Orbit Determination Using Batch Sequential Filter

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Abstract

Data filtering is an important technique used for modeling in many areas of disciplines. The paper discusses the square root information estimation, starting from its beginning in least-squares parameter estimation. Special attention is devoted to discussions of the sensitivity and perturbation matrices, computed solutions and their formal statistics, consider parameters and consider-covariance, and the effects of a prior statistics. The constant-parameter model is extended to include time-varying parameters and process noise, and also the error analysis capabilities are generalized. Efficient and elegant smoothing results are obtained as easy consequences of the filter formulation. This paper characterizes the improved computational efficiency of Batch-Sequential orbit determination. Filter tests consider improvements for several simulated satellite scenarios with several combinations of measurements provide for estimation. One way to improve orbit determination for the satellite is to make use of new estimation techniques. This has been accomplished by applying the Batch-Sequential Filter to the problem of orbit determination. The BSF out performs other nonlinear filters because it treats non-linearity in both the measurement and dynamic functions. The performance of this filter is evaluated in comparison to an existing Kalman Filter.

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1. Introduction

Outer space navigation analyses and orbit determination has relied, mainly upon the method of least-squares introduced by Gauss [3]. In recent years science experiments and mission requirements have become more stringent, and space scientists have found it necessary to introduce more precise and sophisticated models, including stochastic process noise effects[3][6]. Software specialists were at first nonplussed because the new models involved time-varying parameters and process noise in a way which appeared to be at odds with the classical constant parameter estimation software then in use. There was a reluctance to abandon the least-squares methods in favour of the Kalman filter [6], even though the latter technique is flexible enough to accommodate time-varying models with process noise. Reasons for this reluctance included cost, reliability and inertia. The constant parameter estimation software that was already developed, checked out, and proven is only a part of the lengthy and complex orbit determination (OD) process [1][5]. In this framework the constant parameters are referenced to an epoch time, and thus introducing a current state Kalman filter would require costly modification of the entire OD process. Furthermore, OD problems generally involve processing thousands of data points and, for such situations, the Kalman filter is costly to operate. We have proven to give reliable and accurate results, while the Kalman filter in process noise free situations exhibits numeric deterioration and instability [6].

The intention here is to summarize and highlight the epoch-state model. Specializing the results to the epoch-state model greatly simplifies the intimidating algorithms were developed for more general linear models. Our techniques and algorithms are applicable to a broad class of problems even though our development is oriented toward, and was motivated by, orbit determination applications. This application provides initial orbit determination capability and a conventional least square estimator. The orbit determination strategy outlining the use of both the sequential filter and a conventional batch filter [2].

2. Existing System

The existing system is **Kalman filter**, also known as **linear quadratic estimation (LQE)**, that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. A limitation in using an extended Kalman filter is unstable [6].

3. Proposed System

In the proposed system Batch Sequential estimator it inherits advantages of the BSF, such as being able to deal with nonlinear system equations directly, and providing a higher convergence capability starting from initial guesses compared. The proposed filter is used for relative orbit determination for a multiple spacecraft formation flight mission using relative range measurement information. Batch Sequential Filter provides a better convergence performance without taking longer computational time than other conventional filters. This estimator treats nonlinearities more accurately than does the EKF and so converges more robustly and produces more accurate estimates [6].

4. Fundamentals Of SRIF

There are two different types of square root information filter (SRIF). One involves a square root of error covariance matrix and corresponds to a factorization of the Kalman Filter algorithm [8]. The other involves a square root of information matrix [7] and represents a fundamentally different approach to a estimation problem. The SRIF focuses on the computational aspect of linear least squares estimation with emphasis on square root estimation [3]. It includes filter and smoother algorithm developments along with algorithms and techniques to systematically evaluate and analyze estimation performance.

The Batch Sequential Filter corresponds to a both covariance and information matrix formulations [7]. Each formulation has attributes to recommend it in particular situation.

4.1 Terminologies

Over a period of time different estimation techniques such as preliminary orbit determination, least square estimation extended Kalman filter and smoother are evolved using different tracking data. Before the launch of the satellite the orbit estimation accuracy is evolved using simulated tracking data. Following term are used in this process.

4.1.1 Tracking data simulator

These are the simulator used in data tracking system. Each tracking system contains the ground stations, or trackers, that make up that network. We can populate the tracking system with tracking stations manually by creating individual facilities representing the individual ground stations in the system and defining the properties for each facility. Filter uses tracking data to determine the satellite position using a sequential estimation technique [2].

4.1.2 Smoother

Filtered data can be passed into the smoother. Smoothing may be performed over the results of one or more filter runs. Smoother are used to determine the position of satellite [6].

4.1.3 Least square estimators

The least square estimator uses all the tracking data measurement to generate an initial state of the satellite. The measurements are then passed through the least squares algorithm to minimize the position uncertainty [3].

5. Data Flow Diagram

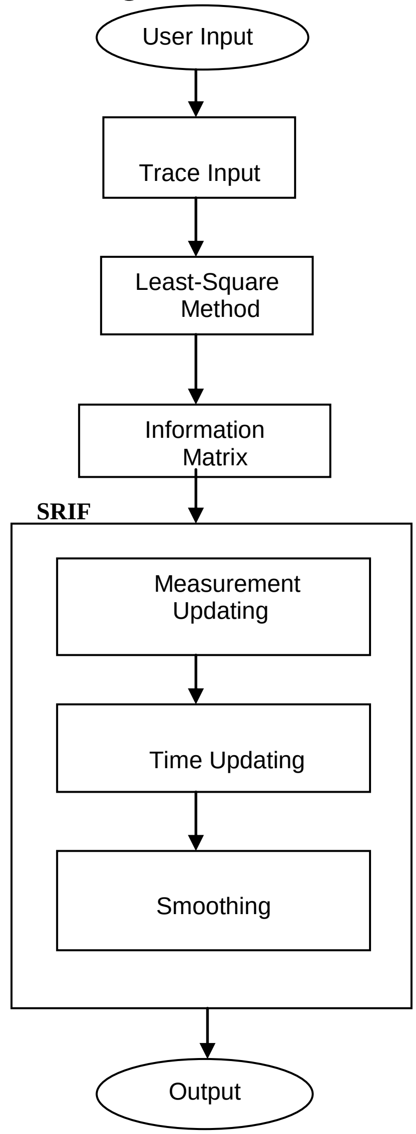

Figure 1.Data Flow Diagram

6. System Architecture

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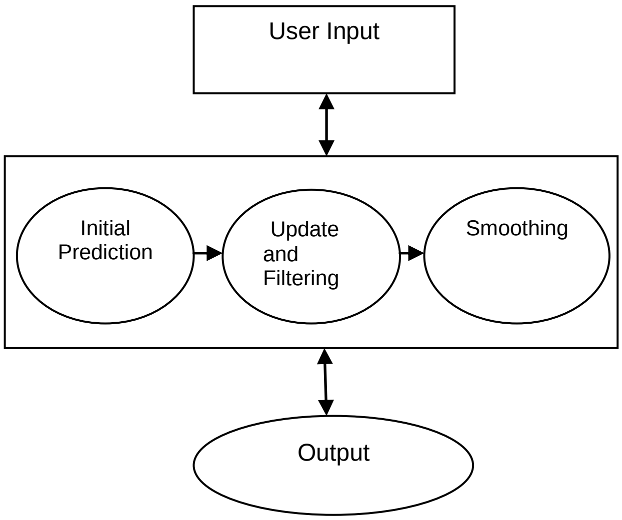

Figure 2.Sytem Architecture

7. Module Description

The modules present in this system are

- User input
- Initial SV of the satellite module
- Prediction and estimation of SV module
- Tracking data module
- Updating and filtering
- Smoothing
- Output

A. User input

In this module it takes input values like x-position, y-position, z-position, x-velocity, y-velocity, z-velocity [1]. This Module interacts with the other modules to have an effective performance of the system.

B. Initial SV of the satellite module

This module generates the initial state vector of the satellite. State vector is also known as elements or fundamental quantities of the orbit. These elements are Px, Py, Pz, Vx, Vy, Vz. First three elements are position vector and last three elements are velocity vector [3].

C. Prediction and estimation of SV

Prediction is nothing but the forecasting the result. Prediction of SV module generates a SV of the satellite taking data from initial SV of the satellite and from tracking data module.

Estimation is the calculation done on the basics of observed behavior of the system. For each predicted SV this module generates the corresponding estimated SV. It takes the data from predicted SV module and tracking data module, and generates the estimated SV [3].

D. Tracking data module

This module contain measured data file. These file contain the values that are measured by antennas [1]. These file stored in specific directory. These data are collected by antennas. Each file contains date, month, year, minute, hour, seconds and milliseconds and measured SV at that instance. This module keeps track of the satellite position. Each data file contains the information about the satellite.

E. Updating and filtering module

The updating module has time and measurement updating. Measurement update mechanization is based on covariance matrix. A process noise time update adds noise to the covariance matrix and thus causes the time varying behavior. There are two different types of square root information filter. One involves a square root of error covariance matrix and corresponds to a factorization of the Kalman Filter algorithm. The other involves a square root of information matrix and represents a fundamentally different approach to a estimation problem. The SRIF focuses [2] on the computational aspect of linear least squares estimation with emphasis on square root estimation. The Batch Sequential Filter corresponds to a both covariance and information matrix formulations. Each formulation has attributes to recommend it in particular situation.

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F. Smoothing

Filtered data can be passed into the smoother. Smoothing may be performed over the results of one or more filter runs. Smoother are used to determine the position of satellite.

G. Output

This module provides the information about the SV of the satellite. This module generates the graph for required SV which is the estimation of SV module. Batch Sequential Filter provides a better convergence performance without taking longer computational time than other conventional filters. This estimator treats nonlinearities more accurately than does the EKF and so converges more robustly and produces more accurate estimates. The below graph shows in figure 3 and 4 gives performance of the error analysis for low earth and geostationary with comparison of Kalman filter and batch sequential filter.

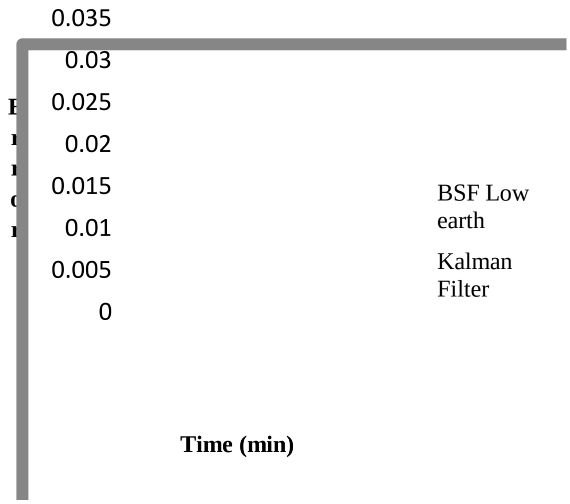

Figure 3: Error analysis for low earth

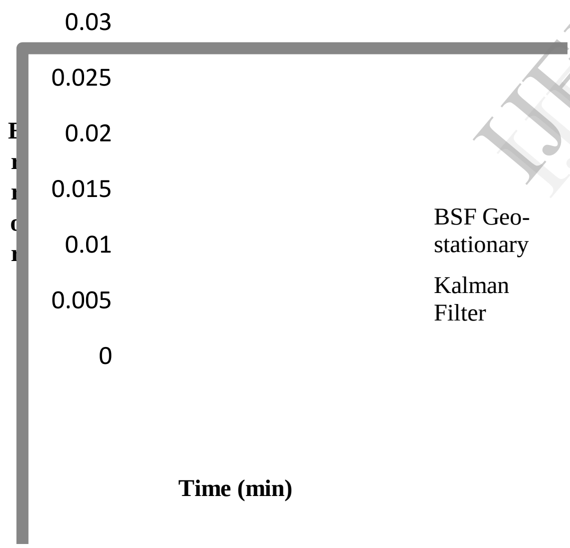

Figure 4: Error analysis for Geostationary

7. Conclusion

This application is developed for the accurately generate the trajectory of the satellite. The performance of the square root mechanized batch-sequential filter in the navigation of the spacecraft. It demonstrated that the SRIF formulation is a viable one for use in mission operations. The sequential filter was heavily used and relied upon during the mission. It is difficult to say what would have transpired had it not been available, or a different filter mechanization used for it is quite conceivable than a less accurate orbit determination. This application is evolved into a robust tool capable of supporting the accuracy and timelines requirements of spacecraft satellite.

The square root batch-sequential filter with process noise is now a tested, accepted tool for interplanetary orbit determination. Essentially the same filter with some added capabilities, ability to model white noise as well as colored noise, smoothed covariance, and smoothed sensitivities will be used in the interplanetary missions.

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