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

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***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.

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.

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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 $k+1$ 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}

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

Moving average of the innovation covariance

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

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

Compare results for estimation error and control error for Kalman filter with and without FDIR.

A. Estimation Error

B. Control response

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.