REVIEW ON GPS PARAMETER DETERMINATION AND CORRECTION USING KALMAN FILTER

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Abstract
In this paper a brief survey is carried out on use of Kalman filter for GPS receiver, where in a two phase Kalman filter is used for adaptive recognition and correction of baseline shifts from GPS measurements. Effective tracking of code and carrier in a GPS receiver even under weak signal conditions is performed using Kalman filter. A Modified Kalman filter is used for accurate GPS position estimation. Conventional GPS L1 phase tracking loop can be replaced by a more robust tracking scheme using a Kalman filter based PLL. Road invariant Extended Kalman filter is used to handle enhanced estimation of GPS errors.

I.INTRODUCTION

Tilting and/or rotation of the ground that may occur during the co-seismic period and instrumental effect can introduce baseline shifts (small steps or distortions in the reference level of the acceleration), which prevent recovery of true ground velocities and displacement through double integration. By defining four kinds of learning statistics and criteria, we analyse the time series of estimated baseline shifts from the first phase Kalman filter and determine the state of the baseline shift, then adaptively adjust the dynamic noise of the combined system and the length of the baseline shift estimation window for the second phase Kalman filter to yield a robust integration solution. After determining the availability of a satellite signal, the GPS receiver tries to track the code and carrier components of the signal[3]. The GPS receiver mostly uses a Delay Lock Loop to track the C/A code sequence and a Costas loop to track the carrier of the received satellite signal. The output of the tracking loops is the decoded form of the navigation message of each satellite. It helps the user to calculate the positions of the satellites. Finally, the user calculates his position using the pseudo-range measurements from the tracking loops[4]. When these loops lose the lock, i.e., when the s ignals are weak, the receivers can no longer track the path unless the code and carrier comes in lock again. This creates disturbance in tracking i.e., the receiver fails to locate its position until the signal becomes strong. An efficient solution for this problem is Kalman filter.

The Kalman filter forms an estimate of a process by using a form of feedback control: it estimates the state of the process at some time and then obtains feedback in the form of measurements. It integrates both the measurement data, and the system properties, to produce a pleasing estimate of the desired state variables in such a manner that minimizes the error statistically. The various algorithms used for GPS receiver position estimate includes Least Squares[5] (LS), Weighted Least Squares (WLS), Evolutionary optimizers[6], Kalman filter (KF) etc. The task of tracking and guiding involves estimation of objects future course and this could be only possible when the system dynamics are modeled into the estimator. Out of the available Navigation algorithms the only filter that makes use of the dynamics in estimation is Kalmanfilter[7]. In addition, KF also provides the uncertainty in its estimation whose performance varies with parameters like process noise matrix, measurement noise matrix, observation matrix etc. So this paper concentrates in improving KFE accuracy with a new observation matrix that replaces the conventional matrix in Kalman filter's covariance update equation. The modeling of KF as GPS receiver position estimator and the details about new designed observation matrix lead to the development of MKFE are discussed in subsequent sections. In this paper, a Kalman filter based PLL is developed and tested as against the conventional Costas PLL currently used for tracking. A software defined receiver (SDR) [7] is used as the platform for testing the proposed Kalman filter based PLL. A road invariant EKF algorithm is proposed to handle the enhanced estimation of the GPS errors. This idea is inspired from the Invariant EKF proposed by Bonnabel et al. [7]. Indeed, the localization problem possesses state invariance with respect to road rotations and the observability of every component of the state vector is kept in the road frame. In this work, the observability of the augmented state space is studied in the algebraic framework.

II.METHODOLOGY

1. *Adaptive recognition and correction of baseline shifts from collocated GPS and accelerometer using two phase Kalman filter.*

1.1 The model for tight integration of GPS and strong motion measurements.

Usually the following observation equations are used for the tight integration of GPS and strong-motion measurements where, L_c and P_c are the observed minus computed phase and pseudorange observations from satellite to receiver, respectively, e is the unit direction vector from satellite to receiver, m is the tropospheric mapping function for wet delay, x and X denote the vectors of the receiver displace- € ment and acceleration, z, dt and b are the tropospheric zenith delay, receiver clock and phase ambiguities, e is the measurement noise, with variances r^2, W_{ak} is the acceleration observation noise, a and u represent the strongmotion acceleration observation and baseline shift, and k is the epoch number.

Kalman filter can be employed for the parameters estimation while given an empirical observation weight and dynamic noise.

1.2 The adaptive recognition of baseline shifts in strongmotion records

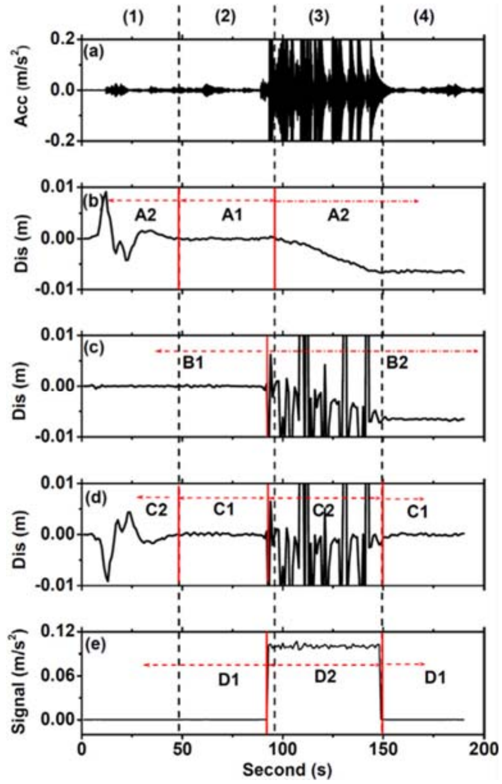

Fig. 1. Adaptive recognition of baseline shifts. Panels (a) represents the raw acceleration observation, (b)–(e) represent four kinds of learning statistics (A, B, C and D in equations (4)–(7)), and (1), (2), (3) and (4) are four periods of the estimated baseline shifts (see text).

Based on the defined learning statistic and criteria, the estimated baseline shifts can be analyzed and adaptively recognized. They can be divided into four time intervals, as shown in Fig. 1. Here, the data come from a shaking table test, Initialization period: (A_2&B_1) or (B_1&C_2), 0–47 s in fig 1.b. The beginning of the data solution. There is no motion and the raw acceleration is nearly zero but the solved baseline shift is not zero. However, the solved baseline shift needs time to converge to finish the initialization. The dynamic noise of the baseline shift should have a very small value.

Static period: (A_1), 47–95 s infig 1.b. In this period, the solved baseline shift is nearly zero and the dynamic noise of the baseline shift also should be very small.

1.3. Experimental test using a shaking table

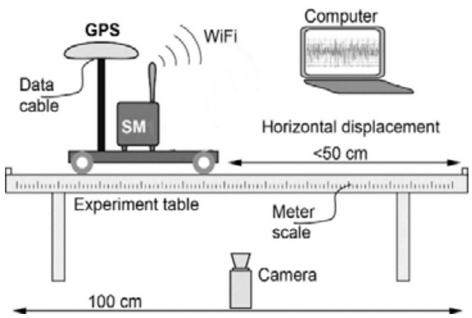

Fig. 3. The experimental platform, including a GPS receiver, a strongmotion sensor (SM) and a video camera.

The experimental platform is shown schematically in fig 3. The GPS antenna and strong-motion sensor can slide along the rail, a camera system (50 Hz) was also set up to record the sledge motion from 10 m . The 1 Hz GPS and 100 Hz strong-motion records were used for the data analysis. Baseline shifts of the strong-motion record were caused mainly by the shifting weight of the cart as it moves along the track. After acquiring a long static record, a simple and one dimensional movement was introduced by sliding the sensors along the track forwards in step-wise with various accelerations, it last about one minute and with max acceleration 1.5 m/s^2, finally resulting in a permanent displacement of 0.3 m.

2.The Tracking Channel of a GPS Receiver

The received signal from a satellite is a combination of PRN code, carrier signal and navigation data. To obtain the position of a GPS receiver, the navigation data should be isolated from the above said combination. In order to achieve this, the tracking channel has to generate two replicas, one for the carrier and other for the code. The initial step is to multiply the incoming signal with the generated carrier replica. This step wipes off the carrier from the incoming signal. The next step is to multiply the signal with the generated code replica and the result of this multiplication gives the navigation data.

2.1 code tracking

Code tracking loop is implemented to obtain a perfectly aligned replica of the code. The goal of this tracking loop is to track the phase of a specific code in the signal that is being received. The code tracking loop in the GPS receiver is a delay lock loop (DLL). It is also called as an early-late tracking loop. The signal that is obtained after the multiplication of incoming signal and a perfectly aligned local replica, is then multiplied with three code replicas, namely, early, prompt and late, separated by a spacing of ½ chip. After the two multiplications, the three outputs are integrated and dumped. The output of these integrations indicates the amount of correlation between specific code replica and the incoming signal. The prompt replica of the code has a phase shift obtained from the acquisition[5]. The early and late have a delay of -½ and +½ chip, respectively, from the prompt.

2.2 carrier tracking

An exact carrier wave replica is generated for the data demodulation using a PLL or Frequency Lock Loop (FLL). The first two multiplications, removes the Pseudo Random Noise code and the carrier component in the incoming signal. The prompt output of the E, P, L code tracking loop is used to wipe off the PRN code. The local carrier frequency is adjusted as per the feedback given by the change in the phase error.

2.3.kalman filter.

A Kalman filter addresses the problems in which the system is considered to be a *linear, white and Gaussian* The Kalman filter discusses the issue of estimating the state of a linear stochastic discrete process

$$x_k = A.x_{k-1} + B.u_k + w_{k-1} \quad (1)$$

With its measurement that is

$$z_k = H.x_k + V_k \quad (2)$$

The random variables W_k and V_k represent the process and measurement noise, respectively. In general, both process noise and measurement noise are assumed to be independent, Gaussian and white. The normal probability distributions of these noises are assumed to be[13].

$$P(w) \sim N(0,Q) \quad (3)$$

$$P(v) \sim N(0,R) \quad (4)$$

Where Q represents process noise covariance and R represents measurement noise covariance.

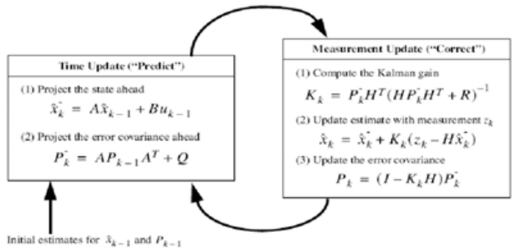

Fig 2 Basic operation of the Kalman Filter.

The n*n matrix A in the state equation relates the previous state at instant k-1 to the state at the current instant, k, in the absence of either a input function or process noise. In general, the transition matrix A might change with each time step, but in the proposed design it is taken as a constant. The matrix *B* relates the control input to the predicted state *x*. The 'H' matrix in the measurement equation gives the relation between state and the corresponding measurement z_k. In general, H might change with each time step or measurement, but in the proposed design it is taken as a constant. The Kalman filter is a special type of filter whose gain varies with time. The variation of Kalman gain depends on the variation of measurement noise statistics and process noise statistics. The measurement noise statistics and its variation depend on C/N_o levels and jamming. The process noise statistics and its variation is dependent on user dynamics. The Kalman filter can optimally separate signal from noise, if it is provided with the relevant process and measurement noise matrices.

3. *Modified Kalman Filter for GPS Receiver Position Estimation*

The GPS receiver either onboard an aircraft or fixed stationary on a building roof as show in Fig.1 uses travel time or Time of Flight (TOF) measurements in determining its position. GPS TOF Si ,Rx measurement is the time elapse of a signal to reach at the receiver, Rx, from ith satellite, Si. For acceptable level of accuracy in position estimate GPS requires minimum of four TOF measurements from individual satellites8. Every TOF corresponds to a range measurement which is formulated as in Eq.1. Solving these set of equations for unknown receiver position is a highly complex process as they are nonlinear9 Hence, Extended Kalman Filter Estimator (EKFE) or KFE with linearised measurement equations is used to estimate the unknown receiver position.

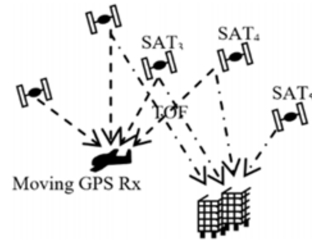

Fig3.1. GPS Receiver Placement Scenarios

4.Kalman filter based Phased Lock Loop.

Two options are taken into consideration:

- A three-state Kalman filter approach with two primary equations. The state variables are: Phase error, Doppler frequency and Doppler frequency rate. Depending upon the C/No value, Kalman gain is selected.

- A classical five-equation Kalman filter. It requires the knowledge of the state noise and the measurement noise.

- Option one has been taken into consideration to implement the proposed Kalman filter based PLL.

4.1. kalman filter based PLL tracking technique.

This Kalman filter based PLL (KFP) algorithm is equivalent to a carrier tracking loop of order three. The duration of one bit navigation message is 20 ms. The Kalman filter estimates the following state vector at the accumulation time tk. Consider the state vector of the Kalman filter,

$$x_k = [\ \Delta\phi_k\ ,\ w_k\ ,\ \alpha_k\ ]^T \quad (1)$$

Where, $\Delta\phi_k$ = The phase difference between the true carrier phase and the phase generated by the PLL's NCO. w_k = The carrier Doppler shift. α_k = The rate of change of carrier Doppler shift. At the start of the interval, Kalman filter begins with an estimate of the state given as

$$x_k = [\ \Delta\hat{\phi}_k\ ,\ \hat{w}_k\ ,\ \hat{\alpha}_k\ ]^T \quad (2)$$

As mentioned earlier, this algorithm uses the three-state Kalman filter approach with two primary equations. The Kalman gain, denoted as K is selected depending upon the C/No value .Therefore, the two covariance equations obtained during the prediction stage and the update stage is not considered. Also, the phase measurement function uses the output of an atan discriminator and so the estimation of the data bit is not considered.

$$yk+1= \text{atan}\ (Qk+1/Ik+1) \quad (3)$$

Where, Q and I indicate the Quadrature and In-phase outputs of the correlator at (k+1) interval. During the initialization stage, the completed acquisition calculations from the acquisition stage are used to initialize the DLL's code phase estimate and the PLL's carrier Doppler shift estimate, ŵ0.The PLL's first two NCO frequencies, $wpll0$ and $wpll1$ are initialized using the acquisition's Doppler shift estimate. PLL's NCO carrier phase is initialized to zero that is ϕPLL0 = 0. The Kalman filter phase difference estimate is initialized using the first accumulations. Δϕ̂0 = -atan2 (Q0, I0). The PLL's carrier Doppler shift rate is initialized to 0 that is α0 = 0. [4] ns are given below.

CONCLUSION

The tight integration model and two phases Kalman filter are used for the combined data solution. Once the transient baseline shift is recognized, the dynamic noise and the length of the baseline shift estimation window are adaptively adjusted for a robust integration solution. The validations show that, the acceleration baseline shifts can be adaptively recognized. In such cases, not only are baseline shifts in the strong-motion accurately corrected, but also the high resolution acceleration records help to constrain the GPS for a better solution. As the two phases Kalman filter adaptively adjusted the estimation strategy, thus, more robust solutions can be provided. Kalman filter produces the optimum output using a combination of measurements and state equation. The algorithm presented, and simulation results, show that the need for frequent reacquisition of the system, under weak signal conditions, is prevented.The observation matrix designed out of first order Taylor's approximation of nonlinear measurement function is modified and used for parameter estimation. The developed algorithm was used to estimate the three dimensional position of the GPS receiver and its performance was evaluated with various SAM. A KFPLL has been designed to replace the conventional carrier tracking loop filter in a software based GPS receiver. Real GPS IF data has been used to test the design and results obtained are shown. A road invariant EKF algorithm has been proposed and tested. In particular, the proposed state space model is observable and a bijective transformation between roads guarantees the continuity of the Kalman filter estimates.

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