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Adaptive dynamic kalman filter for high-performance tilt-angles estimation

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Abstract. Estimation of attitude is a potential task for autonomous vehicles as it directly affects the velocity and position estimates as well as the overall system autonomy. The estimation of attitude angles utilizing gyro measurements always suffers from increasing drift with time. Although accelerometer measurements can provide an absolute estimate of pitch and roll angles for static and low dynamics conditions, they have two drawbacks the effect of additional external acceleration and the inability to capture the high dynamics motion. In this paper, an adaptive Kalman filter (AKF) is utilized for integrating the gyros and accelerometer measurements for enhancing the roll and pitch angles estimates by compensating for the effect of linear acceleration as well as adaptively adapting the Kalman filter measurement covariance matrix. The proposed algorithm is evaluated using real offline measurements for a flying vehicle. Further, a comparative analysis is carried out with the original Kalman filter (KF) algorithm and with the imufilter from Sensor Fusion and Tracking Toolbox from Matlab. The results presented satisfactory performance and enhancement for roll and pitch angles estimate.

1. Introduction

Attitude assessment is used in a variety of applications. With the growth of autonomous systems research, it is crucial to use compact and less pricy components as a result of using Micro-Electrical-Mechanical systems (MEMS) based on Inertial Measurement Units (IMU). The IMU is a sensor platform that produces measures of the status of the vehicle, such as angular rates and acceleration . However, they are combined with inaccurate modeling errors, which cause a quick decrease in attitude computation accuracy if the measurements are used directly in the update process[1].

The Attitude and Heading Reference System (AHRS) has become a popular integrated sensor approach. AHRS is based on data supplied by gyroscopes, accelerometers, and magnetometers capable of providing the stability criteria for attitude computations[2]. The gyro's attitude is inaccurate because it is unbounded owing to its bias and random walk errors. Thus, the attitude can't depend on the gyro's data. Pitch and roll can be calculated from accelerometer data in a stationary or slow-moving autonomous vehicle. This is because the gravity measurement is reliable. To overcome sensor limitations and the influence of external acceleration, a high-level fusion of the IMU's data and the algorithms to adjust for external acceleration is required[3].

The accelerometer measurements always provide acceptable performance for calculating the tilt angles during static or quasi-static modes, as the measurements are only affected by the vehicle acceleration. Nevertheless, with the presence of vehicle dynamics, the external acceleration and centrifugal forces highly affect the accuracy of estimating the tilt angles based on accelerometer measurements[4]. However, because the accelerometer data is fundamentally presented with the reference frame, the component of gravity concerning the body frame varies with changes in the orientation of the sensor. As a result, gravitational acceleration is indistinguishable from external acceleration[5].

In dynamic situations, switching case criteria should be applied for enhancing the efficiency of tilt angles estimation by weighting the measurement data based on the vehicle state. Estimation of vehicle external acceleration potentially affects the performance of calculating the tilt angles based on accelerometer

measurements. An attitude system is generally made up of an IMU and additionally onboard processing boards to calculate the vehicle's attitude[6].

The Kalman filter is an optimum estimator algorithm that can be used for enhancing estimation accuracy based on noisy measurements[7]. It can estimate the attitude orientation by using a two-step method. The initial step is to estimate the current vehicle estimation state based on prior state information and angular rates from the IMU's gyroscope. The Kalman filter gain is then computed using the attitude estimation provided by the accelerometer data from the IMU to update the estimation states[8].

Several algorithms are established for increasing the adaptability of the Kalman filter by adapting the process and measurement noise covariance matrices to provide an acceptable solution for the model-based estimation problems. Adaptive techniques are often established by adapting the Kalman gain by accurately tuning the covariance matrix of process noise or the covariance matrix of measurement noise, or by tuning both matrices together[9].

An adaptive Kalman filter is developed in this research to correct for the vehicle's external acceleration. The presented scheme is designed to accurately estimate the vehicle's external acceleration. Then, compensating the effect on the obtained accelerometer measurements will directly enhance the tilt-angles estimation based on the measurements of an accelerometer in the presence of high dynamics. The primary goal of the flight test is to validate the proposed algorithm. The flight trajectory starts with 3 circle spirals at a height of 120m, then go up for a straight track at a height of 550m makes a U-turn, go down to a height of 100m, and makes a multi extensive circle spirals. The total flight test makes about one-hour Simulations are performed to evaluate the algorithm's accuracy in calculating the angles of attitude and vehicle external acceleration across a highly dynamic situation.

2. Attitude Algorithm

Any device in navigation must know its initial attitude before entering operational mode. The accelerometer is employed to solve the leveling issue, whereas the gyro is used to compute the azimuth. The accelerometer and gyro give components of the gravity and earth's rotation rate to be eliminated denoted by f^b and ω^b respectively.

$$f^b = R_l^b f^l = R_l^b \begin{bmatrix} 0 & 0 & -g \end{bmatrix}^T \tag{1}$$

Where g is the gravity magnitude.

$$R_b^l = \begin{bmatrix} \cos\psi\cos\theta & \cos\psi\sin\theta\sin\varphi - \sin\psi\cos\varphi & \cos\psi\sin\theta\cos\varphi + \sin\psi\sin\varphi \\ \sin\psi\cos\theta & \sin\psi\sin\theta\sin\varphi + \cos\psi\cos\varphi & \sin\psi\sin\theta\cos\varphi - \cos\psi\sin\varphi \\ -\sin\theta & \cos\theta\sin\varphi & \cos\theta\cos\varphi \end{bmatrix} \tag{2}$$

Where ψ (Yaw), θ (Pitch), and φ (Roll) are the angles of rotation about Z, Y, and X axes, respectively

$$\begin{bmatrix} f_x \\ f_y \\ f_z \end{bmatrix} = \begin{bmatrix} g\sin\theta \\ -g\sin\phi\cos\theta \\ -g\cos\phi\cos\theta \end{bmatrix} \tag{3}$$

From (3) pitch and roll, angles can be obtained by

$$\theta = \tan^{-1}\left(\frac{f_x}{\sqrt{f_y^2 + f_z^2}}\right) \tag{4}$$

$$\phi = \tan^{-1}\left(\frac{f_y}{f_z}\right) \tag{5}$$

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The commercial IMU can't sense the earth's rate which makes the yaw angle to be neglected. So, the heading angle can be computed from gyrocompass.

The sensor measurements always lie on the body coordinate system which necessitates a transformation matrix to the local level frame where navigation states are calculated as

$$X^l = R_b^l X^b \tag{6}$$

Where X^l a vector is expressed in the local frame, R_b^l is the matrix of rotation from the body frame concerning the local frame, and X^b is a vector exhibited in the body frame.

At the rotation matrix, the last row is independent of the yaw angle and is dependent on the roll and pitch angles, so it is accessible via:

$$\phi = \tan^{-1}\left(\frac{R_b^l(3,2)}{R_b^l(3,3)}\right) \tag{7}$$

$$\theta = \tan^{-1}\left(\frac{-R_b^l(3,1)}{R_b^l(3,2)/\sin\phi}\right) \tag{8}$$

3. Adaptive Kalman Filter Algorithm

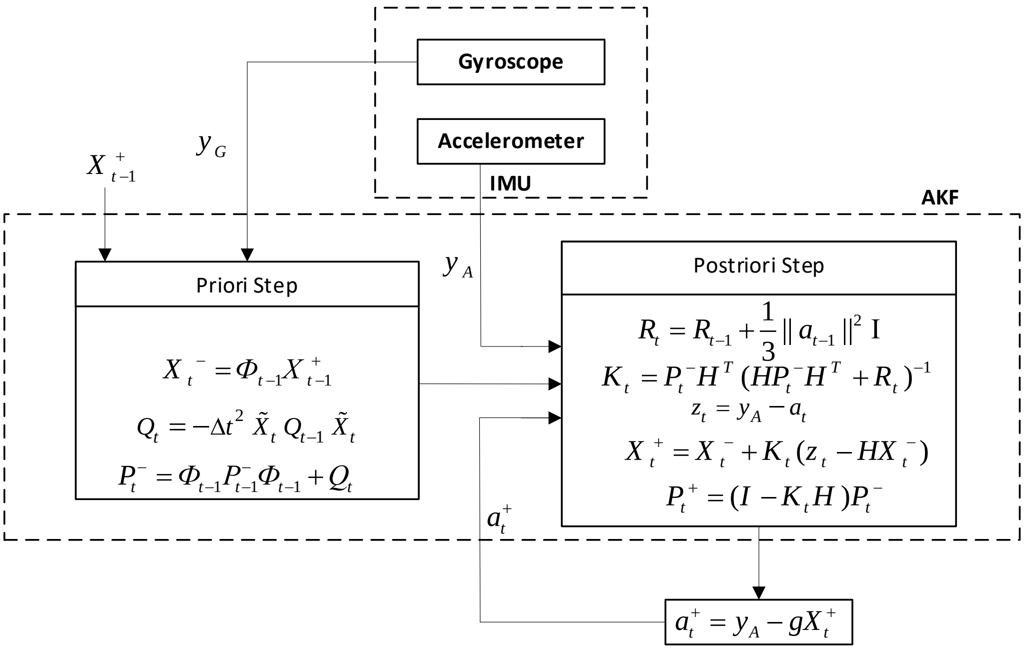

Figure 1. Adaptive Kalman Filter Architecture

In this Algorithm, the gyro's and accelerometer's data are fused into the Kalman filter to estimate the gravity vector in the body frame[10], as shown in Figure 1

Where X_t is the vector state of the last row of the transformation matrix, Φ_t is the transition matrix of state, P_t is the covariance matrix system, Q_t the covariance matrix noise of the model, and R_t is the covariance matrix noise of the measurement.

$$\Phi_t = \mathrm{I} - \Delta t \tilde{y}_G \tag{9}$$

Where $\tilde{y}_G$ the skew-symmetric of Gyro's output, Δt is the timing sample, and I is the identity Matrix.

$$H = g\mathrm{I} \tag{10}$$

Where H is the matrix observation of design and g is the gravity.

$$z_t = y_A - a_t \tag{11}$$

Where y_A is the accelerometer's data and a_t is the external acceleration of the accelerometer.

The model noise covariance matrix Q_t in reality affected by the gyro's disturbance noise due to its drift over time and the measurement noise covariance matrix R_t is always affected by the accelerometer's error due to linear acceleration. The disturbance error can be minimized by modifying the model and measurement noise covariance, preventing the KF from degrading and diverging as in equations 12,13, and 14 based on the work presented in[11].

$$Q_t = -\Delta t^2\, \tilde{X}_{t-1}\, Q_{t-1}\, \tilde{X}_{t-1} \tag{12}$$

$$R_t = R_{t-1} + \frac{1}{3} \| a_{t-1} \|^2\, \mathrm{I} \tag{13}$$

$$a_t^+ = y_A - g\mathrm{X}_t^+ \tag{14}$$

4. Results

To evaluate the proposed algorithm, offline data is utilized. The data is collected from Unmanned Arial Vehicle (UAV) attached to a high-performance Autopilot Pixhawk to be compared [12]. Pixhawk includes MEMS-based IMU sensor model MPU6000 and compass which is attached to 32-bit ARM Cortex M4. Pixhawk includes the embedded Kalman filter for updating position, velocity, and orientations [13]. The reference angles in the result are the output of the embedded Kalman filter that is compared to the proposed algorithm. estimation of tilt angles (roll and pitch) using the gyros measurements based on the direct integration process of angular measurements but it suffers from drift which leads to rapid degradation for the tilt angles estimation as shown in Figure 2 and Figure 3 for pitch and roll angles respectively.

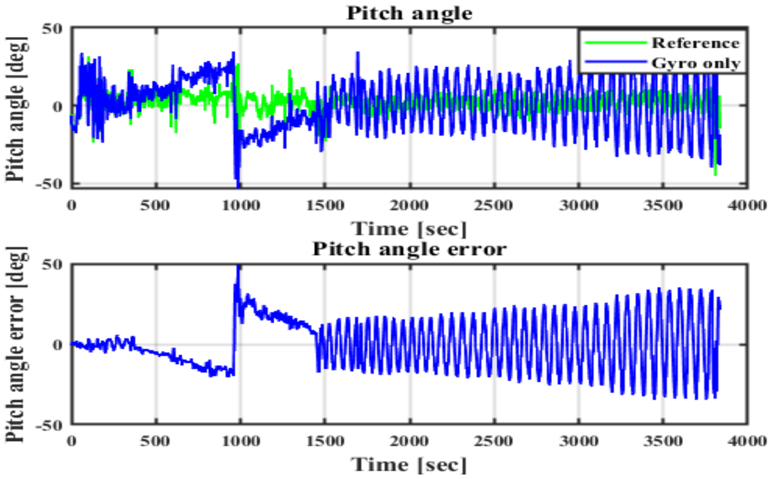

Figure 2. Pitch angle from Gyro only.

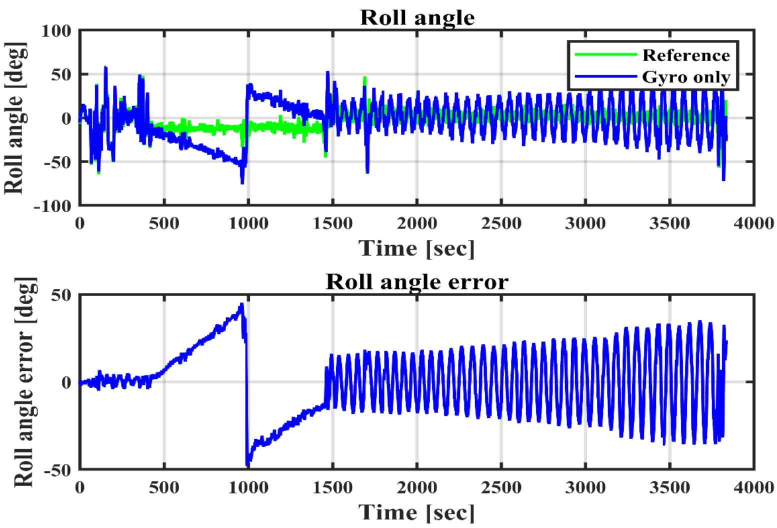

Figure 3. Roll angle from Gyro only.

The estimation of tilt angles using the accelerometer provides an absolute solution without drift with time but, the accuracy of estimates always degraded due to external acceleration particularly with high dynamics as shown in Figure 4 and Figure 5 for pitch and roll angles respectively. Meanwhile, the estimation of tilt angles using the individual measurements of the gyro or accelerometer is not an efficient solution for the applications of UAVs.

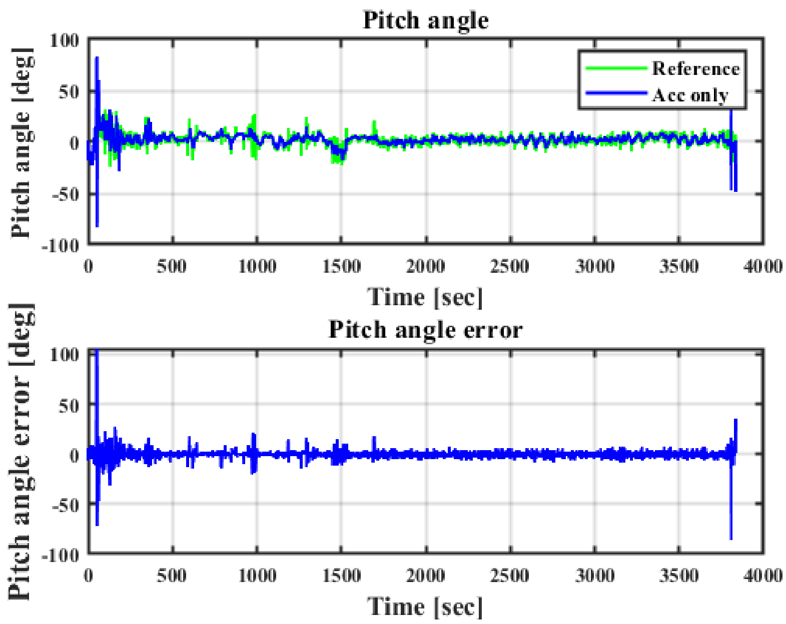

Figure 4. Pitch angle from accelerometer only.

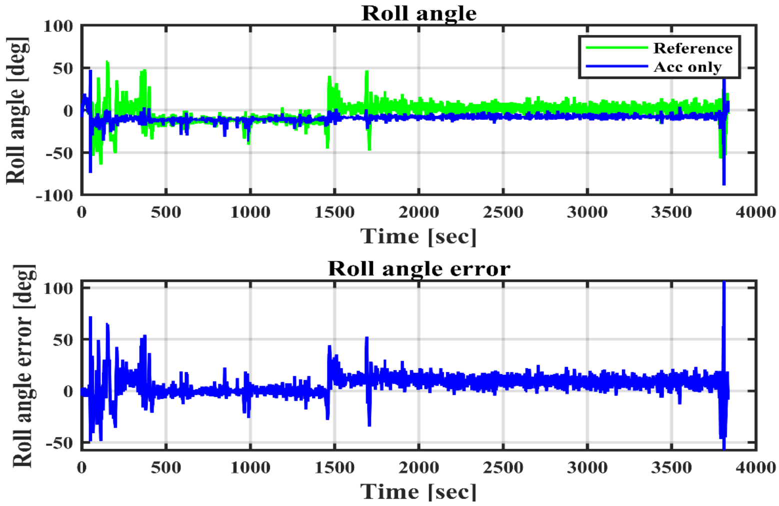

Figure 5. Roll angle from accelerometer only.

The proposed solution for the problem of tilt angles estimation involves the fusion of the accelerometer and gyroscope measurements using (AKF) for estimating the external acceleration. The normal Kalman filter cannot estimate the tilt angles accurately due to the covariance matrix of the model and the covariance matrix of the measurement being constant as presented in the previous section. A comparative analysis is carried out for evaluating the proposed algorithm. The proposed algorithm is compared with the imufilter from Sensor Fusion and Tracking Toolbox from Matlab and the original KF algorithm. The imufilter results demonstrated the efficiency of the proposed algorithm especially, during the high dynamics although, the KF presented divergence and lower efficiency as shown in Figure 6 and Figure 9. A zoom is applied for the first 400 seconds as shown in Figure 8 and Figure 11. The error is presented as shown in Figure 7 and Figure 10.

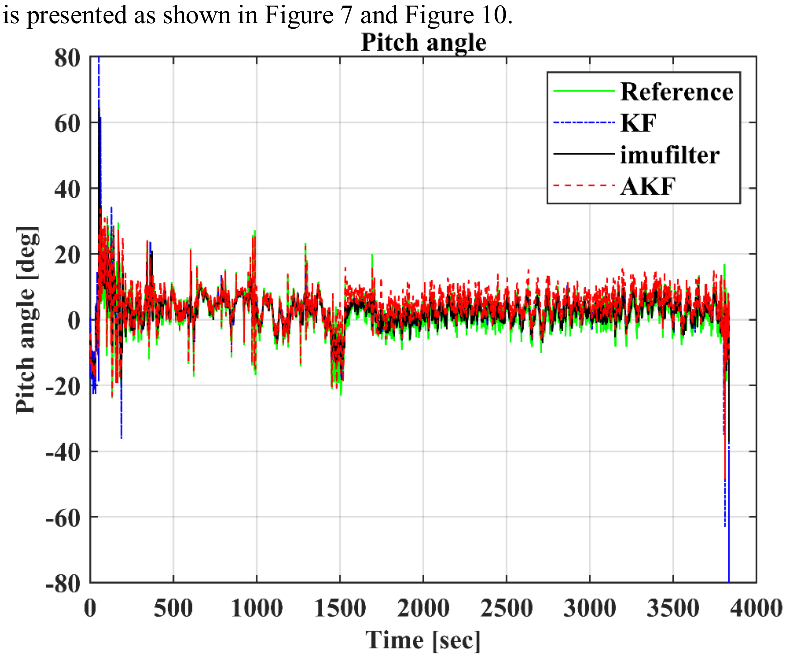

Figure 6. Pitch angle reference, KF, imufilter, and AKF.

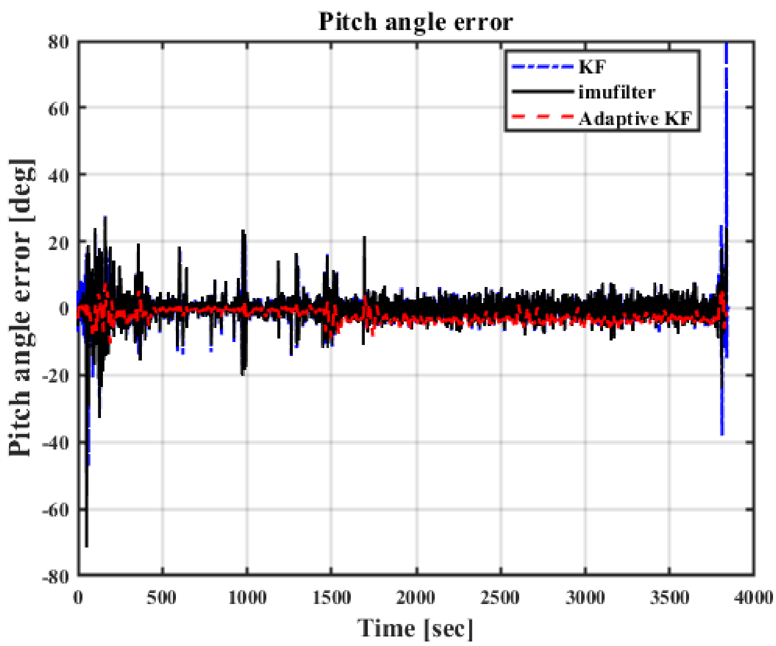

Figure 7. Pitch angle error.

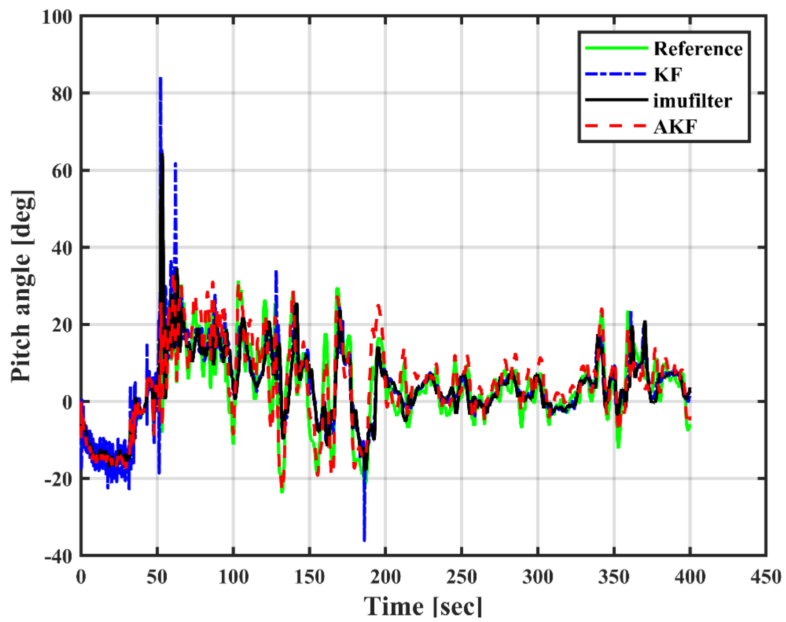

Figure 8. Pitch angle reference, KF, imufilter, and AKF zoom to 400 sec.

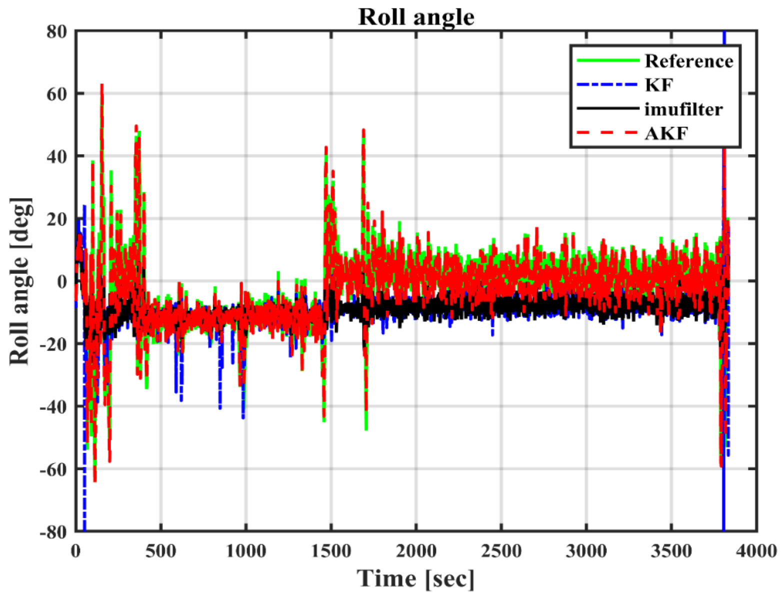

Figure 9. Roll angle reference, KF, imufilter, and AKF.

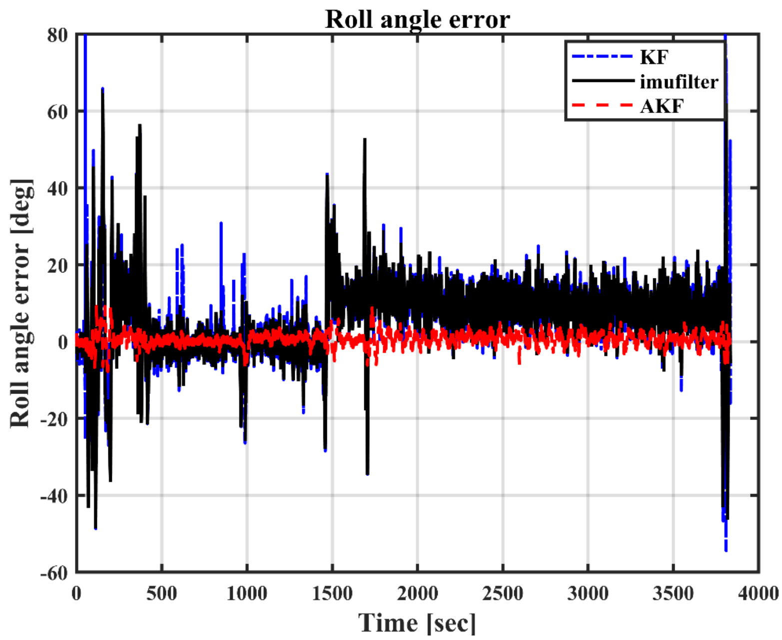

Figure 10. Roll angle error.

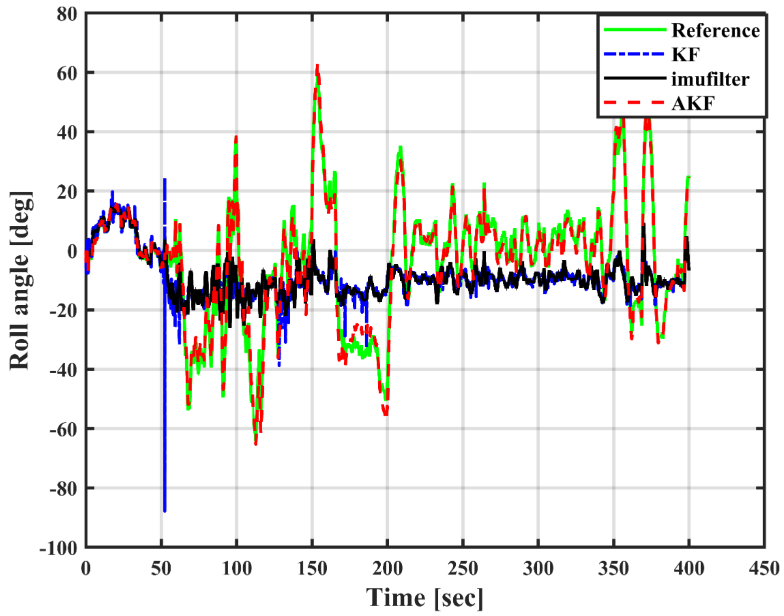

Figure 11. Roll angle reference, KF, imufilter, and AKF zoom to 400 sec.

To evaluate the proposed algorithm's efficiency, a comparative analysis based on statistical results is carried out with the KF and imufilter. The statistical analysis evaluation criteria are the root mean square error (RMSE), maximum errors, and finally, the standard deviation for the calculated error as shown for the pitch channel in Figure 12 and roll channel in Figure 13 respectively.

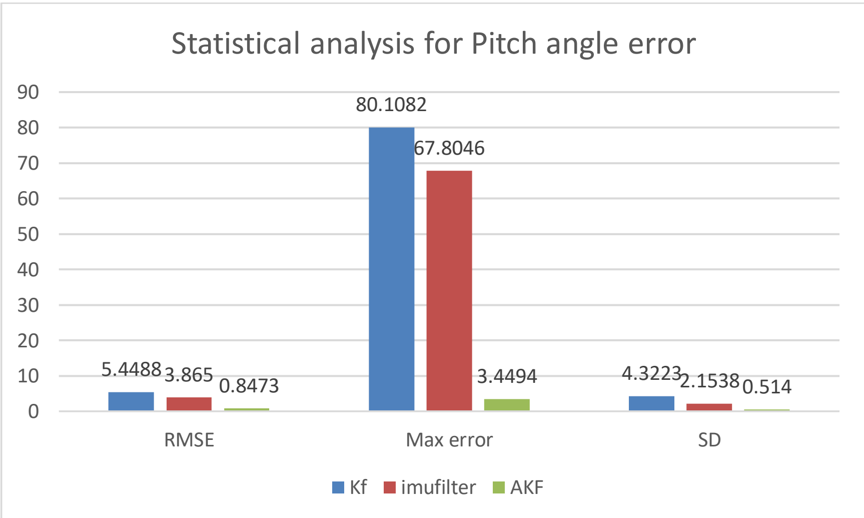

Figure 12. Comparative statistical analysis for pitch angle error.

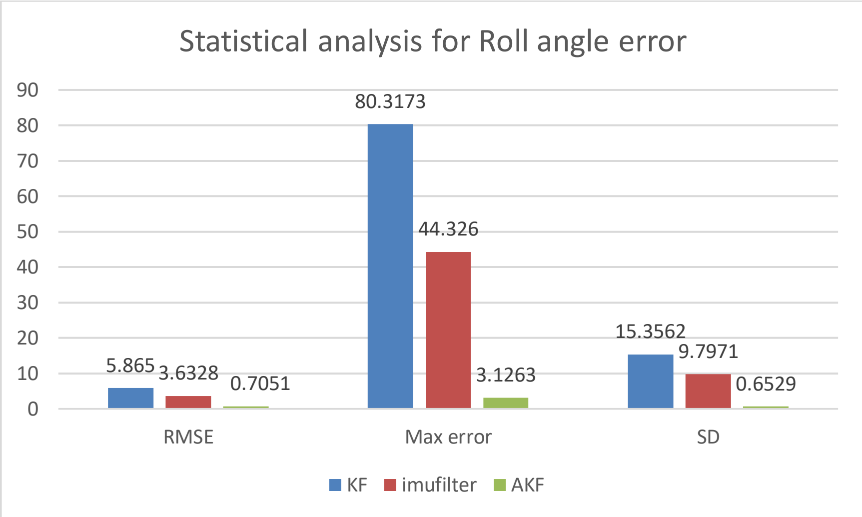

Figure 13. Comparative statistical analysis for Roll angle error.

5. Conclusion

The roll and pitch angles can be calculated from gyroscope or accelerometer. An AKF algorithm for tilt angles estimation is applied in this paper. The proposed algorithm is based on adapting the measurement covariance noise matrix R_t, to give an accurate estimation. This algorithm is tested under dynamic status to present the estimation performance with the original KF and with an imufilter from Sensor Fusion and Tracking Toolbox from Matlab to show the accuracy of the proposed algorithm.

The RMSE in pitch angle is 0.8473 deg for the proposed algorithm, RMSE is 5.4488 deg for the KF and the RMSE is 3.865 deg for the imufilter. Further, the roll angle is 0.7051 deg for the proposed algorithm, RMSE is 5.865 deg for the KF, and the RMSE is 3.6328 deg for the imufilter.

Finally, the proposed algorithm provides high accuracy of the tilt angles estimation comparable with the original (KF) and with an imufilter from Sensor Fusion and Tracking Toolbox from Matlab at the high dynamic with the presence of external acceleration. The work presented in this paper can be extended by using adaptive nonlinear filtering techniques to provide an efficient solution for advanced estimation problems.

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