GPS Time Series Land Slide Monitoring using A Weighted Extended Kalman Filtering with a DIA Procedure

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ABSTRACT

RTK GPS has become a global utility in engineering survey activities. RTK GPS offers an efficient means of providing near instantaneous positions by employing differential GPS positioning whereby users can obtain sub-centimetre/millimetre level position in real time. In RTK GPS all algorithms using code information only are limited to range accuracy of about 0.5-1.0 metres due to code noise. However, range measurement using carrier phase information on the other hand is limited to only 0.5-3.0 millimetres by noise. Thus the use of carrier phase measurements in high precision positioning has become indispensable. Yet in order to use the carrier phase measurements in an urban canyon environment, the user has a couple of positioning errors to deal with.

Using double differencing procedure, this research work uses an exponentially weighted Extended Kalman Filter (EWEKF) with the integration of detection, identification, adaptation (DIA) method as an attempt to remove/isolate the effects of errors such as the multipath, outliers and receiver noise on GPS signals during transmission. The end result shows an improved coordinates solution.

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1. INTRODUCTION

Researchers have focused on defining the different positioning error sources, studying their effects, and searching for methods to decrease, or possibly eliminate these errors in order to achieve better positioning accuracies in RTK set up in an urban canyon environment

One of the major problems is the Multipath error, which occurs when GPS signals are reflected from nearby objects before reaching the antenna. Also, electrical interference occurs when secondary sources or other transmitters and receivers distort the reception of the GPS signals or affect the receiver's circuitry. These are particularly problematic for RTK GPS in an urban canyon environment, because they act as bias during the short location occupations and can prevent satellite tracking.

Besides the afore-mentioned error sources with the use of carrier phase observables, other problems that are associated with RTK GPS positioning is the baseline length which tends to degrade the accuracy as the baseline length increases. This is predominantly due to

atmospheric effects (ionosphere and troposphere), which become de-correlated and thus no longer cancel over longer distances through differencing algorithms.

2. GPS MEASUREMENT MODELS

The observables considered in this paper consist of double differenced between two receivers. For two receiver stations (1 and 2) tracking simultaneously the same set of satellites (*s* and *l*), we have the code double difference equation for dual frequencies as

$$\text{L1:}\quad R_{p,12}^{sl} = \rho_1^s - \rho_1^l - \rho_2^s + \rho_2^l + I_{12}^{sl} + T_{12}^{sl} + M_{p,12}^{sl} - e_{p,12}^{sl} \qquad (1)$$

$$\text{L2:}\quad R_{q,12}^{sl} = \rho_1^s - \rho_1^l - \rho_2^s + \rho_2^l + (f_1 / f_2)^2 I_{12}^{sl} + T_{12}^{sl} + M_{q,12}^{sl} - e_{q,12}^{sl} \qquad (2)$$

Subscripts p, q are used to identify measurements with L1, L2 with frequency f_1 and f_2 respectively.

T_{12}^{sl} is for the tropospheric delay, I_{12}^{sl} is for the ionospheric delay, M_{12}^{sl} is for the multipath delay and e_{12}^{sl} denotes an error for code observations. Similarly, for the combined phase measurements we have

$$\phi_{p,12}^{sl} = \rho_1^s - \rho_1^l - \rho_2^s + \rho_2^l - I_{12}^{sl} + T_{12}^{sl} + \lambda_p N_{p,12}^{sl} + M_{p,12}^{sl} - \varepsilon_{p,12}^{sl} \quad (3)$$

$$\phi_{q,12}^{sl} = \rho_1^s - \rho_1^l - \rho_2^s + \rho_2^l - (f_1/f_2)^2 I_{12}^{sl} + T_{12}^{sl} + \lambda_q N_{q,12}^{sl} + M_{q,12}^{sl} - \varepsilon_{q,12}^{sl} \quad (4)$$

where N_{12}^{sl} denotes ambiguities between satellites *s* and *l* and receivers *1* and *2,* while λ_p, λ_q are the wavelengths of L1, L2 carrier respectively, ε_{12}^{sl} is the error in the carrier phase measurements. One should note here that the above model is equally valid for the future GPS L5 frequency as well.

The double difference code and carrier phase measurements can now be reduced to the form given in equation (5)

$$\begin{aligned} R_1 &= \rho + I + T + M_{p1} - e_1 \\ R_2 &= \rho + (f_1/f_2)^2 I + T + M_{p2} - e_2 \\ \phi_1 &= \rho - I + T + \lambda_1 N_1 + M_{q1} - \varepsilon_1 \\ \phi_2 &= \rho - (f_1/f_2)^2 I + T + \lambda_2 N_2 + M_{q2} - \varepsilon_2 \end{aligned} \quad (5)$$

where $f_1/f_2 = 154/120 = 1.2833333...$.

3. MULTIPATH

Multipath signal propagation has remained a dominant cause of error in RTK GPS positioning. Multipath errors are due to reflected GPS signals from surfaces (such as buildings, metal surfaces etc) near the receiver, resulting in one or more secondary propagation paths. These secondary-paths signals, which are superimposed on the desired direct path signal, always have a longer propagation time and can significantly distort the amplitude and phase of the direct-path signal (Iyiade and Owusu-Nkasah, 2002, Cross et al, 2003).

Multipath error is scaled according to wavelength and is generally therefore nearly 100 times lager for P-code pseudoranges than it is for carrier phase measurements. Instantaneous multipath error can be as large as a few meters for P-code and a few centimetres for carrier phase. Thus, multipath becomes a dominant source of error in the measurement, in a situation in which range and phase data are needed instantaneously.

4. EXPONENTIALLY WEIGHTED EXTENDED KALMAN FILTERING (EWEFK)

The filter describes the evolution of the states, the measurement model relates the state vector to the GPS observations through the design matrix H. Regular updates by the measurement into the state vector is crucial as the system will diverge if there is no measurement provided over a long period of time, driven by the system input noise. The observations for the float filter are double difference carrier phase and code observables.

The EKF uses an over weighting of the most recent data. Here, a scalar parameter τ is introduced such that $0 < \tau < 1$. Since $\tau < 1$, where a value of 1 corresponds to a standard EKF and a value of zero corresponds to keeping only the first measured point. The factor τ^{i-j} weights past data less heavily than more recent data. This feature enables an adaptive algorithm to respond to variations in data statistics by forgetting data from the remote past. Since data acquisition and processing was done in real time and due to the computation problem in an EKF, an exponentially weighted EKF method was implemented.

The process and measurement models and implementation equations for the exponentially weighted EKF are:

For process model:

$$x_k = F(\hat{x}, k-1)x_{k-1} + w_{k-1} \qquad (6)$$
$$w_k \sim N(0, Q)$$

For measurement model

$$z_k = H(\hat{x}, k)x_k + v_k \qquad (7)$$
$$v_k \sim N(0, R)$$

By setting the model covariance matrices equal to

$$R_k = R\alpha^{(k+1)} \qquad (8)$$
$$Q_k = Q\alpha^{(k+1)} \qquad (9)$$

where $\alpha = \exp^{\frac{1}{\tau}}$, and $\alpha > 1$, and constant matrices Q and R, for

The symbol w_k and v_k denotes variance of the process noise and are zero-mean normal distributed white noise and characterized by covariance matrices Q and R respectively. The essential implementations for the extended Kalman filter are given in many literatures such as Strang and Borre (1997).

$$\hat{x}_k^- = f(\hat{x}_{k-1}^+, k-1) \qquad (8)$$
$$P_k^- = F_{k-1}P_{k-1}^+F_{k-1}^T + Q_{k-1} \qquad (9)$$
$$K_k = P_k^-H_k^T\left[H_kP_k^+H_k^T + R_k\right]^{-1} \qquad (10)$$
$$P_k = \left[I - K_kH_k\right]P_k^- \qquad (11)$$
$$\hat{x}_k^+ = \hat{x}_k^- + K_k(z_k - \hat{z}_k) \qquad (12)$$

where $H_K \approx \left.\frac{\partial h(x,k)}{\partial x}\right|_{x=\hat{x}_k^-}$

In the dynamics model of the filter, three states which will be nine variables that are three linear degrees of freedom (position vector), the correspondence velocity variables (velocity vector) and correspondence acceleration variables (acceleration vector) are considered. In this application, the state model can be written as

$$X_k = \left[x, v_x, a_x, y, v_y, a_y, z, v_z, a_z\right]_k^T \qquad (13)$$

This model can be represented by the equation

$$\begin{aligned} x_{k+1} &= x_k + \Delta t v_x + \frac{\Delta t^2}{2} a_x \\ y_{k+1} &= y_k + \Delta t v_y + \frac{\Delta t^2}{2} a_y \\ z_{k+1} &= z_k + \Delta t v_z + \frac{\Delta t^2}{2} a_z \end{aligned} \qquad (14)$$

The relation between the previous states and the current states are govern by the transition matrix (F_k),

$$F = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 & \Delta t^2/2 & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & \Delta t^2/2 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & \Delta t^2/2 \\ 0 & 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad (15)$$

where Δt is the time step between t_{k-1} and t_k (transition time interval in seconds), and the process noise vector w_k is considered to be zero mean white.

$$H_k(x_k) = \left[R^1, R^2, R^3, R^4\right]_K^T \qquad (16)$$

R^1, R^2, R^3, R^4, are the measurement consists of pseudorange and phase observation and hence the relation between the measurements and the states (position vector) is not linear. Equation (16) can be linearised by approximating $H_k(x_k)$ with Taylor series expansion about the predicted value of the states $\hat{x}_k^-$ at $t = k\Delta t$ and retaining only the first-order terms (equation 18). The linearised measurement equation in the extended Kalman filter is defined as

$$z_k = Hx_k \qquad (17)$$

where H is the Jacobian matrix given as follows

$$H = \begin{bmatrix} u_1^1 - u_2^k \\ u_1^2 - u_2^k \\ \cdots \\ u_1^n - u_2^k \end{bmatrix} \qquad (18)$$

where

$$u_1^k = \frac{x_{ECEF}^K - x_1}{\rho_1^k}, \frac{y_{ECEF}^K - y_1}{\rho_1^k}, \frac{z_{ECEF}^K - z_1}{\rho_1^k} \qquad (19)$$

The measurement vector z is expressed as

$$z = \begin{bmatrix} \phi_{q,12}^{k1} - \lambda_q N_{q,12}^{k1} \\ \phi_{q,12}^{k2} - \lambda_q N_{q,12}^{k2} \\ \cdots \\ \phi_{q,12}^{kn} - \lambda_q N_{q,12}^{kn} \end{bmatrix} \qquad (20)$$

5. QUALITY CONTROL

In handling various alternative hypothesis, the Detection, Identification and Adaptation (DIA) method as described by (Teunissen, 1998) was implemented in the software used in processing the observed data. The DIA-procedure consists of the followings steps (de Jong, 1998):

- Detection: In the detection step, a global overall model test is performed on the whole observation set at a given epoch in other to check weather unspecified model errors have occurred.
- Identification: After detecting of model errors, identification of the potential source of these errors is required. After identification, the detected bias is compared with the Minimal Detectable Biases (MDB) value that is a threshold value used to identify biases. If the bias candidate's value is less than the MDB value, the observation is accepted.

- Adaptation: After identification of the alternative hypothesis, adaptation of the recursive filter is needed to eliminate the presence of biases in the state estimation.

How well observations are controlled is a function of the redundancy in the observations. Redundancy numbers could be defined as elements of the principal diagonal of matrix $(P_{\hat{r}}P_l^{-1})$. The redundancy of the ith observation can be expressed as

$$Rd_i = \left(P_{\hat{r}}P_l^{-1}\right)_{ii} \qquad (21)$$

where the subscripts ii indicates the ith diagonal element of the matrix and $P_{\hat{r}}$ is the covariance of the residual. The trace of *Rd* is the observation redundancy (υ), since *Rd* is idempotent (unchanged in value following multiplication by itself) and the trace of an idempotent matrix equals its rank (Leick, 1995). Each diagonal element of *Rd* corresponds to that observation's contribution to the overall redundancy. Assuming that the observation is uncorrelated (that is the observation covariance matrix is diagonal), the diagonal elements (ν_i) is

$$\nu_i = \frac{P_{\hat{r}_{ii}}}{P_{l_{ii}}} \qquad (22)$$

The MDB is the smallest error on a particular observation which the model or system will be able to detect. The MDB for the ith observation can be expressed as (Lachapelle and Ryan, 2000)

$$\left|\nabla_i\right| = \frac{\delta_0}{\sqrt{Rd_i}}\sigma_{l_i} \qquad (23)$$

where σ_{l_i} is the standard deviation of the *ith* observation and $\left|\nabla_i\right|$ is the magnitude of the N by 1 vector ∇_i.

6. EXPERIMENTS

Due to correlation in the results generated during data processing, only the results generated on two consecutive days are presented here. Multipath delay was constantly the main error, due to the location of the antenna position. Figure 1 shows the pseudorange multipath error on two consecutive days

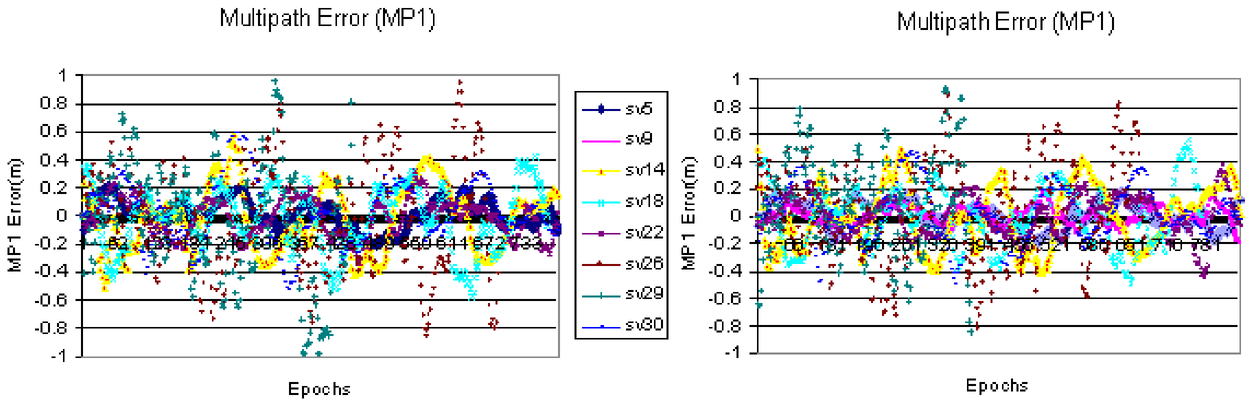

Figure 1: Shows the pseudorange multipath error on L1 for all the tracked satellites on day 1 on the left while that of day 2 is on the right, there was loss of lock in some of the satellites during the observation period.

The filtered time series antenna coordinates of the monitoring point is shown in Figure 2. During data processing some observations were rejected as a result of possible outliers.

The amount of data used is a trade-off between computational speed and observability of the system dynamics. More so, since no process noise was assumed in the estimation, a shorter block of data is advantageous. It was also observed that using very large data did not greatly reduced the number of iterations to convergence, but did greatly increase the computation time per iteration.

After the filter had been properly tuned, it was found to converge readily coarse initial conditions. Tuning, involved prescribing a fictitious amount of integer state process noise covariance (matrix) to prevent the filter gains associated with the integer states from going to zero.

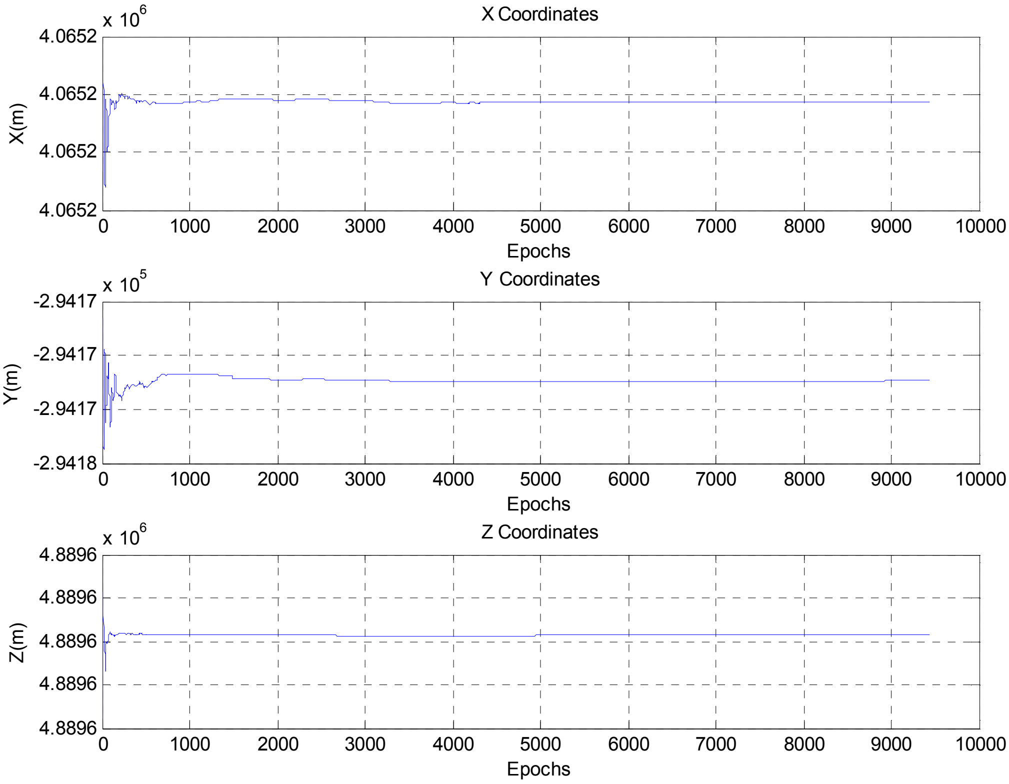

Figure 2. Depicts the computed X, Y, Z coordinates with the x, y and z coordinates sigma as 0.004metres, 0.003metres and 0.005metres respectively.

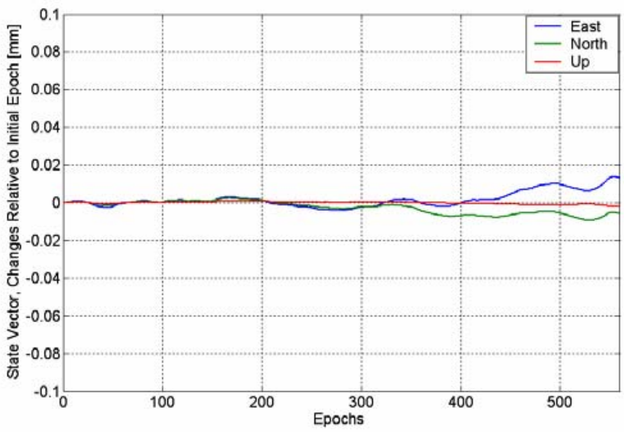

Figure 3 depicts the baseline estimation using an exponentially weighting of data in an Extended Kalman Filter. Here, more importance is given to the most recent measurement.

Further more, in other to study landslide deformation. Displacements are obtained by differencing the coordinates of observed GPS data from two consecutive observations. The obtained time series coordinate differences are shown in Figure 4.

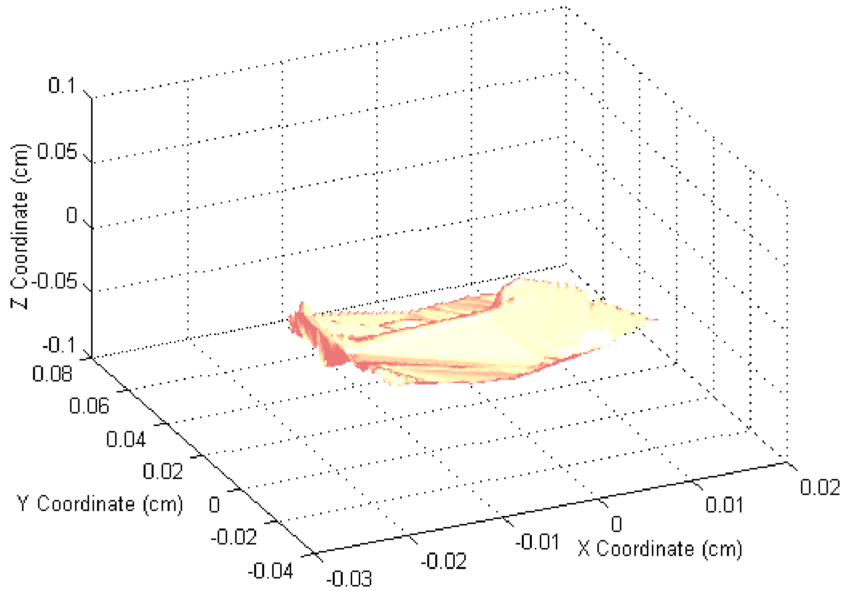

Figure 4: Depicts the coordinate differences between two consecutive observations.

7. CONCLUSION

The use of GPS technology is a very useful tool in continuous monitoring of a structural deformation of a building in other to determine its behaviour. However, there are some limiting factors in attaining better accuracy in GPS observations among them is the multipath. The use of Kalman filtering reduced the noise in other to achieve a better positioning accuracy. Finally, statistical testing can be efficient if the stochastic models are correctly known or well estimated. Numerical results indicate that GPS techniques are very reliable for structural deformation monitoring and other environmental related monitoring. There are rooms for improvement in this paper and further research work is still going on.

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