Fault Detection to Increase Reliability of Kalman Filter for Satellite Attitude Determination

Louw UJ[1], Jordaan HW[2], Schoeman JC[3]

***Abstract*— The Kalman Filter is a state estimator that is often used in attitude determination of satellites. A Kalman filter is highly sensitive to anomalies that occur in sensors. A good example of this is the reflection of a solar panel on a sun sensor that changes the perceived sun vector. This in term influences the estimation of the attitude by the kalman filter and consequently the control of the satellite. Detecting anomalies in sensors and omitting the sensor reading from the measurement update of the Kalman Filter could increase the stability and reliability of the Kalman filter for satellite attitude determination.**

I. INTRODUCTION

The Extended Kalman filter... Various prediction methodologies... Various sensor anomalies... (specific anomalies such as solar reflection).

II. RELATED WORK

A. Extended Kalman Filter

Explanation of EKF for attitude estimation.

B. Sensitivity of Kalman Filter

The effect of sensor anomalies on kalman filter.

III. SENSOR ANOMALIES

List of sensor anomalies and a model of specific anomalies. (solar panel reflection)

A. Reflection

‘ Previous work done by Cilden-Guler et al. [1] provides models that determine albedo effects from the earth and adjust the CSS measurements to improve accuracy. Model of Reflection with pgfplots.

The assumption is made that the solar panel can be modelled as a simple plane. Therefore light that hits the solar panel will reflect in the same way that a shadow is cast. It is also assumed that if any reflection from the solar panel hits the sun sensor, the sun sensor will then default to the reflection ray instead of the modelled sun vector. To model reflection from the solar panels to the sun sensor only two corners of the solar panel and two corners of the sun sensor can be taken into account.

IV. ANOMALY DETECTION

To be able to recover from sensor anomalies or to exclude the sensor from the kalman filter, the anomaly must be detected and the sensor from which the anomaly in the data occurs must be classified.

A. Detection

The first step to implementing a FDIR for kalman filter robustness is to detect whether an anomaly has occured on one of the filters. There are various different methods for fault detection, with both supervised and unsupervised methods. However this study will only focus on a single method proposed by Silva et al. [4] to detect failures in sensors.

The proposed method by Silva et al. [4] uses Dynamic Mode Decomposition (DMD), which was originally developed by Schmid et al. [3] and further expanded to include control by Proctor, Brunton, and Kutz [2], to provide an estimation of a sensor vector based on the previous measurement fo the sensor as well as the measurements of the other sensors in the system. DMD was first developed in the fluids community and constructs a matrix $\mathbf{A}$ to relate the state vector x with the following time step of the state vector, x_{k+1}. The state vector in our case will be the measurement vector of the specific sensor that we want to monitor.

$$x_{k+1} = \mathbf{A}x_k \tag{1}$$

Where x_k and x_{k+1} over a time period will be denoted as $\mathbf{X}$ and $\mathbf{X}'$ respectively.

The method of DMD however is useful for high order systems where the calculation of $\mathbf{A}$ is computation intensive. This is not the case for our system and using DMD is not justifiable. Therefore we calculate the pseudo-inverse of $\mathbf{X}$, denote it as $\mathbf{X}^\dagger$, and $\mathbf{A}$ can be calculate as

$$\mathbf{A} = \mathbf{X}\mathbf{X}^\dagger \tag{2}$$

This necessitates the required data for the state vector. The article by Silva et al. [4] however includes the $\mathbf{B}$ to relate the vector measurements of the other sensors to adjust the predicted state, x_{k+1} of the monitored sensor.

$$x_{k+1} = \boldsymbol{A}x_k + \boldsymbol{B}y_k \tag{3}$$

Where y_k is the other sensor measurements. This is adjusted for our use case, where y_k is the control inputs for the magnetotorquers and reaction wheels and x_k is all of the sensor measurements. Consequently, the model of 3 denotes the prediction of the sensor measurements in time step $k+1$

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[1]Louw UJ is with Faculty of Electronic & Electrical Engineering, Electronic System Laboratory, University of Stellenbosch, Stellenbosch Central, Stellenbosch, 7600 louwuj@gmail.com

based on the current sensor measurements and control inputs. Thereafter, as implemented by Silva et al. [4] the model is adjusted by with a Kalman Filter. From $\boldsymbol{A}$ and $\boldsymbol{B}$ the Kalman filter can be implemented to predict x_{k+1}

$$\hat{x}_{k+1} = A\hat{x}_k + By_k + K(x_k - \hat{x}_k) \tag{4}$$

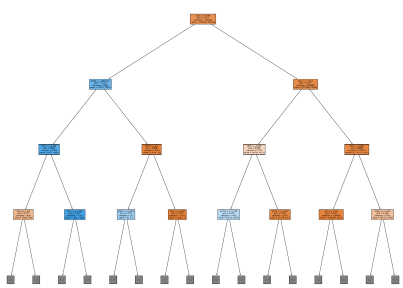
After the calculation of $\hat{x}_{k+1}$ Silva et al. [4] proposes a moving average of the innovation covariance

$$\boldsymbol{V}_k = \frac{1}{N}\sum_{i=k-N}^{k}(x_i - \hat{x}_i)(x_i - \hat{x}_i)^T \tag{5}$$

The moving average is used as an additional input parameter to a decision tree that classifies binary anomalies based on the $\boldsymbol{x_k}$. According to

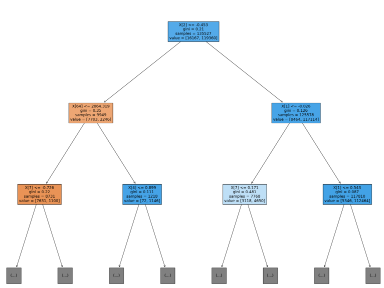
Decision Tree (Discuss gini index)

$$GI = 1 - \sum_{i=1}^{n}(P_i)^2 \tag{6}$$



B. Isolation

Decision tree or any other multi-classifying method.



C. Recovery

Backtracking on kalman filter... Removing sensor measurement update... If a fault is predicted, the estimated vector model from the kalman filter is used to to determine the reference position for the control as well as the calculations for the control.

V. Testing Methodology

Simulation... Induce anomalies based on physical models or at a specified timestamp.

VI. Results

Three scenarios are implemented, a satellite that never experiences reflection, a satellite that experiences reflection without any recovery method and a satellite with a recovery method. The subsets of detecting the fault and recovering from the fault will be isolated and discussed separately. Therefore the results for recovery based on perfect detection can be shown to show the possibilities of the recovery method. Compare results for estimation error and control error for Kalman filter with and without FDIR.

The simulation is run for 20 orbits, with each orbit running for $5700s$. If a fault is induced, it is induced after the first two orbits and the specific anomaly then occurs for the following 18 orbits.

A. Perfect Designed Satellite Without Reflection

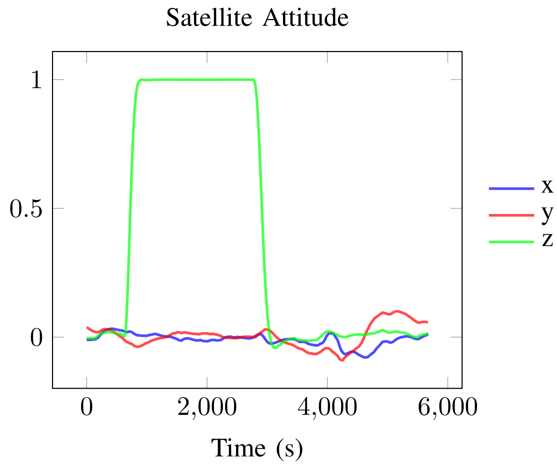


Fig. 1. Quaternions.

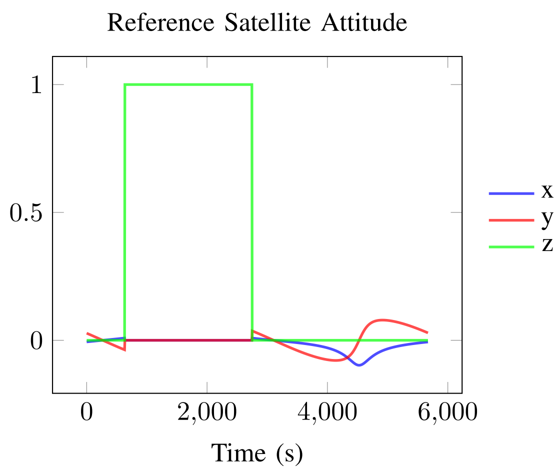


Fig. 2. Reference Quaternions.

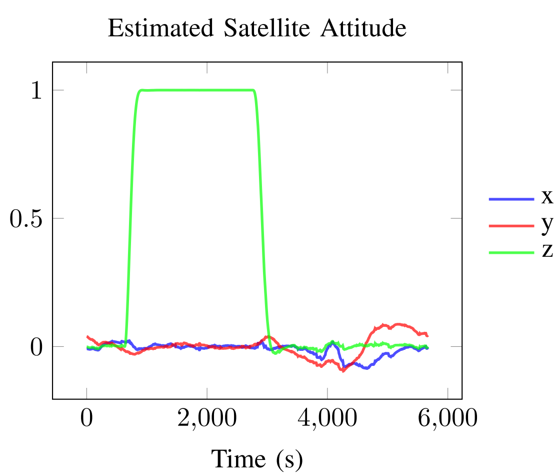


Fig. 3. Estimated Quaternions.

B. Reflection without any recovery

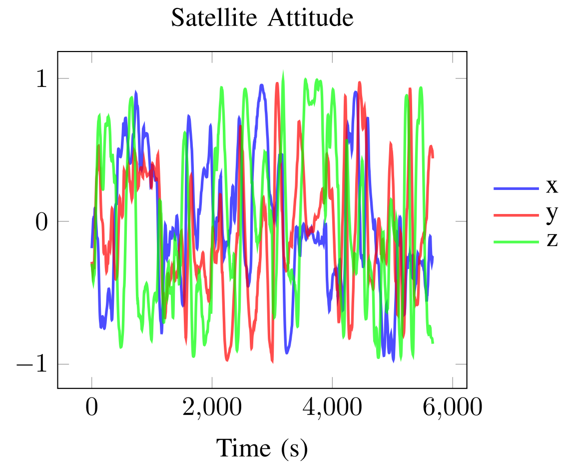


Fig. 4. Quaternions.

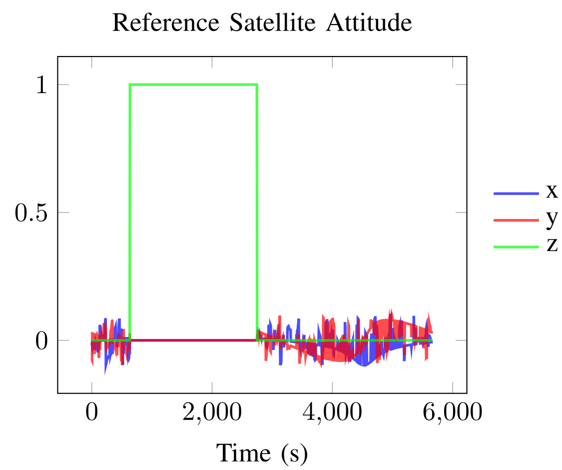


Fig. 5. Reference Quaternions.

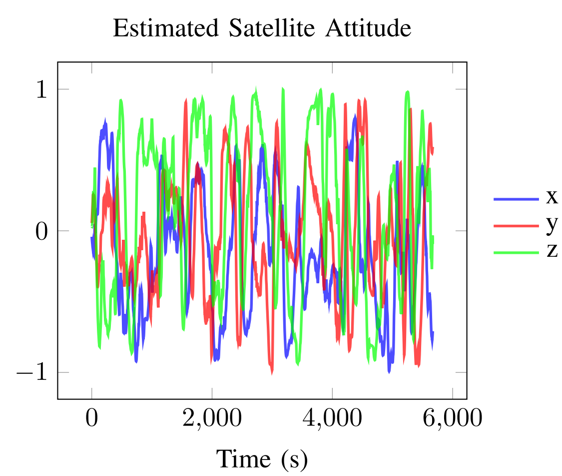


Fig. 6. Estimated Quaternions.

C. Recovery with Perfect fault prediction

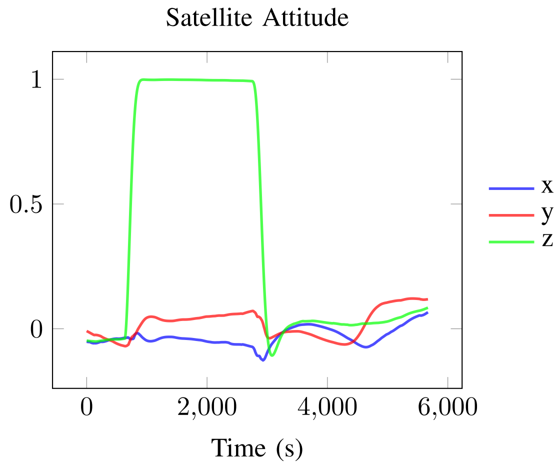


Fig. 7. Quaternions.

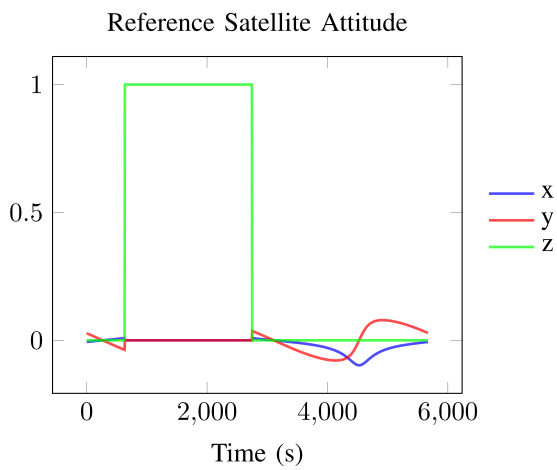


Fig. 8. Reference Quaternions.

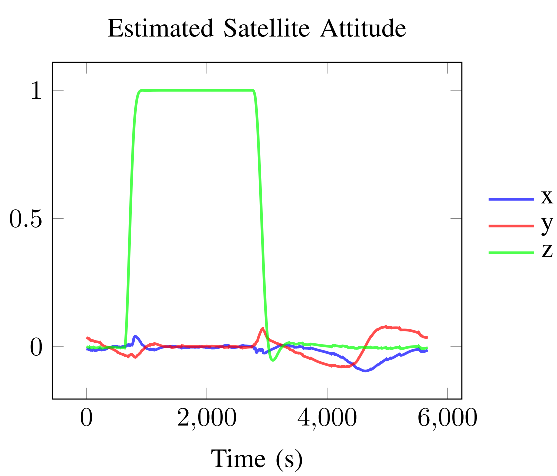


Fig. 9. Estimated Quaternions.

D. Fault Prediction Isolation and Recovery of Proposed Method

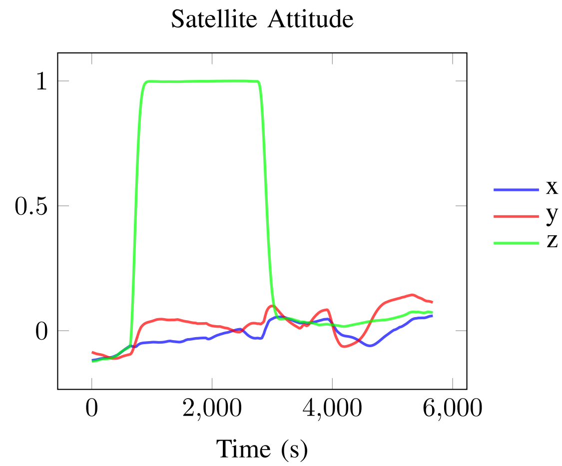


Fig. 10. Quaternions.

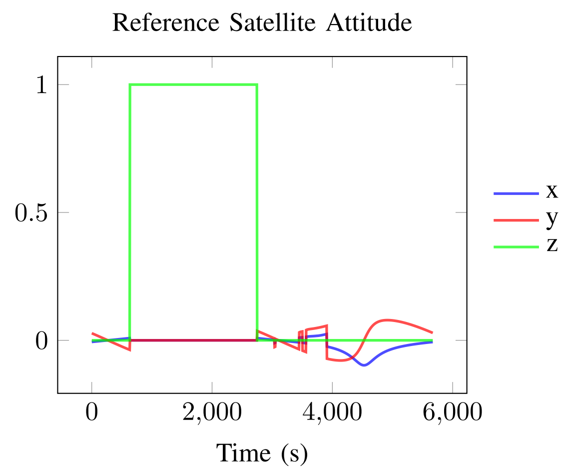


Fig. 11. Reference Quaternions.

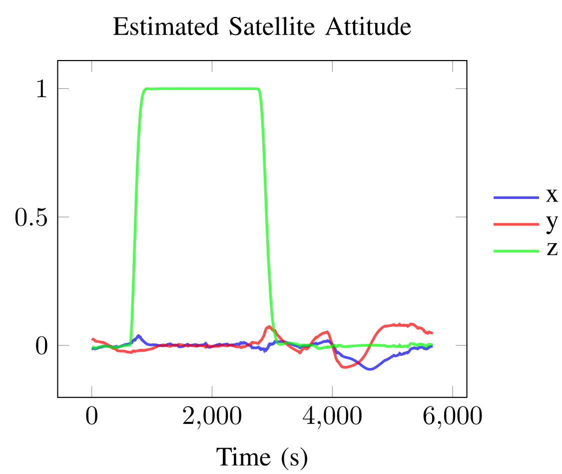


Fig. 12. Estimated Quaternions.

VII. CONCLUSIONS

Results from kalman filter and attitude determination as well as control compared for EKF with and without FDIR.

APPENDIX

Table of anomalies

ACKNOWLEDGMENT

References are important to the reader; therefore, each citation must be complete and correct. If at all possible, references should be commonly available publications.