. 0 and I are the zero matrix and identity matrix respectively. As a result, in an accumulated data processing, the precision of the estimated unknown parameters improve by a magnitude of the epoch number (in terms of variance of the measurement). So, it is unnecessary to repeat the computation of the design matrix for each epoch. Besides, it is worth mentioning that the correlation between the unknown parameters does not change. Presuming there are no temporal and spatial correlations among the epochs, the corresponding stochastic model can be specifically determined as:

$$Q = blkdiag(Q_1, Q_2 ... Q_i) \quad (6)$$

with Q_i is the stochastic model for each epoch and $blkdiag$ is a MATLAB function to build a diagonal matrix with the inputs.

In pseudolite kinematic positioning, the geometry varies with the movement of the rover, and the design matrix can be constructed as follows:

$$A = \begin{bmatrix} a_1/\lambda & 0 & & 0 & 0 \\ a_1 & 0 & & 0 & I \\ 0 & a_2/\lambda & & 0 & 0 \\ 0 & a_2 & & 0 & I \\ & & \ddots & & \\ 0 & 0 & & a_i/\lambda & 0 \\ 0 & 0 & & a_i & I \end{bmatrix} \quad (7)$$

The carrier phase integer ambiguity vector remains constant in each epoch, unless a cycle slip or signal block out occurs. The stochastic model for kinematic positioning is the same as the static positioning stochastic model, defined in equation (6). It should be noted this functional model can be equally realized by the Kalman filter as well.

III. Least squares and integer least squares

A. Integer least-squares esimation

By apply the classical least-squares approach, as well as the above defined mathematical models, the unknown parameters and their variance and covariance matrix can be estimated as:

$$\hat{x} = (\hat{x}_r, \hat{N})^T = (A^T PA)^{-1} A^T Py \quad (8)$$

$$\hat{Q}_{\hat{x}} = (A^T PA)^{-1} = \begin{bmatrix} Q_{\hat{x}_r} & Q_{\hat{N}\hat{x}_r} \\ Q_{\hat{x}_r\hat{N}} & Q_{\hat{N}} \end{bmatrix} \quad (9)$$

$\hat{x}_r$ and $\hat{N}$ are the so-called float solution with their variance and covariance matrices as $Q_{\hat{x}_r}$ and $Q_{\hat{N}}$ respectively. Recall the integer constraint of the ambiguity term N, further step is required to find this integer vector. Providing the estimates and their variance covariance matrix from least-squares, the ILS problem is conducted by searching for an integer ambiguity vector $\breve{N}$ which minimizes the following objective function:

$$\left\| \hat{N} - \breve{N} \right\|^2_{Q_{\hat{N}}} = (\hat{N} - \breve{N})^T Q^{-1}_{\hat{N}} (\hat{N} - \breve{N}) \quad (10)$$

There are several ways of resolving the objective function in equation (10), an efficient searching procedures applied in this paper can be found in [8].

Generally, there are several integer candidates can be found from equation (10). To validate, or more precisely, to discriminate the most likely integer candidate from the second most likely integer candidate, statistics, such as the R-ratio test in [6] and W-ratio test in [2], which are defined in the following, are preferred.

$$R = \frac{\left\| \hat{N} - \breve{N}_2 \right\|^2_{Q_{\hat{N}}}}{\left\| \hat{N} - \breve{N}_1 \right\|^2_{Q_{\hat{N}}}} \quad (11)$$

$$W = \frac{\left\| \hat{N} - \breve{N}_2 \right\|^2_{Q_{\hat{N}}} - \left\| \hat{N} - \breve{N}_1 \right\|^2_{Q_{\hat{N}}}}{2\delta \left\| \breve{N}_2 - \breve{N}_1 \right\|_{Q_{\hat{N}}}} \quad (12)$$

where $\breve{N}_1$ and $\breve{N}_2$ are the most and second most likely integers from LAMBDA. δ can be either a prior variance or a posteriori variance. By comparing these ambiguity validation statistics with critical values, the user decides whether accept the most likely integer or not.

The ILS success-rate is also a very good indicator for ambiguity resolution. Comparing with the IR, ILS has been proved to be optimal in terms of maximizing the ambiguity resolution success-rate. Even though there is no exact formula to calculate, a good approximation of the ILS success-rate based on the ambiguity dilution of precision (ADOP) [13] can be applied, as shown in equation (13).

$$P_{ILS} \approx (2\Phi(\frac{1}{2ADOP}) - 1)^n \quad (13)$$

where n is the ambiguity dimension and Φ is the cumulative normal distribution function. $ADOP$ is calculated with equation (14), as follows:

$$ADOP = \sqrt{\left| Q_{\hat{N}} \right|^{\frac{1}{n}}} \quad (14)$$

B. Constructing the online stochastic model

It has been mentioned that an empirical stochastic model can be used in pseudolite positioning. However, when the integer ambiguities have been correctly resolved, a *covariance-matching* method can be used to construct a more realistic stochastic model for real-time applications. The *covariance-matching* method has been further modified in [3] as the following term in a least-squares sense:

$$\hat{Q}_i = \frac{1}{m} \sum_{j=0}^{m-1} v_{i-j} v^T_{i-j} + A' (A^T PA')^{-1} A'^T \quad (15)$$

where m indicates the *width of moving windows*. It should be noted that A' represents the design matrix without the integer ambiguity term. The stochastic model constructed with equation (15) can be used in the computation of epoch $i+1$, and by the virtue of this smoothing, it is more reliable than the empirical-value based model. More specifically, this model can be applied when re-tracking the lost pseudolite signals or an outage of the receiver batteries and the integer ambiguity can be recovered shortly.

IV. NUMERICAL ANALYSIS

To analyze the ambiguity resolution and validation in the case of pseudolites static and kinematic positioning, two experiments, one single-frequency static and one single-frequency kinematic, were carried out in the pseudolige test bed of Wuhan University. Six pseudolites are built on the ceiling of a building and the coordinates of the pseudolites have been precisely determined by a total station. After double differencing, there are five ambiguities to be determined.

The base stations and rover stations (both static and kinematic) coordinates were surveyed, which means their precise coordinates were known as well. For static positioning, the rover was set up one a station, and 120 epochs were collected with a sampling rate of 2 seconds. For kinematic positioning, the rover was placed on a station for 11 epochs and then moved to another station for 11 epochs. The time intervals (around 20 epochs, 40 seconds) between two stations are not taken into consideration. The first epoch in each station is used for the analysis of kinematic positioning. So altogether, 18 different stations were occupied and 18 epochs are taken into consideration for kinematic. The three dimensional illustration of the pseudolites, the base station and the rover station are shown in Figure 1 and 2.

A. *Ambiguity resolution and validation performance*

The correct integer ambiguities have been obtained beforehand for further analysis. The true rover positions were used to linearize equation (1) and (2), so as to obtain A and y in equation (3). A stochastic model with the pseudo-range measurement error of 0.38 meter and 0.01 cycle was firstly used.

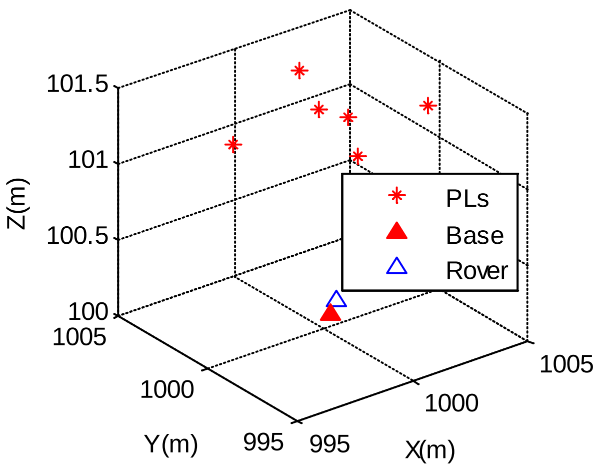

Figure 1: Static pseudolites and stations configuration

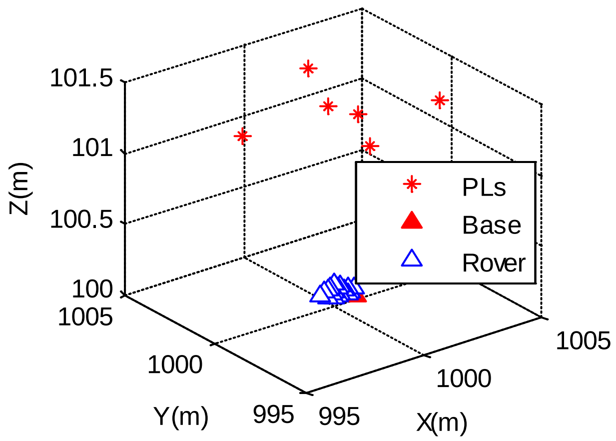

Figure 2: Kinematic pseudolites and stations configuration

For static positioning, the design matrix in equation (5) (first term for an accumulated solution and second term for an epoch by epoch solution) was applied. Firstly, the data was processed epoch by epoch. Unfortunately, the integer ambiguities in none of these epochs can be successfully resolved. There are two potential reasons: 1) the pseudolite geometry is too weak, with the ILS success-rate as only 0.2914 for each epoch and the ambiguity validation is unable to perform because the resolved most likely integer candidate cannot separate from the second most likely integer candidate. 2) The bad quality of pseudo-range measurements. It should be noted that each carrier phase measurement contributes totally to the corresponding integer ambiguity and ambiguity resolution in an epoch by epoch solution entirely relies on the pseudo-range measurements. If the pseudo-range measurements are biased, the ambiguity resolution results will be biased as well. A better solution is to apply a more realistic stochastic model, which will be discussed later.

If the static data was processed by accumulating epochs, the design matrix as the first term of equation (5) was applied. Unfortunately, the performance of ambiguity resolution doesn't perform well as expected. Even though by accumulating the data in each epoch, the precision of the integer ambiguity variance covariance matrices improves by a magnitude of the epoch number, the correlation between individual ambiguities remains the same. In other words, the inside structure of the variance covariance matrix doesn't change and this probably indicate that the ambiguity resolution performance is still highly suffered from the bad pseudo-range measurements no matter for one epoch or multi-epochs together.

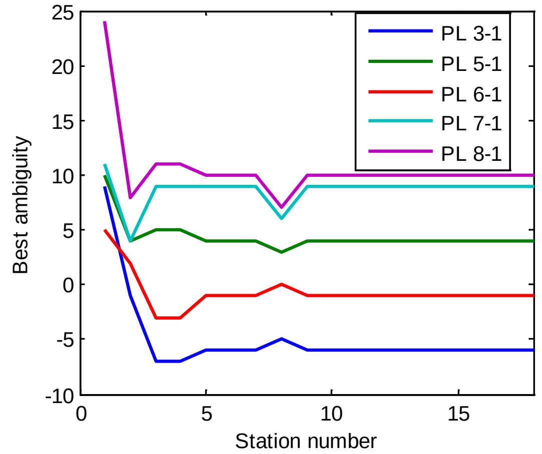

Figure 3: The most likely integer ambiguities by accumulating the kinematic data

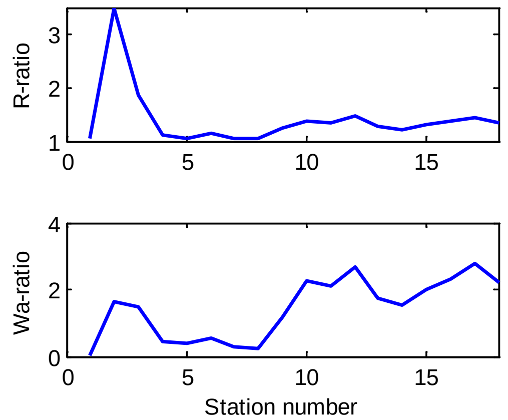

Figure 4: Ambiguity validation statistic by R-ratio and W-ratio for accumulating the kinematic data

In the case of kinematic positioning with epoch by epoch solution, the design matrices are derived the same as in static positioning. Among all the 18 stations, due to the bad geometry, the integer ambiguities cannot be successfully resolved either. Because the distance is short between pseudolites and receivers, and the region is limited for the 18 rover stations, the ILS success-rate approximated by the ADOP in each epoch changes slightly and fluctuates around 0.7253.

When processing the data by accumulating the epochs, the results are shown in Figure 3. The correct integer ambiguity vector is [-6 4 -1 9 10], and it can be seen from Figure 3 that from the fifth epoch onwards, we can get the correct integer ambiguity and the ILS success-rate becomes sufficiently close to 1. However, in the eighth epoch, the most likely integer candidate is not correct, which can be explained from the bad quality of the pseudo-range measurements in this epoch. As a matter of fact, the second most likely integer candidate from this epoch is the correct one, which implies that due to the biases in the pseudo-range measurements, particularly for this epoch, the resolved ambiguity float solution is biased, and consequently, the corresponding ambiguity resolution result is not correct. The ambiguity validation statistics by R-ratio and W-ratio are plotted in Figure 4. The more R-ratio closes to 1 and Wa-ratio close to 0, the less likely we can separate the two most likely integer candidates; specifically can be seen from the eighth epoch. However, it is worth mentioning that these two statistics cannot validate the correctness of the resolved integer ambiguity, as for epoch 2 and 3, even though the most likely integer candidate can highly be separated from the second most likely one, it is not correct. Therefore, one important note is that these two ambiguity validation statistics can give reliable performance only in case of a high ILS success-rate, but not guaranteed because of the bias.

B. Improving the ambiguity resolution and validation performance by the online stochastic model

In order to have better ambiguity resolution and validation results, a more realistic stochastic model is indispensable. It has been shown that due to the poor geometry and the bad quality of pseudo-range measurements, it is extremely hard to construct a reliable stochastic model. However, when the correct integer ambiguity vector is available, the stochastic model can be re-constructed as shown in equation (15). By smoothing the residuals for several epochs (adjusted by the window width), the stochastic model begins to capture the essence of the measurements, and therefore becomes more reliable. With this newly built stochastic model, ambiguity resolution and validation performance can be quickly recovered in the case of a loss of signal, receiver batteries outage, etc.

To illustrate the effects of the online stochastic model, the static and kinematic data have been re-processed with a window width of 9 epochs, which means that the data in the first 9 epochs were used to construct the stochastic model for the tenth epoch, and by moving the window, the stochastic model for the coming epoch can be constructed from the previous nine epochs.

The static data was processed first with epoch by epoch. Apart from the first nine epochs, which were used to construct the stochastic model, all the other 111 epochs can resolve the integer ambiguities correctly, and from the 10th epoch, the ILS success-rate for each epoch is extremely close to 1.0. The ambiguity validation performances by R-ratio and W-ratio are also fairly good, as can be seen from Figure 5. Note the epoch number starts from 10. For the accumulated processing, there is no doubt that the integer ambiguity can be successfully resolved since even one epoch is enough to resolve the integer ambiguity by applying the online stochastic model.

In the case of kinematic data, epoch by epoch ambiguity resolution performance is not as good as we expected. Among 9 stations, only one station can successfully resolve the integer ambiguity. Recall that the rover was employed in each station for 10 epochs and then move to the next station (around 40 seconds movement was not considered), it means that in a kinematic scenario, it is very difficult to reliably model the temporal stochastic property of measurements, especially when the epoch gap is too long. When processing the kinematic data by accumulating each epoch, the first time to fix requires only two stations, which is much better than the original stochastic model (5 stations for first time to fix).

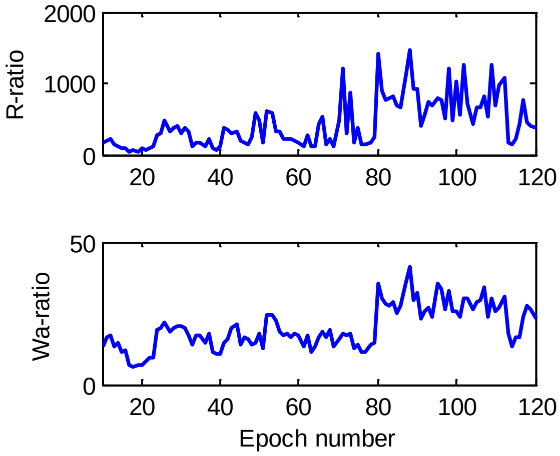

Figure 5: Ambiguity validation statistic by R-ratio and W-ratio for static data processed epoch by epoch

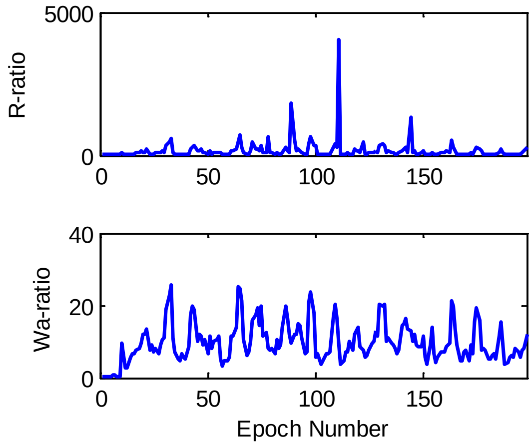

Figure 6: Ambiguity validation statistic by R-ratio and W-ratio for the whole kinematic data processed epoch by epoch

The whole kinematic data, including the static epochs on each station, was processed epoch by epoch using the online stochastic model. The results are fairly good as the integer ambiguities in 189 epochs (all together 198 epochs, 9 epochs were used to generate the online stochastic model) can be successfully resolved. From the 10th epoch onwards, the ILS success-rates are almost 1.0. The ambiguity validation statistics by R-ratio and Wa-ratio tests are plotted in Figure 6. Apparently, since the ILS success-rate approaches to 1.0, the ambiguity validation tests can be performed reliably after 9 epochs because of the more realistic model constructed. In Figure 7, as an example, the quality of the online stochastic model for each station is shown by the Wa-ratio values. As we know that there are around 40 seconds between any two stations, the online stochastic model estimated from the previous station to the coming station is affected by the time gap between two stations, which then results in a sudden drop in the Wa-ratio values at the start of each station, as indicated by the red star in Figure 7. This clearly shows that in pseudolite kinematic positioning, the multipath varies with the surrounding obstructs and modeling the multipath is a challenging issue.

According to the results from both the static and kinematic data sets, it can be concluded that by using the online stochastic model, the ambiguity resolution and validation performances can be improved dramatically, and in most cases, even instantaneous ambiguity resolution can be performed.

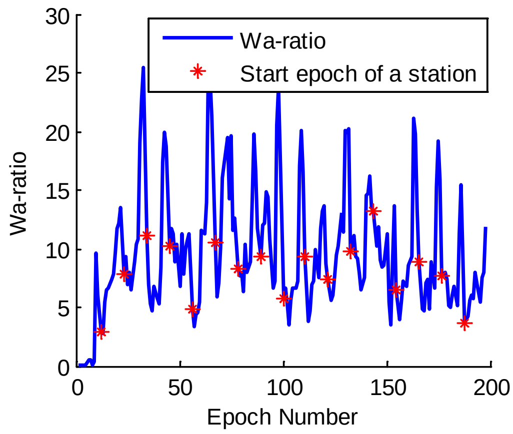

Figure 7: The quality of the online stochastic model at the beginning ofeach station

V. CONCLUDING REMARKS

This paper analyzes the ambiguity resolution and validation procedures for precise pseudolite positioning. Experimental results have shown that ambiguity resolution and validation is very difficult to be successfully conducted because of the pseudolites geometry (limited number of available satellites) and the measurement quality, which surfers highly from the multipath in the surrounding scenarios. For static pseudolite positioning by accumulation the epochs, the ambiguity variance and covariance matrices only changes the magnitude of the precision, however, the inter-correlations among the ambiguities are still the same. In case of kinematic positioning by accumulation, the movement of the receiver allows the geometry to improve not only by the precision but also by the inter-correlations and as a consequence, the integer ambiguity can be resolved in several epochs.

Since, during the experiments, the real application of pseudolite positioning was bothered by the signal block out quite often, an online stochastic model is introduced to construct a more reliable and realistic stochastic model. According to the results presented, integer ambiguity resolution and validation can be greatly improved, and even can be recovered instantaneously.

For future work on precise pseudolite positioning, more attention should be paid to linearization error and the multipath effects in the kinematic scenarios.

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