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Tracking maneuvering spacecraft with filter-through approaches using interacting multiple models

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ABSTRACT

When spacecraft maneuver unknowingly, traditional orbit determination filters diverge. This paper postulates using Interacting Multiple Models and covariance inflation methods to filter-through unknown maneuvers. This work proposes accurate methods for real-time tracking of a non-cooperative, maneuvering spacecraft and compares the performance to traditional techniques. Results show that a filter-through Interacting Multiple Model orbit determination filter can converge on a post-maneuver orbit in real-time with similar performance to off-line Initial Orbit Determination approaches.

1. Introduction

Recent space activities, especially Anti-Satellite (ASAT) demonstrations, have perpetuated the need for fast and accurate Space Situational Awareness (SSA). The United States National Security Space Strategy highlights that space-based assets are vital for conducting military operations [1]. United States Air Force (USAF) leadership echoes the fact that space challenges will continue to grow as more commercial and foreign governments own and rely on space assets. Space is becoming a contested environment and future space operations are dependent upon accurate and up-to-date information on the locations of other space objects.

It is feasible to imagine mission profiles in the near future where spacecraft no longer utilize maneuvers for just station-keeping or achieving a permanent orbit location. The Center for Space Research and Assurance at the Air Force Institute of Technology (AFIT) investigates short term tactical spacecraft missions [2]. This work also includes developing techniques to track, predict, and estimate the orbital states of non-cooperative tactical spacecraft that perform multiple unknown maneuvers at unknown times with unknown thrusts. Determining the orbits of these spacecraft requires adapting known orbital estimation techniques to handle unplanned maneuvers.

Tracking non-cooperative maneuvering spacecraft is divisible into two large categories: data association and real-time tracking. Data association studies revolve around matching a track of observations with a spacecraft that potentially maneuvered. The literature reveals several different data association focus areas including "nearest-neighbor", Multiple Hypothesis Tracking (MHT), and Joint Probabilistic Data Association filters [3,4]. These efforts typically run during post-processing and focus on resolving Uncorrelated Targets (UCTs). Conversely, the real-time tracking branch of research begins with the assumption that the identity of the tracked spacecraft is known. With this assumption, techniques from missile and aircraft tracking are convertible for use in estimating the orbits of maneuvering spacecraft [5,6].

The majority of literature on tracking maneuvering spacecraft focuses on the data association problem; however, there is interest in real-time tracking of high-priority

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maneuvering spacecraft. For these missions, there is an abundance of observations at frequent intervals. The Extended Kalman Filter (EKF) is preferred for this application due to its speed and forward-moving (sequential) prediction capabilities [7]. The Batch Least Squares (BLS) filter is used operationally to provide orbit estimates as it combines batched observations to minimize errors. BLS filtering is designed for a small amount of observations over longer periods and it updates an epoch offline; whereas, the EKF sequentially updates the state estimate after every observation. Wright et al. have published multiple articles to support designing EKFs for spacecraft tracking [8–11]. They show that when determining a new or post-maneuver orbit, an effective method is to perform an Initial Orbit Determination (IOD) first, a BLS filter next to refine the epoch state, then run an EKF sequentially on old and incoming data.

There are three methods to recover a post-maneuver orbit: a new IOD, filtering-through, and performing maneuver reconstruction [12]. An IOD is typically the start to the data association routine, and reconstruction occurs after the association. The filter-through approach for tracking spacecraft is largely unstudied. Typically, observations greater than 3σ are thrown out until data association is performed later. Spacecraft orbit determination filters are not designed to adapt and process post-maneuver observations; instead, the observations are not processed until after association and maneuver reconstruction. Tracking high-priority maneuvering spacecraft in real-time requires developing new adaptive routines to filter-through post-maneuver observations given the assumption of proper association.

Hujsak was one of the first to suggest the idea of adding process noise covariance at regular intervals (shot-gunning) within an EKF to aide in reconstructing spacecraft maneuvers within a filter [8,13]. The idea is effective; filter divergence is prevented through covariance inflation. Covariance inflation is also present in fading memory filters to weight newer observations [14,15]. Others have adapted state covariance via the process noise covariance to properly account for dynamics model uncertainties [16–18].

When developing the covariance inflation filter-through approach, a trade-off occurs. The larger the covariance inflation, the less likely the probability of divergence, however, the greater the errors. Conversely, a smaller post-maneuver covariance inflation reduces errors but increases the probability of divergence. The National Research Council recommended using Multiple Model Adaptive Estimation (MMAE) approaches for handling maneuvers because using multiple model filtering techniques can increase convergence speed [19]. The Interacting Multiple Mode (IMM) filter provides a method to mix Gaussian models in real-time and weight the results from the most likely model [20–22]. Utilizing the IMM approach prevents the need to solve the problem of determining the optimal covariance inflation size which requires running optimization routines that are typically not forward progressing in time. Although the IMM is considered sub-optimal, the results show its effectiveness in post-maneuver orbit estimation.

In this work, an approach is presented to use covariance inflation after an impulsive maneuver is detected to prevent filter divergence and re-converge on the new orbit all while progressing continually forward in time. This research effort provides a method to handle unplanned maneuvers in high-priority spacecraft tracking. It overcomes the shortfall of filter divergence and the need for post-processing reconstruction. Algorithms are developed to detect the maneuver in real-time, inflate the state covariance, transition to an IMM and continually track the spacecraft. These techniques are designed to directly aide the SSA effort by providing a real-time tracking methodology for maneuvering spacecraft. The paper is organized in the following fashion: Section 2 provides a quick overview of the background theory, Section 3 develops the algorithm, Section 4 provides simulation details, Section 5 provides results, and Section 6 provides relevant conclusions.

2. Theory

2.1. Orbit estimation

Utilizing the state notation found in [23], define the state vector of the spacecraft, $\mathbf{x}$, as the combination of the position from the center of the Earth to the spacecraft, $\mathbf{r}$, and velocity, $\mathbf{v}$, of the spacecraft in the I, J, K coordinate frame:

$$\mathbf{x} = \begin{bmatrix} r_I & r_J & r_K & v_I & v_J & v_K \end{bmatrix}^T \tag{1}$$

Under the influence of Earth's gravity where μ is Earth's gravitational parameter and r is the magnitude of the spacecraft position vector, the time derivative of the state and the two-body equations of motion are

$$\dot{\mathbf{x}} = \begin{bmatrix} v_I & v_J & v_K & -\frac{\mu r_I}{r^3} & -\frac{\mu r_J}{r^3} & -\frac{\mu r_K}{r^3} \end{bmatrix}^T \tag{2}$$

Using the equation of variation define the Jacobian matrix, $\mathbf{A}(t)$:

$$\mathbf{A}(t) = \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} = \frac{\partial \dot{\mathbf{x}}}{\partial \mathbf{x}} = \begin{bmatrix} 0 & \mathbf{I} \\ \mathbf{\Lambda} & 0 \end{bmatrix} \tag{3}$$

$$\mathbf{\Lambda} = \begin{bmatrix} \frac{-\mu}{r^3} + \frac{3\mu r_I^2}{r^5} & \frac{3\mu r_I r_J}{r^5} & \frac{3\mu r_I r_K}{r^5} \\ \frac{3\mu r_I r_J}{r^5} & \frac{-\mu}{r^3} + \frac{3\mu r_J^2}{r^5} & \frac{3\mu r_K r_J}{r^5} \\ \frac{3\mu r_I r_K}{r^5} & \frac{3\mu r_K r_J}{r^5} & \frac{-\mu}{r^3} + \frac{3\mu r_K^2}{r^5} \end{bmatrix} \tag{4}$$

Expanding $\dot{\mathbf{x}}$ in a first order Taylor series and solving the differential equations produces a State Transition Matrix (STM), $\mathbf{\Phi}(t, t_0)$. The STM propagates based on the differential equation

$$\dot{\mathbf{\Phi}}(t_i, t_0) = \mathbf{A}(t_i)\mathbf{\Phi}(t_i, t_0) \tag{5}$$

with initial conditions such that $\mathbf{\Phi}(t_0, t_0)$ is the identity matrix, $\mathbf{I}$. Applying a non-deterministic approach in discrete time and state form at time t_i [24]

$$\overline{\mathbf{x}}_{i+1} = F_i \hat{\mathbf{x}}_i + \mathbf{w}_i \tag{6}$$

where $\hat{\mathbf{x}}_i$ is the state vector estimate of length n output from an orbit determination filter. The bar above $\overline{\mathbf{x}}$ represents the state propagated to the next observation; whereas, $\hat{\mathbf{x}}$ represents the updated estimate after considering observations at t_i. F_i represents a numerical integration of nonlinear dynamics