A SELF-TUNING KALMAN FILTER FOR AUTONOMOUS SPACECRAFT NAVIGATION

Son H. Truong
National Aeronautics and Space Administration (NASA)
Goddard Space Flight Center (GSFC)
Greenbelt, Maryland, USA 20771
E-mail: son.truong@gsfc.nasa.gov

Abstract

Most navigation systems currently operated by NASA are ground-based, and require extensive support to produce accurate results. Recently developed systems that use Kalman filter and GPS data for orbit determination greatly reduce dependency on ground support, and have potential to provide significant economies for NASA spacecraft navigation. These systems, however, still rely on manual tuning from analysts. A sophisticated neuro-fuzzy component fully integrated with the flight navigation system can perform the self-tuning capability for the Kalman filter and help the navigation system recover from estimation errors in real time.

Key words: Kalman Filter, Neuro-Fuzzy System, GPS.

Introduction

Autonomous navigation has the potential both to increase spacecraft navigation system performance and to reduce total mission cost. The Goddard Space Flight Center (GSFC) Flight Dynamics Analysis Branch (FDAB) has spent several years developing high-accuracy autonomous navigation systems for spacecraft using NASA's space and ground communications systems and enhanced these systems to support spacecraft using the Global Positioning System (GPS).

GSFC FDAB has developed navigation algorithms to meet a real-time accuracy goal of better than 20 meters (1σ) in position and 0.03 meter per second (1σ) in velocity using GPS Standard Positioning System (SPS) with selective availability (SA) corruption at typical levels. These algorithms, which are based on mature onboard navigation systems developed for spacecraft using NASA's space and ground communications systems, consist of the following core components:

- An extended Kalman filter (EKF) augmented with physically representative models for the gravity, atmospheric drag, and time bias and drift state process noise to provide a realistic state error covariance.
- A high-fidelity state dynamics model to reduce sensitivity to measurement errors and provide high-accuracy velocity estimates, permitting accurate state prediction during signal outages or degraded coverage.
- Initialization and enhanced fault detection capabilities using instantaneous geometric GPS solutions.

Detailed mathematical specifications are defined in Reference 1. Algorithms selected to meet the GPS navigation performance goals are summarized in Reference 2.

The FDAB has implemented these algorithms in a prototype GPS navigation software called the GPS Enhanced Orbit Determination Experiment (GEODE), which executes within the resource constraints of currently available flight processors (e.g., <400 kilobytes memory and <0.5 million instructions per second). Processing of raw pseudorange measurements from existing GPS receivers on the EP/EUVE and TOPEX/POSEIDON (T/P) spacecraft indicates that these navigation algorithms can provide accuracy of 10 meters ($1\ \sigma$) in total position and 0.01 meter per second ($1\ \sigma$) in total velocity with SA at typical levels. Without SA active, experiments performed in a realistically simulated flight environment produced converged solutions with errors of 15 meters maximum and 4 meters rms in total position, as shown in Fig. 1. Improvements to the baseline algorithms to achieve real-time onboard accuracy of better than 2 meters ($1\ \sigma$) are discussed in Reference 2.

The core requirement for on-board autonomous navigation is a method of state estimation that handles uncertainties robustly, is capable of identifying estimation problems, flexible enough to make decisions and adjustments to recover from these problems, and compact enough to run on flight software. Current method of using EKF for state estimation requires manual tuning by support personnel. The re-tuning process is more complex when dealing with geosynchronous or high-eccentricity orbits.

This paper discusses an approach to produce a high accuracy onboard navigation system that can recover from estimation errors in real time. The self-tuning capability is achieved by a neuro-fuzzy component augmented to the Kalman filter.

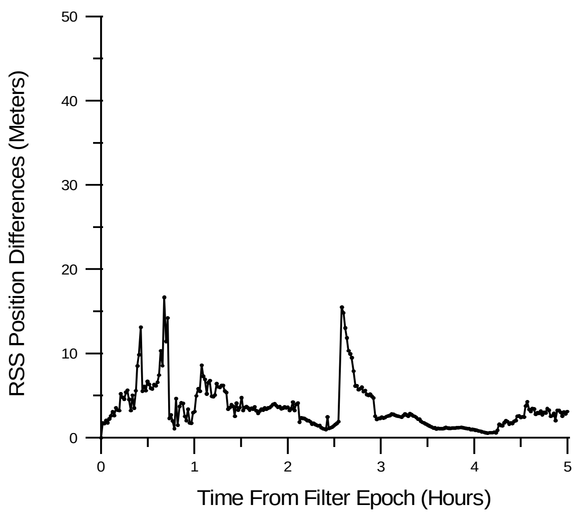


Figure 1: GEODE Solution versus Truth Position Differences without SA Active

Extended Kalman Filter for Navigation

Orbit state estimation algorithm for FDAB autonomous navigation systems consists of an EKF that uses physically connected noise covariance models to account for force model and measurement errors. The state vector consists of at least the user spacecraft position and velocity vectors. For GEODE, additional components include the atmospheric drag coefficient correction, the GPS receiver time bias correction, and the time bias drift correction. The state vector estimation processing is performed at regular intervals, e.g., every 30 seconds, to propagate the filter state vector and covariance to the measurement time, update the state and covariance based on the measurements, and ouput telemetry data.

The state covariance matrix, [P], represents the filter uncertainty in the estimated state vector. It is initialized or reinitialized using ground uplinked parameters.

For GEODE, the state covariance P and the process noise covariance [Q] are [9X9] matrices, while the measurement noise covariance R is a scalar. To avoid the use of square roots and to guarantee nonnegativity of computed matrices, [P] and [Q] are factored into unit upper triangular matrix [U] and diagonal matrix [D]. These [U] and [D] matrices are time propagated and measurement updated in the Kalman filter process, instead of [P] and [Q].

Parameters for [Q] and [R] are uplinked to the onboard navigation system to start or re-start the estimation process, or whenever the filter re-tuning is needed. For GEODE, there are nine parameters for [Q] and one parameter for [R]. Generally, parameters related to small unmodeled noises or to small errors in modeled accelerations that are not very well defined, are the ones to be updated in the re-tuning process.

Several navigation fault detection tests are performed on the updated state and covariance. The Filter Convergence Test is the major test. If the filter has not converged and if the RSS position sigma, RSS velocity sigma, and semimajor axis sigma are all below their respective ground commandable convergence tolerances, then filter re-tuning is required. The current tuning process is performed by ground support analysts. Updated tuning parameters are uplinked to the onboard system to reset the filter.

Neuro-Fuzzy Systems

Neural networks and their learning capabilities have enjoyed a strong popularity with the development of the perceptrons in the 1960s and especially, after more powerful learning algorithms were discovered in 1985. A neural network is considered as a computing system that is made up of a number of simple, highly interconnected processing elements. Neural networks are used in many applications, from robot control to financial forecasting. A drawback of neural networks is that for some applications they do not always work as expected, and for the user a neural network simply is a black box. The user cannot learn from it.

Fuzzy logic is based on the idea of fuzzy sets, i.e. sets without clearly defined boundaries that can be used to model linguistic terms. Fuzzy systems associate with the process of formulating the mapping from a given input to an output using fuzzy logic that provides a basis from which decisions can be made, or patterns discerned. Fuzzy systems can be used for the same tasks as neural networks. They are successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Fuzzy systems are not, however, created by a learning algorithm. A major problem is that its parameters must be tuned manually, usually in an error-prone and time-consuming process.

Neuro-fuzzy systems are built from the idea of applying neural network algorithms to automatically determine and tune parameters of fuzzy systems. That combination could avoid drawbacks of both neural networks and fuzzy systems, and constitutes an interpretable model that is capable of learning and using problem-specific prior knowledge.

Various neuro-fuzzy models have been developed. The Adaptive Neuro Fuzzy Inference System (ANFIS) model and its generalization for multiple inputs/outputs systems are used to prototype the self-tuning component for autonomous navigation using Kalman filter. This preliminary choice is mainly based on the model efficiency, software availability, and the fuzzyness of filter outputs.

Several neuro-fuzzy system models are described with details in References 3 and 4.

Neuro-Fuzzy System for a Self-Tuning EKF

The self-tuning method discussed in this paper is to optimize navigation autonomy for GEODE that uses GPS as main tracking system. This method, however, can be applied without significant modifications to any other system that uses Kalman filter for autonomous navigation.

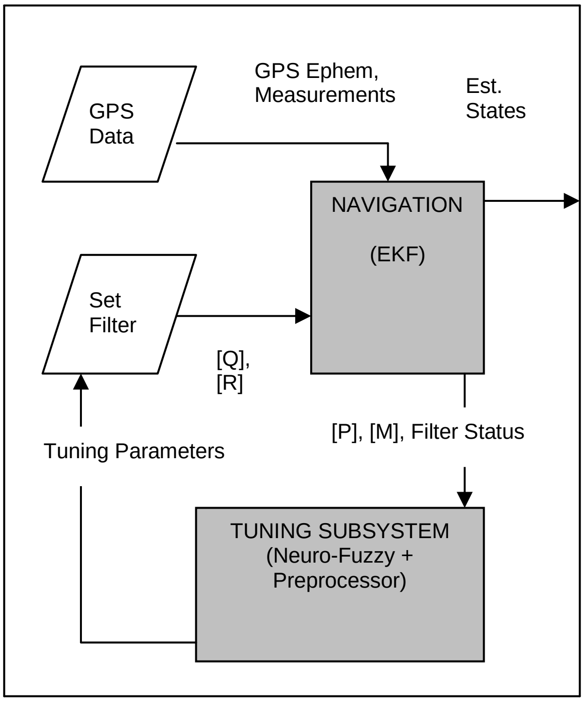


Figure 2: High-level Architecture of a Self-tuning Kalman Filter

Fig. 2 illustrates a high-level architecture of the integrated system.

Outputs from the filter include the state error covariance matrix [P], measurement residual [M], and appropriate information relating to the filter and satellite status. [P] and [M] are gathered in time series, limited by a reasonable preset time window. When the filter is not convergent and covariances hit preset thresholds, which are less generous than those set by the Filter Convergence Test, the re-tuning process is needed. Functional representations for [P], [M] time series are then determined (e.g., using a least-squares polynomial fitting), and the preprocessor forms an input vector to the neuro-fuzzy system. The neuro-fuzzy system analyzes these inputs to produce tuning data to be used to adjust [Q] and [R].

Input patterns and target parameters are specifically modeled to train the neuro-fuzzy system for a given user spacecraft. The training process is performed prior to the operational use of the system.

Prototype for Phase I Development

The real scenario of the self-tuning navigation system can be much more complex than as described above. The main problem, however, is simply to find a mapping between the behavior of the filter output (e.g., state error covariance) and the tuning parameters. The primary phase of the development of the self-tuning Kalman Filter for autonomous navigation is therefore to build a simple prototype that can prove the existence of such a mapping. The target navigation system for this prototype is GEODE. For LEO user spacecraft, there are three parameters that are related to errors in the acceleration models for solar gravity, lunar gravity, and solar pressure; or to unmodeled accelerations from polar motion, tidal effects, random venting, etc. These parameters need to be updated via the tuning process. Preliminary examination of output data from different cases shows that patterns of velocity variances (or standard deviations) are adequate in the determination of tuning parameters. The tuning subsystem prototype for Phase I is simply a three inputs/three outputs neuro-fuzzy system augmented by a preprocessor that gathers filter outputs (i.e. state error covariance) in time series, determines if the filter re-tuning is needed, and uses least-squares process to fit them to second degree polynomials. The preprocessor also builds a vector that functionally represents the behavior of the covariance and that is input to the neuro-fuzzy system. Parameters are tuned using the hybrid option that is a mixture of least-squares and backpropagation techniques. An asymmetric and closed sigmoidal function is used for membership function.

Fig. 3 shows a high-level diagram of the Phase I prototype.

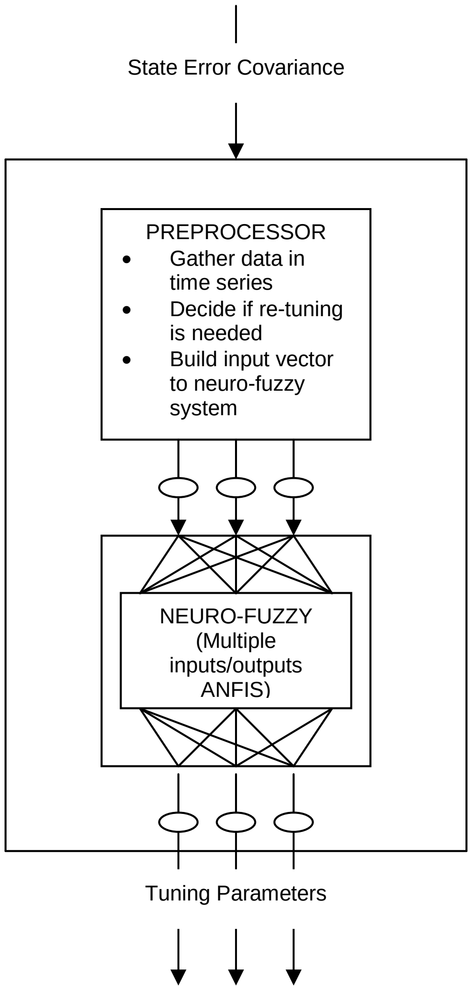


Figure 3: High-level Diagram of the Phase I Tuning Subsystem Prototype

Test Results

Data from the GEODE processing of real GPS pseudorange measurement with SA on, obtained from an experimental receiver flown on the TOPEX/POSEIDON (T/P) spacecraft on November 17, 1993, were used to test the Phase I prototype.

Fig. 4 shows the convergence of the in-track velocity standard deviation from the T/P testing. Similar curves are seen in other components as well as in the corresponding position standard deviations. This behavior reflects a filter status where correct tuning parameters are provided.

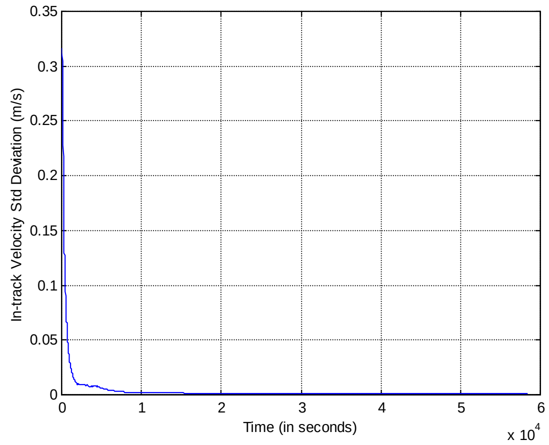
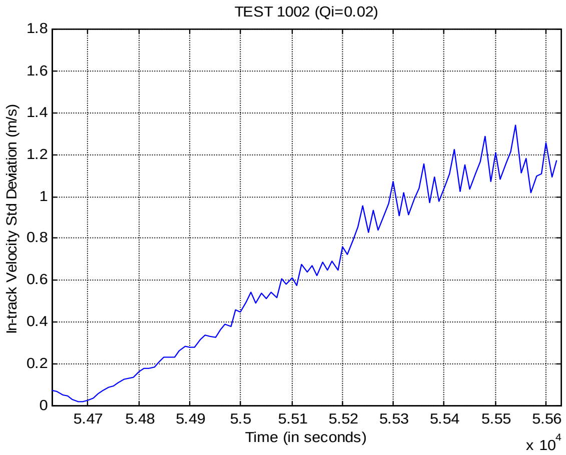


Figure 4: In-track Velocity Standard Deviation from the T/P Testing

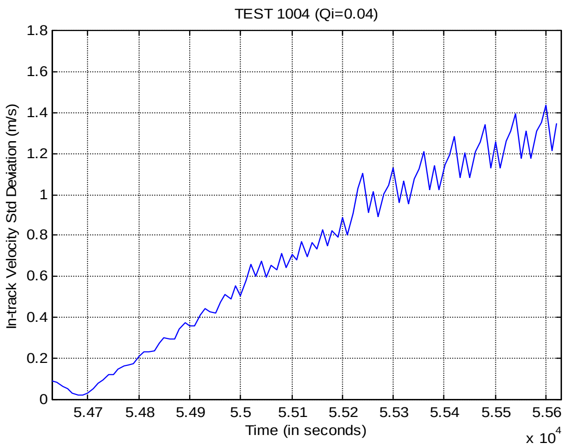
To train the neuro-fuzzy system, standard deviation patterns and corresponding target tuning parameters for fifty cases are used. Fig. 5 shows 3 patterns that correspond to different errors in one of three tuning parameters, Qi.

Results from preliminary testing of this Phase I prototype show that errors in tuning parameters are identified and the system can be well recovered from these errors. The average testing error is 0.0024 for parameters ranging from 0.02 to 0.8. Fig. 6 shows the average difference between the in-track velocity standard deviations obtained from the correct Qi and from that determined by the prototype.

These test results are encouraging for this preliminary work. It is still premature, however, to have a good conclusion about the quality and practicality of this method of self-tuning when applying to the complex operational scenario of a real autonomous navigation system.



(a)



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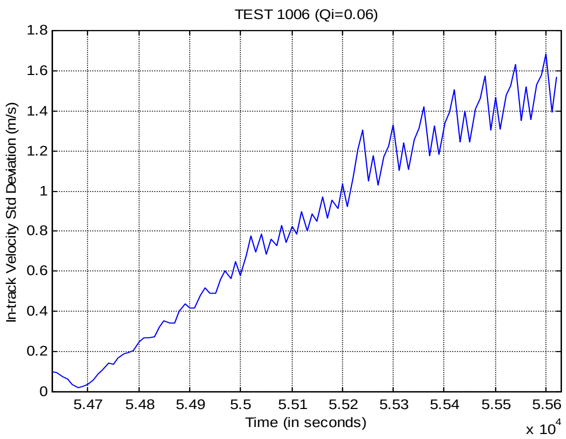

(c)

Figure 5: Patterns of In-track Velocity Standard Deviations from T/P Testing for Different Errors in a Tuning Parameter

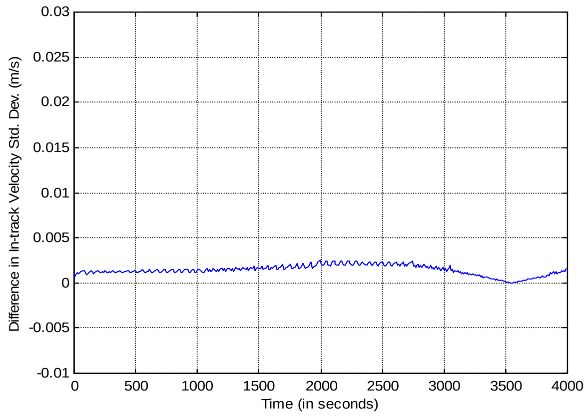

Figure 6: Average Errors in Phase I Prototype Testing (for In-track Velocity Standard Deviation)

Future Directions

Phase II of the development of the self-tuning Kalman Filter for autonomous navigation is to refine the self-tuning method to accommodate to a much more complex operational scenario and to accordingly complete the system prototype.

Phase III will involve the extension of the self-tuning filter to cover geosynchronous spacecraft, and high-eccentricity orbits. For these cases, more parameters need to be updated in the re-tuning process and the tuning frequency is projected to be much higher.

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