GPS Ambiguity Resolution for Long-Baseline Kinematic Applications

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Introduction

The Canadian Hydrographic Service (CHS) in collaboration with the Canadian Coast Guard (CCG) is establishing a seamless datum to modernize its bathymetric survey operations. Two main aspects of the use of a seamless datum are: 1) the relation between geodetic (ellipsoidal) height obtained from GPS and chart datum, and 2) the precise (better than ±10 cm) GPS kinematic positioning (particularly the height) of a survey vessel. For example, for the St. Lawrence River, which has a 300-km-long navigation channel, this would eliminate the installation of more than 70 tide staffs every survey season, which costs more than $250,000 annually. Besides being out-dated and costly, the use of tide staffs introduces various errors associated with water transfer. The 3D GPS positioning (especially the height) of the survey vessel provides all the information required to map the profile of the river or sea bed along with depth data recorded by echo-sounders.

Problem Statement

It has been a continuing challenge to determine and fix the GPS carrier-phase ambiguities, especially for long baselines. Moreover, the challenge is even greater for kinematic GPS applications. We have faced just this challenge in processing GPS data collected for hydrographic sounding. Generally, the difficulty in solving the ambiguities is due to the decorrelation of biases in the GPS observations. As is well known, the GPS observations at the base and remote stations will be influenced by different atmospheric effects and satellite orbit bias as the baseline length between the stations gets longer [*Tiberius et al.*, 1999]. Furthermore, when the pseudorange observations are incorporated with the carrier-phase observations, multipath can be the dominant error source that makes it difficult to solve the ambiguities because of its quasi-random behaviour over a relatively short time span. In kinematic situations, it is not easy to model the observation noise because the dynamics of a moving object may mask some aspects of the observation noise which usually can be well modeled statistically by an elevation angle dependent function.

Objectives

The objective of the research reported in this paper is to improve the carrier-phase ambiguity resolution methods and associated algorithms to achieve more precise and reliable kinematic GPS positioning over distances up to, and even longer than, 75 km for the support of bathymetric surveys in real time (but not exclusively for bathymetric applications).

Methodology

Which strategy will be preferable for dealing with long baselines and kinematic situations? Is the situation different for real-time applications? In our case, the answer is a Kalman filter approach combined with an ambiguity search method which can handle the functional and stochastic models in an optimal way.

Kalman Filter Approach

We have found that a Kalman filter approach can efficiently implement quality control schemes such as cycle-slip handling (detection, identification and adaptation) and observation noise modeling procedures. However, fundamental concerns related to its implementation are: 1) How to reduce the number of unknown parameters in the filter state vector? 2) How to ensure the observability of the given system model under the rank deficiency condition? 3) Which implementation method is efficient?

Basically, the problem is that the number of unknown parameters is much greater than that of the observations. This is an inherent problem of carrier-phase applications and turns out to be a substantial one in such an approach as ours which tries to estimate all the bias parameters and the observation noise (except for the multipath in the carrier-phase observations). To reduce the number of unknown parameters, the double differencing scheme is used in our approach. In addition, dual-frequency carrier phases (L1 and L2) and code pseudoranges (P1 and P2, or C/A and P2) are used to increase observation redundancy. Furthermore, the unknown parameters are transformed to ensure the observability of the given system model. A separate Kalman filter is implemented for each double-difference time series because its programming and stochastic modeling are easier.

Quality Control

We face two problems related to the quality control of the observations when implementing our Kalman filter approach. How do we implement a robust cycle-slip (or outlier) handling routine? How do we model the observation noise? These problems are especially critical in applications requiring real-time, long baseline and kinematic operation.

To overcome the first problem, we use a masking technique based on a logical intersection of necessary and sufficient conditions for cycle-slip detection and identification. When a cycle-slip happens, we can see a spike in the quadruple-difference (obtained by differencing consecutive triple-difference observations) time series (Figure 1a and 1b). This provides a necessary condition for cycle-slip identification. As a conventional approach incorporated within a Kalman filter, we can use prediction residuals to detect a cycle-slip (Figure 1c). However, this should be used carefully because the prediction residuals are very sensitive to the dynamics of a moving object and the sampling rate of the observations. As another approach, the ionospheric delay estimates can be used (Figure 1d). However, this also should be used carefully because there are cases when a cycle-slip cannot be detected such as when cycle slips of the same size (in distance units) occur simultaneously on L1 and L2, not to mention the very obvious case when cycle slips in both carrier phases cancel each other in the ionosphere-free combination ($\frac{1}{77}n1 - \frac{1}{60}n2 = 0$). Nevertheless, in a wide sense, these two approaches – prediction residuals and ionospheric delay estimates – provide sufficient conditions for detecting cycle-slips.

For the observation noise modeling, we have found that the dynamics of a moving object can sometime mask the behaviour of the observation noise which otherwise usually can be well modeled statistically by an elevation angle dependent function. To overcome this problem, we use the quintuple-difference (differencing consecutive quadruple-difference observations after deleting cycle-slip spikes) time series to estimate the mean bias and standard deviation (Figure 2). In this case, we assume that the effects of the unknown parameters, except the parameter related to geometric range (in fact, this parameter reflects the dynamics of a moving object.) and white Gaussian observation noise, are removed in the quintuple-difference time series.

Ambiguity Search Process

Using the estimates of the state vector (Figure 3), we can transform the original carrier-phase double-difference observations to the other ones to be used at the ambiguity search process. The purpose of this transformation is to reduce the number of unknown parameters at the ambiguity search step. However, there can be some cost to pay for this transformation (i.e., the observation noise is increased and time-correlated). We use an ionosphere-free transformation to reduce this cost. As a matter of fact, we have found that the transformed observations are similar to the ionosphere-free linear combination but have smaller observation noise. The time-correlated observation noise can be estimated using the variance-covariance matrix which is obtained adaptively from the Kalman filter.

For the observation equations related to the transformed observations, we assume that carrier-phase multipath is ignorable and the satellite orbit bias is merged into the white noise when modeling the observation noise using the quintuple-difference time series (of course, the second assumption is not required if a precise orbit is used.). For the ambiguity search process, we use the independent-ambiguity-search approach [*Hatch*, 1990]. Since there remain four unknown parameters in the observation equations after the observations are transformed, we always have eight search levels (four search levels for $\mathbf{N}1$ and $\mathbf{N}2$, the L1 and L2 ambiguities, respectively) regardless of the number of double-difference observations. In this case, the search space may be enormous even if a small search window is used. This means that the ambiguity search process may be so time-consuming that it is not appropriate for a real-time system. In order to overcome this problem, we use an efficient ambiguity search engine, namely OMEGA (Optimal Method for Estimating GPS Ambiguities) [*Kim and Langley*, 1999].

Results

We have tested our technique using a kinematic data set. The dual-frequency data were recorded at a one second sampling interval on board a hydrographic sounding ship at Trois-Rivières, on the St. Lawrence River, 130km upstream (southwest) of Québec City, on 22 October 1998 and simultaneously at one reference station (Trois-Rivières DGPS) in the Canadian Coast Guard (CCG) DGPS and OTF network.

Figure 1 shows the cycle-slip detection and identification procedures. So far, we have found that the performance of these procedures is almost perfect as far as cycle-slip detection and identification are concerned. However, we have found that cycle-slip adaptation should be executed carefully because the ability to detect a slip of one cycle is sensitive to the dynamics of a moving object. In Figure 2, we can see an example of how the dynamics of a moving receiver can mask the behaviour of the observation noise.

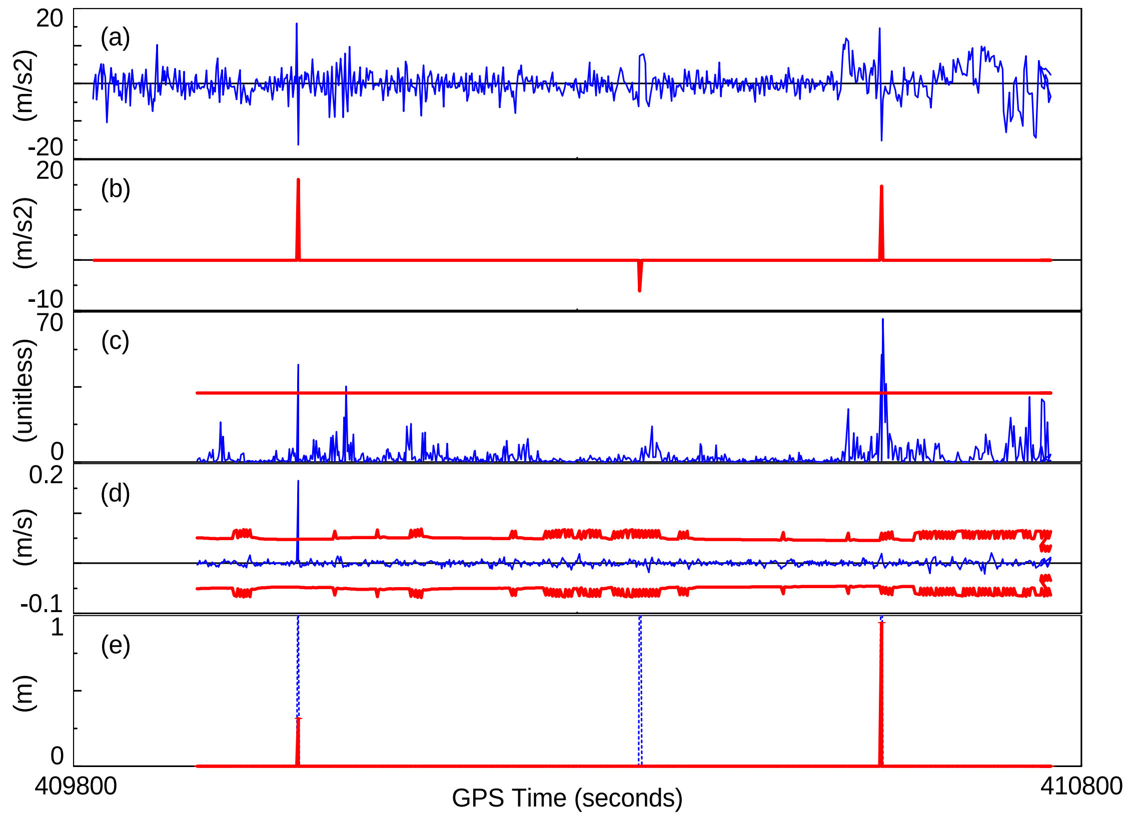

Figure 1. Example of cycle-slip detection and identification procedures (PRN15&30): (a) L1 Quadruple-difference time series; (b) Cycle-slip candidates detected by spikes; (c) Cycle-slip candidates detected by the Kalman filter prediction residuals (95% confidence level); (d) Cycle-slip candidates detected by the ionospheric delay estimates (95% confidence level); and (e) Masking results (cycle-slip identification).

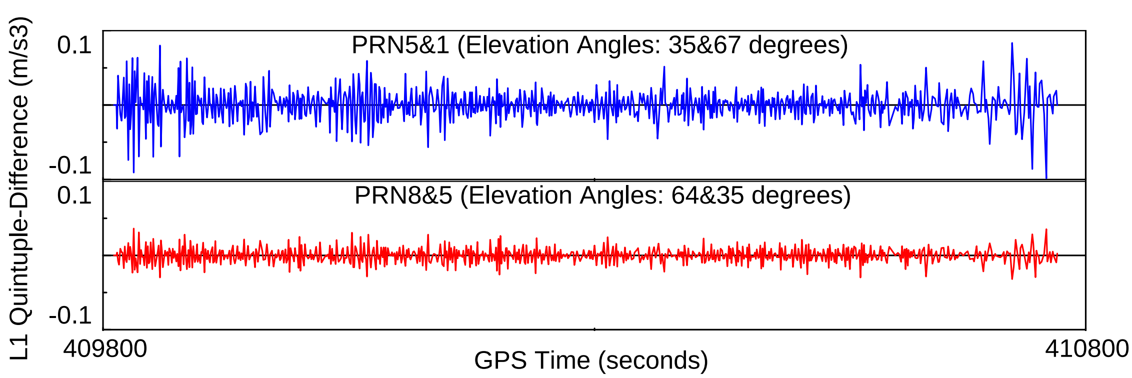

Figure 2. Observation noise modeling using Quintuple-difference time series.

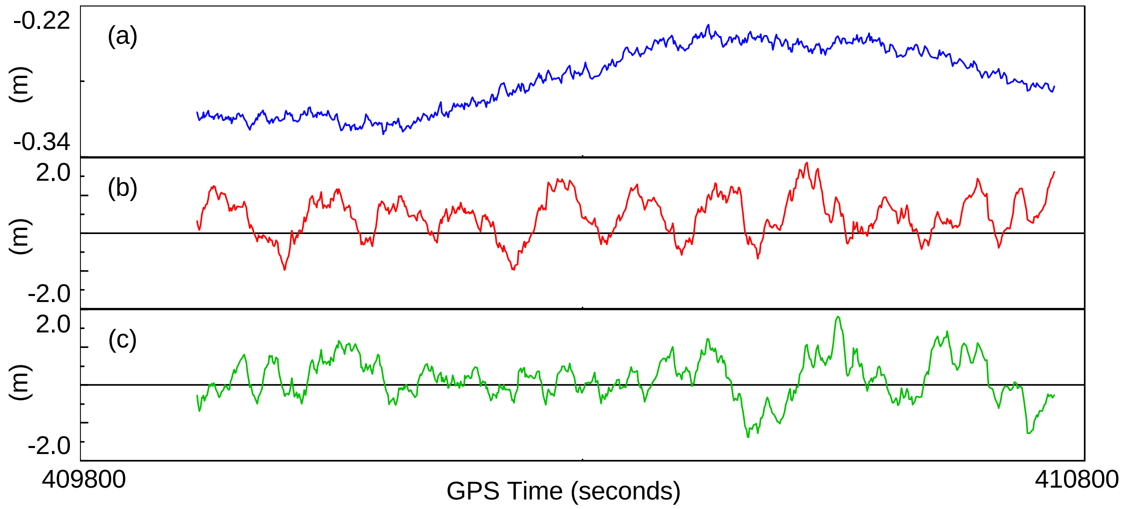

Figure 3. Kalman filter estimates (PRN9&8): (a) Ionospheric-delay; (b) Multipath in C/A pseudoranges; and (c) Multipath in P2 pseudoranges.

Figure 3 shows the performance of the Kalman filter. Each parameter estimate includes two unknown parameters, i.e., initial (at the start of observations) multipath bias and carrier-phase multipath. A more complete description of how the filter operates will be submitted for journal publication.

Discussion and Conclusion

We have developed a prototype approach to solve the ambiguity fixing problems. The main feature of the technique, which may differ from other approaches, is that the system takes into account those problems – the decorrelation of biases, the quasi-random behavior of multipath and the observation noise all in kinematic mode – at the same time within the functional and stochastic models for the GPS observations. In other words, we do not simply ignore these problems and hope their effects are averaged out. Instead, all the bias parameters and the observation noise (except multipath in the carrier-phase observations) are estimated while a software process for quality control of the observations is proceeding. Our new approach also features improved computational efficiency of the ambiguity search process by reducing the search space and the use of a new algorithm for the quadratic form of the residuals.

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