11th ANKARA INTERNATIONAL AEROSPACE CONFERENCE **AIAC-2021-118**
8-10 September 2021 - METU, Ankara TURKEY

GYROLESS BACKUP ATTITUDE ESTIMATION ALGORITHM FOR NANOSATELLITES USING MAGNETIC FIELD DERIVATIVES IN THE LOSS OF SUN SENSOR MEASUREMENTS

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ABSTRACT

The main aim of this study is to design a low-cost attitude filter for nanosatellites. Since Sun sensors and magnetometers are widely used commercial off-the-shelf attitude sensors, the attitude estimation algorithms using these sensors are needed for either primary or backup modes. Throughout the study, QUEST aided multiplicative extended Kalman filter (MEKF) is used to obtain fine attitude and angular velocity estimation. Although this set of sensors has proven to give satisfactory estimation results, the problem arises when Sun is not visible. For the eclipse period, the estimation must be updated by only magnetometer data. Magnetometer measurements are used to generate another vector pair based on magnetic field derivative and QUEST processes these two vector sets to provide attitude information for updating the MEKF. The proposed method provides 5 degree attitude accuracy in eclipse period without changing the structure of the filter between different conditions. When Sun sensor is available, fine estimation is achieved as having lower than 1 degree attitude error.

INTRODUCTION

Recently, system miniaturization and the decrease in launch expense with technological growing have made nanosatellites popular for space research due to low cost. Thanks to their various benefits, nanosatellites have become ideal platforms for also scientific operations [Millan et. al., 2019].

Despite their many advantages, nanosatellites have some important disadvantages such as power and mass limitations. As a result of these drawbacks of nanosatellites, the limitation of available sensors also poses a challenge in terms of attitude determination. If several sensors are available, an accurate attitude estimation is obtained easily. However, due to the reasons mentioned above, nanosatellites can use a limited number of sensors which give less accurate measurements [Sabzevari et al., 2020].

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In the solution of attitude determination problem, gyroscopes, Star trackers, Sun sensors, Earth horizon sensors and Three-Axis Magnetometers (TAM) can be regarded as the standard attitude sensors. Among these TAM, Sun sensor and gyroscopes are very commonly used for nanosatellites. Depending on the budget and mass limitations for specific missions, it is possible to see that gyros are removed from this trio and the attitude is estimated with a dynamics-based filtering algorithm using only Sun sensor and TAM measurements.

Thanks to TAM's small volume and mass, reliable performance, low power consumption and firm installation, they are used in almost every low-Earth orbit nanosatellite [Ma, H. and Xu, S., 2014] and fused with other sensors such as Sun sensor. Since Sun sensor cannot provide information during the eclipse phases for an Earth orbiting satellite, attitude determination algorithm relies only on the magnetometer measurements.

Attitude and rate estimation by TAM and Sun sensor has been studied extensively in the past couple of decades. If initial conditions are known, the most straightforward method is to use an extended Kalman filter by updating vector measurements of TAM and Sun sensor in sunlit areas and only TAM in the shadow [Theil et al., 2003; Santos and Waldmann, 2009]. Another method is the non-traditional approach which is pre-processing the vector measurements by one of the static attitude estimator (e.g. QUEST, TRIAD, SVD) and use the calculated attitude information as the measurements in the Kalman filter [Hajiyev and Cilden, 2016]. This approach provides fast convergence to the real states and it is more robust to the case of parallel measurement vectors if adaptive covariance matrix is used [Hajiyev and Soken, 2020]. But the problem, when using the nontraditional filter, arises in the eclipse phases, since one vector can not be processed within the static attitude estimator. Thus, during the eclipse phases, the designed filters either just propagate the states or change the structure to solve the magnetometer only estimation problem [Hajiyev and Cilden-Guler, 2018].

As magnetometer-only attitude estimation becomes a necessity during eclipses, the primary challenge here is being able to get full three-axis attitude information from the instantaneous magnetometer measurements. To overcome this problem, different methods for estimating the attitude and angular rates from the magnetometer data have been proposed.

One of the first solutions was proposed by [Natanson et al., 1990], whose method estimates attitude and angular rate by calculating the first and second derivatives of magnetometer data using finite differencing within the known environmental conditions. Then, this study was enhanced by taking the dynamical equations into account for a spinning satellite in [Challa et al., 2000]. In [Psiaki et al., 1990], magnetometer only extended Kalman filter was proposed to estimate the attitude and attitude rate for gravity gradient stabilized spacecraft. The tumbling spacecraft attitude and attitude rate estimation by magnetometer data was studied by [Ma, H. and Xu, S., 2014; Shou et al., 2010]. Another solution is proposed by [Searcy and Pernicka, 2012], who suggested a two-step Kalman filter for both magnetometer derivative estimation, and attitude and rate estimation.

In this study, the attitude estimation filter is designed considering two different periods in orbit: sunlit and eclipse periods. The filter uses TAM and Sun sensor measurements to estimate the attitude and angular rate when the Sun is visible. In eclipse, same states are estimated this time using only TAM measurements, both the vector magnetic field measurements and their time derivatives. In both cases, there are 2 vector sets and the states are estimated by pre-processing the measurements in QUEST and then running the multiplicative extended Kalman filter (MEKF) with QUEST estimated quaternion vector as measurements. Different than other magnetometer-only attitude estimation methods, the proposed method uses the measurements in a cascaded filtering structure that incorporates: a pre-filter for magnetic field derivative estimation, QUEST for providing quaternion measurements to the filter, and the actual MEKF algorithm. Even though the measurement availability changes in different periods, the proposed algorithm can ensure continuous attitude and attitude rate estimates without changing its structure. Instead of using vector measurements in the filter, the use of the QUEST algorithm for pre-processing provides advantages mostly in terms of the convergence speed[Esit, M., Yakupoglu, S., and Soken, H.E. , 2021]. Moreover, when the measurements are pre-processsed with the QUEST the R_k covariance matrix becomes adaptive as it depends on the estimation covariance of the QUEST. Last, when used with the Unscented Kalman Filter (UKF), because of the linearized measurement model, QUEST can significantly decrease the computational load. As a result, a QUEST aided MEKF, which can run using only the magnetometer measurements, provides a robust, computationally efficient alternative algorithm for nanosatellite attitude estimation.

METHOD

QUEST

Quaternions are used for attitude representation in most of the designed attitude filters for spacecraft, since quaternion vector has no singularity and kinematics can be described without requiring trigonometric functions. The quaternion set is defined as

$$\boldsymbol{q} = \begin{bmatrix} \boldsymbol{q_{1:3}^T} & q_4 \end{bmatrix}^T = \begin{bmatrix} q_1 & q_2 & q_3 & q_4 \end{bmatrix}^T \ , \tag{1}$$

with

$$\boldsymbol{q_{1:3}} = \hat{\boldsymbol{e}} \sin(\vartheta/2)\, ; \quad q_4 = \cos(\vartheta/2) \ , \tag{2}$$

where $\hat{\boldsymbol{e}}$ is the axis of and ϑ is the angle of rotation.

QUEST which is one of the most widely used static attitude determination algorithms, gives the attitude information by point-by-point calculations. In particular, it is based on finding the solution of Wahba's Problem which is given by

$$L(A) = \sum_{i=1}^{N} a_i - \boldsymbol{q}^T K(B)\, \boldsymbol{q} = \lambda_0 - \boldsymbol{q}^T K(B)\, \boldsymbol{q} \tag{3}$$

where a_i is weight value of each measurement, A is the direction cosine (attitude) matrix given by

$$A(\boldsymbol{q}) = \left(q_4^2 - \boldsymbol{q_{1:3}^T q_{1:3}}\right) I_3 + 2\boldsymbol{q_{1:3} q_{1:3}^T} - 2q_4[\boldsymbol{q_{1:3}} \times] \ . \tag{4}$$

Here I_3 stands for 3x3 identity matrix. $K(B)$ is the symmetric traceless matrix as

$$K(B) = \sum_{i=1}^{N} a_i [\boldsymbol{b_i} \otimes]^T [\boldsymbol{r_i} \odot]^T = \begin{bmatrix} B + B^T - (\operatorname{tr} B)\, I_3 & \boldsymbol{z} \\ \boldsymbol{z}^T & \operatorname{tr} B \end{bmatrix} \tag{5}$$

where $\boldsymbol{b_i}$ is 3x1 vector measurement in the body frame and $\boldsymbol{r_i}$ is 3x1 modelled reference vector. $[a\otimes]$ and $[a\odot]$ are both 4×4 skew-symmetric matrices as

$$\begin{aligned} [a\otimes] &= \begin{bmatrix} -[a\times] & a \\ -a^T & 0 \end{bmatrix} \\ [a\odot] &= \begin{bmatrix} [a\times] & a \\ -a^T & 0 \end{bmatrix} \end{aligned} \tag{6}$$

where $[\boldsymbol{a}\times]$ is the skew-symmetric for any vector $\boldsymbol{a} = \begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix}^T$ as

$$[\boldsymbol{a}\times] = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \tag{7}$$

The relation of B and z are given below.

$$B = \sum_{i=1}^{N} a_i \boldsymbol{b_i} \boldsymbol{r_i}^T \tag{8}$$

$$\boldsymbol{z} = \begin{bmatrix} B_{23} - B_{32} \\ B_{31} - B_{13} \\ B_{12} - B_{21} \end{bmatrix} = \sum_{i=1}^{N} a_i \left(\boldsymbol{b_i} \times \boldsymbol{r_i} \right) \tag{9}$$

The loss function $L(A)$ is minimized by finding the maximum eigenvalue $\lambda_{\max}$ of $K(B)$ as

$$L(A) = \lambda_0 - \lambda_{\max} \tag{10}$$

with

$$K(B)\boldsymbol{q_{opt}} = \lambda_{\max} I_4 \boldsymbol{q_{opt}} \tag{11}$$

where $\boldsymbol{q_{opt}}$ is the optimum quaternion and λ_0 is the initial eigenvalue. Then, QUEST method was introduced to solve the eigenvalue finding problem by converting it to a root finding problem for the quartic function given by [Shuster and Oh, 1981].

$$0 = \psi(\lambda) = \lambda^4 - (a+b)\lambda^2 - c\lambda + ab + c\,\mathrm{tr}(B) - d = \prod_{i=1}^{4} (\lambda - \lambda_i) \tag{12}$$

where λ_i values are the eigenvalues of $K(B)$ and

$$\begin{aligned} a &= \mathrm{tr}(B)^2 - \mathrm{tr}(\mathrm{adj}(S)) \\ b &= \mathrm{tr}(B)^2 + \boldsymbol{z}^T \boldsymbol{z} \\ c &= \det(S) + \boldsymbol{z}^T \boldsymbol{z} \\ d &= \left(\boldsymbol{z}^T S \right) (S\boldsymbol{z}) \\ S &= B^T + B \end{aligned} \tag{13}$$

For minimized $L(A)$, λ_{max} must be very close to λ_0. Therefore, by having initial value as λ_0, Newton-Raphson method can be used to solve the problem for obtaining the value of λ_{max}. Then, by having the λ_{max}, optimal value of quaternion can be determined by

$$\hat{\boldsymbol{q}} = \boldsymbol{q_{opt}} = \frac{1}{\sqrt{\gamma + |\boldsymbol{x}|^2}} \begin{bmatrix} \boldsymbol{x} \\ \gamma \end{bmatrix} \tag{14}$$

with

$$\begin{aligned} \boldsymbol{x} &= \left(\lambda_{\max}^2 - \mathrm{tr}(B)^2 + \mathrm{tr}\left(\mathrm{adj}(S)\right) \right) \boldsymbol{z} + \left(\lambda_{\max} - \mathrm{tr}(B) \right) \boldsymbol{z} + S^2 \boldsymbol{z} \\ \gamma &= \det\left(\left(\lambda_{\max} + \mathrm{tr}(B) \right) I_3 - S \right) \end{aligned} \tag{15}$$

Pre-filter for Additional Vector Pair

The available sensors, TAM and Sun Sensor, provide attitude estimation when the Sun is visible. However, the satellite may not see the Sun for a certain period of time in each orbit. In that eclipse period, only TAM measurements are available and the estimation must be continued without changing the structure of the filter. There is always chance to use only magnetometer vector measurements in the filter in eclipse as in standard filtering algorithm for vector measurements [Hajiyev and Cilden-Guler, 2018]. However, in this case, there is need for changing the filter structure and have a nonlinear measurement update scheme. In contrast, we would like to keep the QUEST aided structure for simplicity.

To be able to keep the original structure of the filter and continue with the QUEST pre-processed measurements there is need for an additional vector. The second vector set can be derived from the magnetic field vector by estimating the derivative of the measured magnetic field, and together with the original magnetic field vector these two vectors can be used to obtain the attitude by QUEST method.

Let $\boldsymbol{B_b}$ and $\boldsymbol{B_i}$ denote the magnetic field vectors in the body frame and inertial frame, respectively. The transformation equation is given as

$$\boldsymbol{B_b} = A\boldsymbol{B_i} \tag{16}$$

where A represents the direction cosine matrix. Taking the time derivative of each side as

$$\dot{\boldsymbol{B}}_{\boldsymbol{b}} = A\dot{\boldsymbol{B}}_{\boldsymbol{i}} + \dot{A}\boldsymbol{B_i} = A\dot{\boldsymbol{B}}_{\boldsymbol{i}} - [\boldsymbol{\omega}\times]\, A\boldsymbol{B_i} \tag{17}$$

$$\dot{\boldsymbol{B}}_{\boldsymbol{b}} + [\boldsymbol{\omega}\times]\, \boldsymbol{B_b} = A\dot{\boldsymbol{B}}_{\boldsymbol{i}} \tag{18}$$

Eq.(18) can be rewritten as

$$\boldsymbol{b_3} = A\boldsymbol{r_3} \tag{19}$$

where

$$\boldsymbol{b_3} \equiv \dot{\boldsymbol{B}}_{\boldsymbol{b}} + [\boldsymbol{\omega}\times]\, \boldsymbol{B_b} \tag{20}$$

$$\boldsymbol{r_3} \equiv \dot{\boldsymbol{B}}_{\boldsymbol{i}} \tag{21}$$

Thus, the second vector set to be used by QUEST in eclipse is obtained as $\boldsymbol{b_3}$ and $\boldsymbol{r_3}$.

Since $\boldsymbol{B_i}$ is known, then $\dot{\boldsymbol{B}}_{\boldsymbol{i}}$ or $\boldsymbol{r_3}$ can be simply computed. On the other hand, in order to determine $\boldsymbol{b_3}$, the value of $\dot{\boldsymbol{B}}_{\boldsymbol{b}}$ is needed. Since magnetic field measurements are noisy and its derivative cannot be accurately calculated with a first order approximation, a filter must be used that will smooth the measurements and provide more accurate results before using for attitude estimation.

A linear Kalman filter can be used to obtain the derivative of magnetic field, by assuming that the magnetic field vector can be modelled as third-order Markov process [Searcy and Pernicka, 2012]:

$$\frac{d^3\boldsymbol{B_b}}{dt^3} = \boldsymbol{\upsilon} \tag{22}$$

where $\boldsymbol{\upsilon}$ is zero-mean Gaussian white noise.

The state vector and state equation of the filter are

$$\boldsymbol{\chi} = \begin{bmatrix} \boldsymbol{B_b} \\ \dot{\boldsymbol{B}}_{\boldsymbol{b}} \\ \ddot{\boldsymbol{B}}_{\boldsymbol{b}} \end{bmatrix} \tag{23}$$

$$\dot{\boldsymbol{\chi}} = \frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix} \boldsymbol{B_b} \\ \dot{\boldsymbol{B}}_{\boldsymbol{b}} \\ \ddot{\boldsymbol{B}}_{\boldsymbol{b}} \end{bmatrix} = \begin{bmatrix} 0_3 & I_3 & 0_3 \\ 0_3 & 0_3 & I_3 \\ 0_3 & 0_3 & 0_3 \end{bmatrix} \boldsymbol{\chi} \tag{24}$$

and the observation equation is

$$\boldsymbol{\gamma} = \begin{bmatrix} I_3 & 0_3 & 0_3 \end{bmatrix} \boldsymbol{\chi} = \tilde{\boldsymbol{B}}_{\boldsymbol{b}} \tag{25}$$

Thus, by using the measurements, the filter provides estimation of magnetic field derivative ($\dot{\boldsymbol{B}}_{\boldsymbol{b}}$) vector. This estimated magnetic field derivative, TAM measurement and angular velocity, which is estimated through attitude filter, are used to construct the vector $\boldsymbol{b_3}$ as given in Eq.(20).

Multiplicative Extended Kalman Filter

Kalman filters are frequently used in satellite attitude and angular velocity estimation. Considering the nonlinear system and measurement models for the problem, we can use an EKF, which is based on linearized models and a widely preferred attitude and angular velocity estimation algorithm.

$$\hat{\boldsymbol{x}}_{\boldsymbol{k+1/k}} = f\left(\hat{\boldsymbol{x}}_{\boldsymbol{k/k}}, \boldsymbol{u_k}, k\right) + \boldsymbol{w_k} \ , \tag{26}$$

$$P_{k+1/k} = F_k P_{k/k} F_k^T + Q_k \ , \tag{27}$$

where $\boldsymbol{x}$ is the state vector, P is the state covariance matrix and $\boldsymbol{u}$ is the system control input vector. $\boldsymbol{w}$ represents the zero-mean Gaussian white noise with the covariance of Q. F is the partial derivative matrix or Jacobian matrix given by [Hajiyev and Soken, 2020]

$$F_k \triangleq \left.\frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}}\right|_{\hat{\boldsymbol{x}}_{\boldsymbol{k/k}}} = \begin{bmatrix} -\left[\hat{\boldsymbol{\omega}}_\times\right] & I_3 \\ 0_3 & J^{-1}\left(-\left[\hat{\boldsymbol{\omega}}_\times\right]J + \left[J\hat{\boldsymbol{\omega}}_\times\right]\right) \end{bmatrix}. \tag{28}$$

The estimation state $\boldsymbol{x}$ consists of quaternion and angular rate $\begin{bmatrix} \boldsymbol{q^T} & \boldsymbol{\omega^T} \end{bmatrix}^T$ called global state. However, due to the state propagation with kinematics equation, norm constraint of quaternion can be violated when the full state vector is used. MEKF that satisfies the quaternion norm constraint, has become one of the most common satellite attitude estimators [Auman, A.J., 2015]. MEKF overcomes quaternion norm constraint problem using three-component local attitude error in the filter, and updating the global quaternion estimate by quaternion multiplication. In the filter, the local error state vector is defined as $\boldsymbol{\Delta}\hat{x}\left(t\right) = \begin{bmatrix} \boldsymbol{\delta\hat{\vartheta}^T} & \boldsymbol{\delta\hat{\omega}^T} \end{bmatrix}^T$. The rotation error vector $\boldsymbol{\delta\vartheta}$ is used as the local state of the MEKF and derived by small angle approximation as

$$2\boldsymbol{\delta q_{1:3}} \approx \begin{bmatrix} \delta\phi \ \delta\theta \ \delta\psi \end{bmatrix}^T \equiv \boldsymbol{\delta\vartheta} \ , \tag{29}$$

where error quaternion is defined as

$$\boldsymbol{\delta q} = \boldsymbol{q} \otimes \hat{\boldsymbol{q}}^{-1} = \boldsymbol{q} \otimes \begin{bmatrix} -\hat{\boldsymbol{q}}_{\boldsymbol{1:3}} \\ \hat{q}_4 \end{bmatrix} = \begin{bmatrix} \hat{q}_4\boldsymbol{q_{1:3}} + q_4\hat{\boldsymbol{q}}_{\boldsymbol{1:3}} - \boldsymbol{q_{1:3}} \times \hat{\boldsymbol{q}}_{\boldsymbol{1:3}} \\ q_4\hat{q}_4 - \boldsymbol{q_{1:3}^T}\hat{\boldsymbol{q}}_{\boldsymbol{1:3}} \end{bmatrix}. \tag{30}$$

where $\otimes$ stands for quaternion multiplication.

After that, the global quaternion is updated by using error quaternion at every time step k by

$$\hat{\boldsymbol{q}}_{\boldsymbol{k+1/k+1}} = \boldsymbol{\delta}\hat{\boldsymbol{q}}_{\boldsymbol{k+1/k+1}} \otimes \hat{\boldsymbol{q}}_{\boldsymbol{k+1/k}} \ , \tag{31}$$

for $\boldsymbol{\delta q} = [\boldsymbol{\delta q_{1:3}^T} \ 1]^T$. Then normalization should be done for the global quaternion estimation.

Since QUEST algorithm gives directly quaternion measurements to the filter by pre-processing the vector measurements, the observation matrix can be written as follows,

$$H_k = \begin{bmatrix} I_3 & 0_3 \end{bmatrix}. \tag{32}$$

The estimation covariance for the QUEST is used as the measurement noise covariance in the filter. Thus, measurement covariance matrix changes adaptively throughout the filtering process and is given by [Shuster and Oh, 1981]

$$R_k = \left[\sum_{i=1}^{N} \frac{1}{\sigma_i^2}\left(I_3 - \boldsymbol{b_i}\boldsymbol{b_i^T}\right)\right]^{-1}. \tag{33}$$

where N stands for the total number of the vector measurements.
The Kalman gain is calculated by

$$K_k = P_{k+1/k} H_k^T \left(H_k P_{k+1/k} H_k^T + R_k \right)^{-1} . \tag{34}$$

Finally, the state vector and the state covariance matrix are updated by

$$\hat{\boldsymbol{x}}_{\boldsymbol{k+1/k+1}} = \hat{\boldsymbol{x}}_{\boldsymbol{k+1/k}} + K_k \left(\tilde{\boldsymbol{y}}_{\boldsymbol{k+1}} - h\left(\hat{\boldsymbol{x}}_{\boldsymbol{k+1/k}}, k \right) \right) , \tag{35}$$

$$P_{k+1/k+1} = \left(I - K_k H_k \right) P_{k+1/k} . \tag{36}$$

Overall Attitude Filter

When the Sun is visible, there are two sensors providing measurements: TAM and Sun sensor. These measurements and the corresponding vectors in the inertial frame that are obtained from the orbit data, are processed by QUEST method and attitude information is obtained. By using this attitude as the measurement in the MEKF, the attitude and angular rate vectors are estimated recursively.

In the absence of Sun sensor measurements (in eclipse), the proposed pre-filter is used to obtain another vector set in addition to the magnetic field measurements. QUEST method gives the attitude by using these two vector sets. Once again the determined attitude by the QUEST is used as the measurements in the MEKF, and the filter can still get measurements in eclipse periods.

The Figure 1 represents the general view of the presented attitude estimation algorithm.

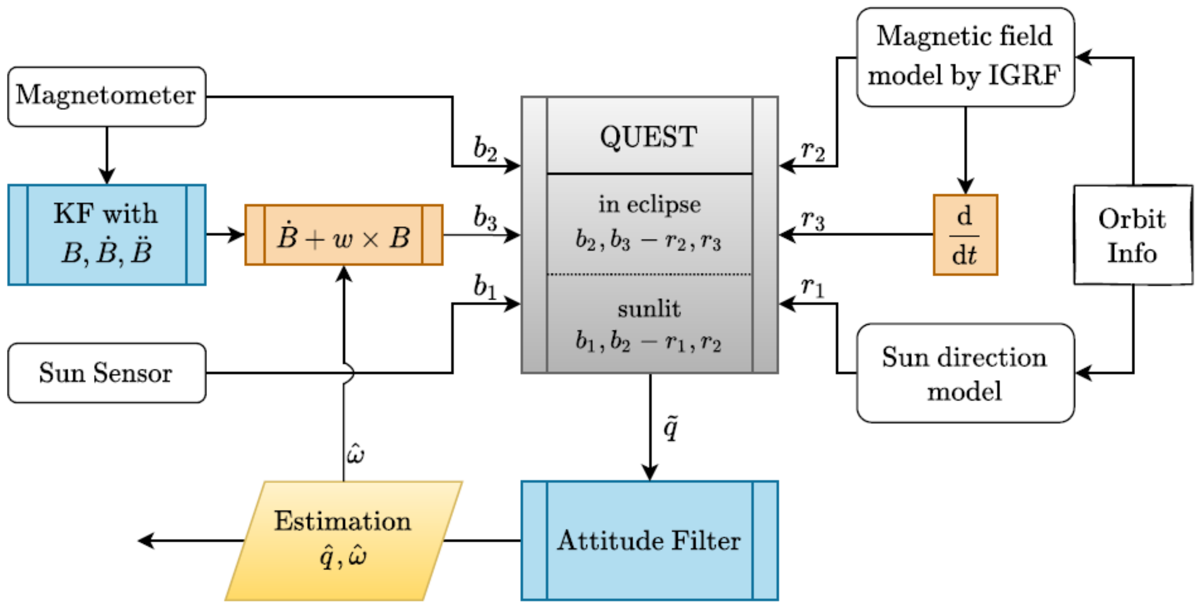

Figure 1: Overview of proposed attitude estimation method

RESULTS AND DISCUSSION

The presented attitude estimation method is tested for a nanosatellite. Besides, the results for a filter, which does not calculate and use the magnetic field derivatives and only propagates the states during the eclipse periods without any update, are demonstrated for comparison. Simulation runs for 36000 seconds including 6 eclipse passes for the satellite and the sampling time is $\Delta t = 1$ s. The moment of inertia matrix for the satellite is as follows $J = diag\begin{pmatrix} 0.037 & 0.037 & 0.01 \end{pmatrix}$ kgm^2.

The TAM sensor noise is defined by zero mean Gaussian white noise with a standard deviation of 300 nT. Likewise, the standard deviation of the Sun sensor is set to 0.002 as zero mean Gaussian white noise. In addition, the gyro bias is initialized at 8.7×10^{-4} rad/sec and characterized by zero mean Gaussian white noise with a standard deviation of $\boldsymbol{\sigma_u} = 6.6554 \times 10^{-6}$ rad/sec^2. The gyro measurement noise is zero mean Gaussian white noise with a standard deviation of $\boldsymbol{\sigma_v} = 2.3271 \times 10^{-5}$ rad/sec.

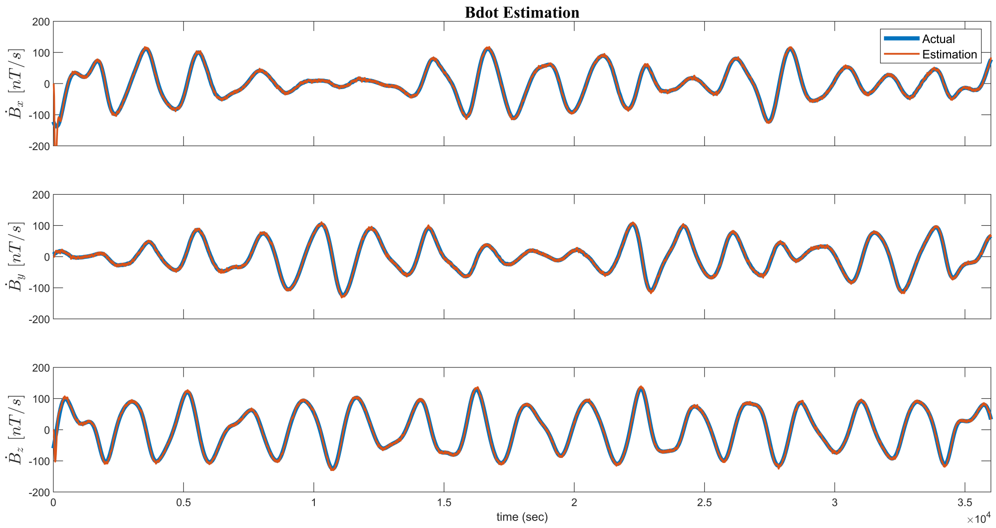

Figure 2: Bdot estimation

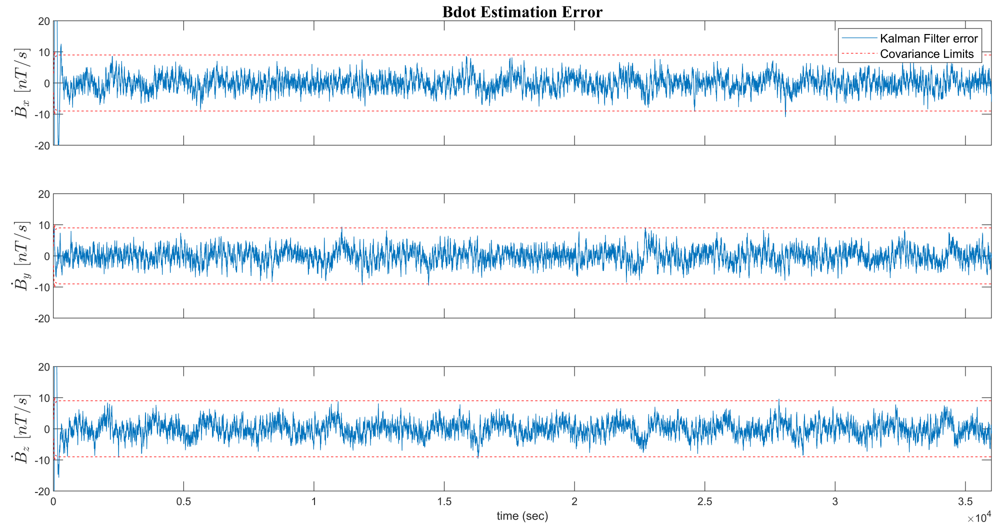

Figure 3: Bdot estimation error

Figure 2 and 3 show the results of the magnetic field derivative estimation by the Kalman filter. 250-300 seconds after the initialization, the filter converges to the real value and estimation values remain within the 3σ error of $10\,nT/s$.

In Figure 4, the attitude estimation errors are presented for each method. The eclipse period is shown as the shaded areas. As both algorithms apply same estimation processes out of the eclipses, they provide similar estimation accuracy. During the eclipse periods, it is seen that the proposed method is superior to a filter that does not use magnetic field derivatives and only propagates the states. Using the magnetic field derivative highly improves the attitude estimation accuracy. After a couple of orbits, pre-filter gives better magnetic field derivative outputs and this ensures attitude estimation accuracy being less than 3 degrees (each axis - 1 sigma) during eclipse periods. However, the estimation error may become as large as 20 degrees when the QUEST does not use magnetic field defectives and the MEKF only propagates the states in eclipses.

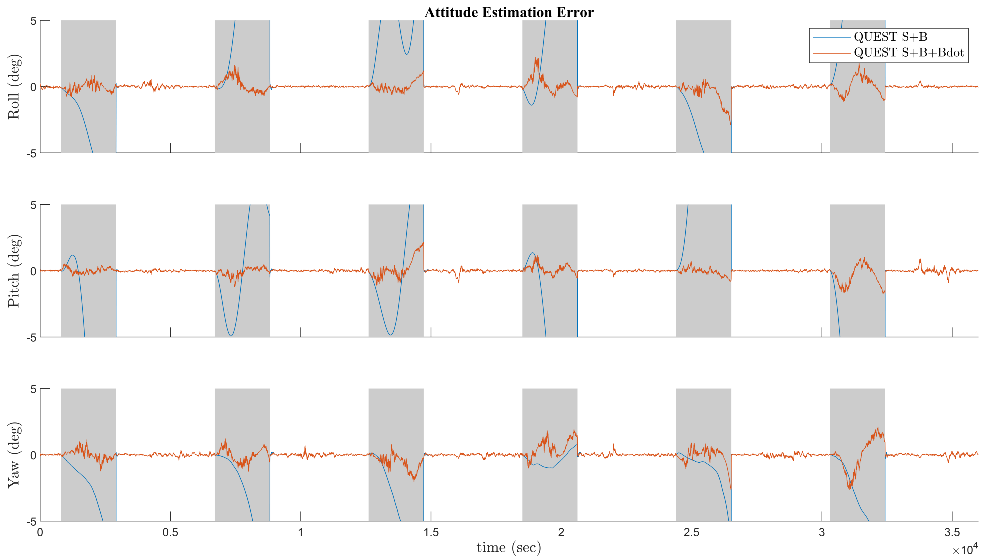

Figure 4: Attitude estimation error comparison

In figure 5, the attitude estimation errors are demonstrated for the proposed algorithm and traditional EKF, which uses directly the vector magnetometer and Sun sensor measurements, excluding the QUEST block. Attitude estimation accuracy is less than 3 degrees (each axis - 1 sigma) during eclipse periods for both filters. However, the convergence time of the traditional EKF (approx. 150s) is longer than the proposed algorithm. Although both filters present very similar characteristics in terms of accuracy, we can say that the proposed algorithm is more advantageous in terms of the convergence time.

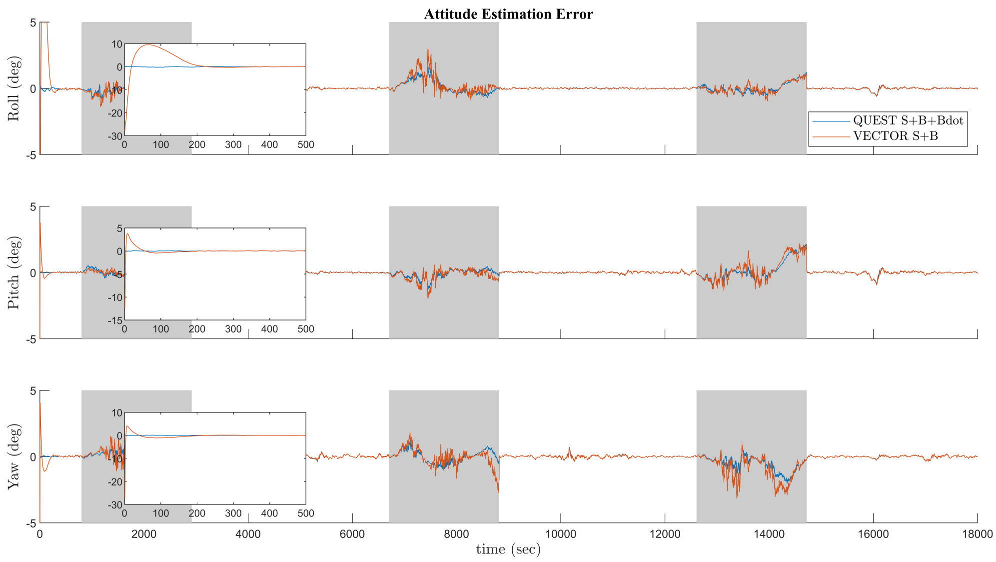

Figure 5: Comparison of attitude estimation error of QUEST Aided and Traditional EKFs

CONCLUSION

In this study, a gyroless backup attitude estimation algorithm for nanosatellites is developed using the magnetic field derivatives in the loss of Sun sensor measurements. Unlike the traditional attitude estimation filters, QUEST algorithm is used as a pre-processor for vector measurements and gives directly quaternion measurements to the attitude filter. Therefore, the update part of the Multiplicative Extended Kalman Filter (MEKF) becomes linear. However, during the eclipse phases, the filter cannot update the states since the QUEST algorithm cannot not give measurements because of only one vector input. In this study, the derivative of the magnetic field is used as a second input to the QUEST during the eclipses. Since the use of finite differencing for magnetic field derivative determination does not provide accurate estimation, a Kalman filter is included in the algorithm block to get fine estimation of magnetic field derivatives. The simulations are done for a Sun-synchronous low earth orbit nanosatelite having uncertainty in its moment of inertia and gravity gradient disturbance. It is assumed that residual magnetic moment disturbance is approximately known and compensated by the controller. We compared the proposed algorithm with the OUEST aided MEKF that does not update the states in eclipses due to lack of sufficient vector measurement for the QUEST and the traditional MEKF. Results indicate that the QUEST aided MEKF satisfies fast convergence and adding magnetic field derivatives highly improves the performance of QUEST aided filter during the eclipse periods. Using the magnetic field derivatives as a measurement in the eclipse increases the attitude estimation accuracy whereas the estimation error when the states are only propagated grows up to 20 degrees. The proposed filter and the traditional MEKF exhibit very similar properties, especially when the Sun sensor measurements are available, but the convergence time of the proposed filter is shorter. Although this method has been tested for nanosatellite, it can be applied for any satellite that has Sun sensor and TAM as a primary or backup estimation filter.

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