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Critical Analysis of Filtering Methods for IMU

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ABSTRACT: The Objective of this work is to investigate real time measurement of accelerometer and gyroscope parameters using MEMS based inertial measurement unit (IMU). The Errors caused by external accelerations influence the Accelerometer. That makes accelerometers unreliable and inaccurate. Similarly Gyroscopes also have offset due to their disturbances. This project presents a consolidated and exhaustive study of complementary and Kalman filter for acceleration due to gravity measurement using inertial measurement unit. The complementary filter algorithm uses low-pass filter and high-pass filter to deal with the data from accelerometer and gyroscope while Kalman filter takes the tilting angle and gyroscope bias as system states. The results showed that both Complementary and Kalman filter are less sensitive to parameter variations.

KEYWORDS: Consolidated, Exhaustive, Inertial Measurement Unit, Gyroscope, Accelerometer, Filter

I. INTRODUCTION

IMU is an electronic device that measures accelerations, rotation rates and possibly earth magnetic field with the use of tri-axis accelerometer, tri axis gyroscope [1], MEMS (Micro-Electro-Mechanical-system) based IMU, the size of IMU is dramatically reduced to chip size along with the reduction in cost and power consumption [2]. Such a leap in IMU significantly accelerated many research and development work. One of the applications of MEMS IMU is orientation sensing, which has a significant role in different fields. In 2013, M. Pedley documented the mathematics of orientation using a MEMS three-axis accelerometer and also made an analysis on the regions of instability (gimbal lock) [6]. As the data from the accelerometer is in general very noisy and susceptible to external acceleration interference, when it is used to measure the gravitational acceleration, it is hard to obtain accurate result in vibrating environment such as in a car or an airplane.

The measurement only using accelerometer is not effective enough to get accurate data although the accelerometer data is stable and without drift in long term. But the gyroscope offers angular velocities and the signals are not vulnerable to external forces comparing to accelerometers. Therefore, a tri-axis gyroscope and a tri-axis accelerometer. The gyroscope also has its own disadvantages i.e. drift. by considering the advantages and disadvantages of gyroscopes and accelerometers, the IMU data fusion is an essential for a reliable sensors especially for real time applications. In terms of IMU data fusion algorithm, the complementary filter [6]-[10] and Kalman filter [10]-[14] are mostly used. Kalman filter is an iterative filter, which is efficient but high computational complexity. The complementary filter uses relative easy algorithm, which only requires light computation and easy to implement. This paper presents comparison of complementary and Kalman filter in IMU error dynamics. A comparison was made on the experiment results obtained. From the results there is a small difference between these two filters. However, complementary filter gives better result

II. GYROSCOPES

A gyroscope is an instrument, consisting of a wheel mounted into two or three gimbals providing pivoted supports, for allowing the wheel to rotate about a single axis. A set of three gimbals, one mounted on the other with orthogonal pivot axes, may be used to allow a wheel mounted on the innermost gimbals to have an orientation remaining independent of the orientation, in space, of its support. Gyroscope is a device used for measuring or maintaining orientation and angular velocity. It is a spinning wheel or disc in which the axis of rotation (spin axis) is free to assume any orientation by itself. When rotating, the orientation of this axis is unaffected by tilting or rotation of the mounting, according to the conservation of angular momentum Gyroscopes can be used to construct gyrocompasses, which complement or replace magnetic compasses (in ships, aircraft and spacecraft, vehicles in general), to assist in stability (bicycles, motorcycles,



and ships) or be used as part of an inertial guidance system .The MEMS gyroscopes are popular in some consumer electronics, such as smartphones.

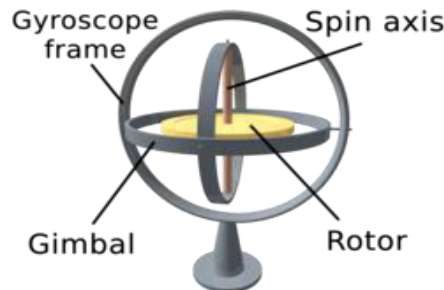


Figure (1) . Representation of 3 axis Gyroscope .

III. ACCELEROMETER

Accelerometer is a tool that measures proper acceleration. The acceleration of a body in its own instantaneous rest frame is different from coordinate acceleration, which is in a fixed coordinate system. For example, an accelerometer at rest on the surface of the Earth will measure an acceleration due to Earth's gravity, straight upwards (by definition) of acceleration due to gravity , $g \approx 9.81 \text{ m/s}^2$. Accelerometers in free fall (falling toward the center of the Earth at a rate of about 9.81 m/s^2) will measure zero. An accelerometer at rest relative to the Earth's surface will indicate approximately one. The acceleration due to gravity upwards because the Earth's surface exerts a normal force upwards relative to the local inertial frame. To obtain the acceleration due to motion with respect to the Earth, this "gravity offset" must be subtracted and corrections made for effects caused by the Earth's rotation relative to the inertial frame .which is represented by figure (2)

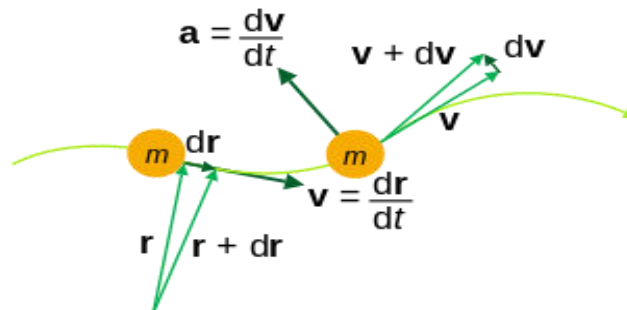


Figure (2).Kinematic quantities of a classical particle: mass m, position r, velocity v, acceleration.

In static conditions if you want to find pitch/roll the following are needed

- 1) X-axis reading
- 2) Y-axis reading
- 3) Z-axis reading

$$\text{Pitch} = \text{atan2}(\text{acc}_x, \sqrt{\text{acc}_y^2 + \text{acc}_z^2}) \quad (1)$$

$$\text{Roll} = \text{atan2}(\text{acc}_y, \sqrt{\text{acc}_x^2 + \text{acc}_z^2}) \quad (2)$$

Depending on how orientation of sensor might have to switch X and Y values .

IV. COMPLEMENTARY FILTER

The complementary filter is a computationally inexpensive sensor fusion technique that consists of a low-pass and a high-pass filter .TheIdea behind complementary filter is to take slow moving signals from accelerometer and fast moving signals from a gyroscope and combine them. Accelerometer gives a good indicator of orientation in static conditions.Gyroscope gives a good indicator of tilt in dynamic conditions .So the idea is to pass the accelerometer signals through a low-pass filter and the gyroscope signals through a high-pass filter and combine them to give the final rate.

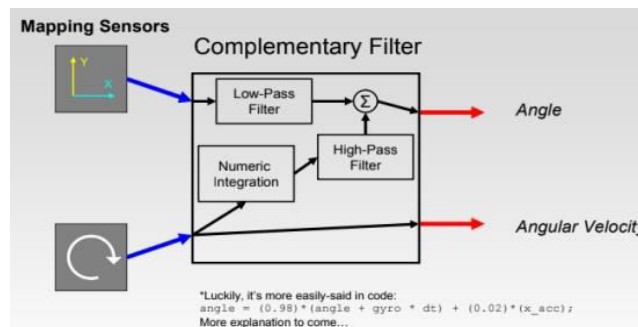


Figure (3) . Complementary filter with low pass,high pass and numeric integration.

The key-point here is that the frequency response of the low-pass and high-pass filters add up to 1 at all frequencies .This means that at any given time the complete signal is subject to either low pass or high pass.

Equation for low-pass filter

$$y[n]=(1 - \alpha) * X[n] + \alpha * [n - 1](3)$$

for angles obtained from accelerometers

where x[n] is the pitch/roll/yaw that you get from the accelerometer and y[n] is the filtered final pitch/roll/yaw which you must feed into the next phase

the Equation for high-pass filter is as follows

$$y[n] = (1 - \alpha) * y[n - 1] + (1 - \alpha) * (X[n] - X[n - 1])(4)$$

For angles obtained from gyroscopes

Where ,x[n] is the pitch/roll/yaw that you get from the gyroscope, y[n] is the filtered final pitch/roll/yaw which you must feed into the next phase of your program.

The transfer function for the input passing through the low pass filter= $1 / (1+Ts)$, The transfer function for the input passing through the high pass filter= $Ts / (1+T s)$

$$\text{Total angle} = \alpha_1 + T s + [Ts / (1+T s)] * s * \beta$$

The total gain of the two filter is 1

Gain₁(s) + Gain₂(s) = 1 ,Here, α = accelerometer data input β/s = calculated angle

From gyroscope passing through an integrator $T = \text{filter cutoff frequency}$

V.KALMAN FILTER

The AHRS design here provides themeasurements for the low speed aircraft which is a dynamic system as the condition of aircraft changes simultaneously with respect to time. For a dynamic system by predicting the future value from the previous data the situation of the system can be guessed .For this type of system which are continuously changing theKalman filter is the perfect to make an educated guess of what happened. As this filter predict future from previous data so some initial value is considered in the beginning. The representation of Kalman filter is follows.

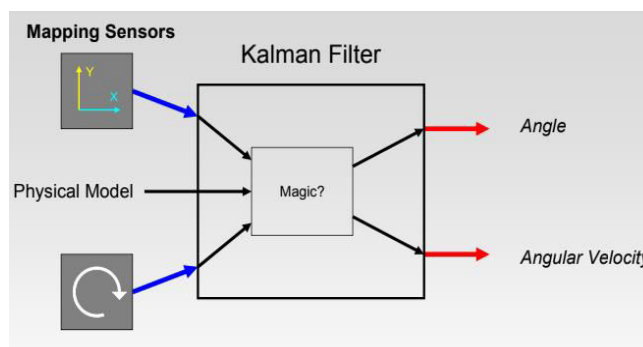


Figure (4) . Representation of Kalman filters with angles.



VI. COMPARISON OF COMPLIMENTARY FILTER AND KALMAN FILTER

A simple estimation technique that is often used in the flight control industry to combine measurements is the complementary filter. This filter is actually a steady state Kalman filter (i.e., a Wiener filter) for a certain class of filtering problems. This relationship does not appear to be well known by many practitioners of either complementary or Kalman filtering. One exception is the tutorial which discusses this relationship without going into the mathematical details. The complementary filter users do not consider any statistical description for the noise corrupting the signals, and their filter is obtained by a simple analysis in the frequency domain. The proponents of the Kalman filtering approach work in the time domain and do not pay much attention to the transfer function or frequency domain (Wiener filter) approach to the filtering problem, since it is a less general approach to the filtering problem. The Wiener filter solution to this class of multiple-input estimation problems appeared in the literature the review of complementary filtering and shows how this technique is related to Kalman and Wiener filtering. Since both Kalman and complementary filtering are under consideration for use in the Space Shuttle Reentry and Landing Navigation System, the relationship between them should be well understood.

VII. SIMULATION RESULTS

To compare the estimation accuracy of both the filters, simulation is carried out for a common input to both filters. The characteristics of the gyroscope are set to resemble that of a practical gyroscope by introducing some errors of a practical sensor. Also, the input is applied to the filters by introducing some practical errors and noise as well. The specification of gyroscope and accelerometer used for the simulation is as follows. These specifications are chosen to resemble the characteristics of practical sensors. The input given to these sensors is varied in all the three-perpendicular axis. For analyzing the filters for inertial measurement unit a sample input is given to the sensors. The sample contains movements in the following order

1. A movement of 30 degrees in the direction of x axis and back to the 0 degrees
2. A movement of 55 degrees in the direction of y axis and back to the 0 degrees
3. A movement of 115 degrees in the direction of z axis and back to the 0 degrees

All these movements are again brought back to the zero point after some time with a gradual movement. Now these movements in the form of quaternions are given as an ideal input to the IMU by using another mat file function in which the data related to the movement is stored.

Also some noise is introduced into the system to resemble the practical system and its specification are

Gyroscope Noise = 7.6154×10^{-7}

Accelerometer Noise = 0.0015398

Gyroscope Drift Noise = 3.0462×10^{-12}

Linear Acceleration Noise = 0.00096236

Simulation is done with a frequency of 100 Hz and over a sample rate of 1100 samples.

Table 1. Specifications of Gyroscope and Accelerometer

Sensor specification	Value	Units
Gyroscope		
Angular rate	+/-125 to +/- 2000	°/s
Resolution	0.0625	°/s / LSB
Output noise	0.1	°/s
Offset bias	+/- 1	°/s
Temperature drift	+/- 0.015	°/s / K
Voltage drift	0.1	°/s / V



Accelerometer		
Acceleration range	+/- 2 to +/- 16	g
Resolution	1	mg / LSB
Offset bias	+/- 80	mg
Output noise density	150	$\mu\text{g} / \sqrt{\text{Hz}}$
Temperature drift	+/- 1	mg / K
Voltage drift	1.5	mg / V

VIII. RESULTS

The graphs represent the actual input to the sensors and estimated orientation by using the different filters

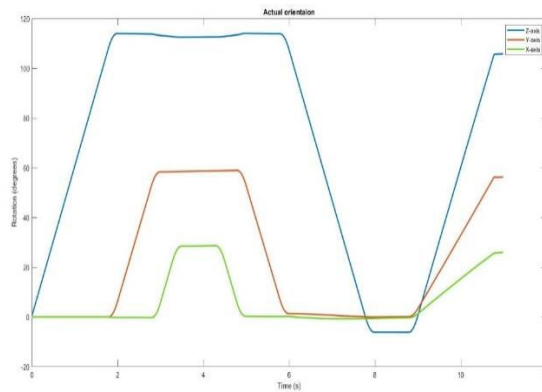


Figure (5) :Actual input w.r.t to the angular moment

1st graph shows the actual input given to the sensor with the corresponding angular movements as previously mentioned

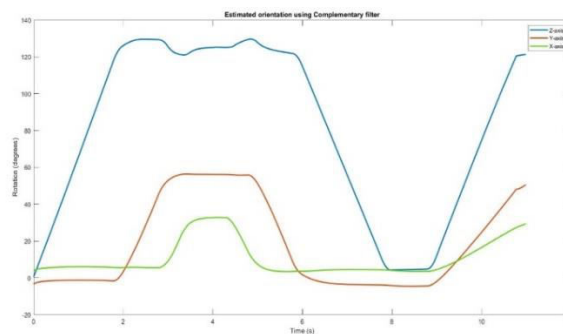


Figure (6) :Orientation estimated using the complementary filter

The 2nd graph shows the orientation estimated using the complementary filter

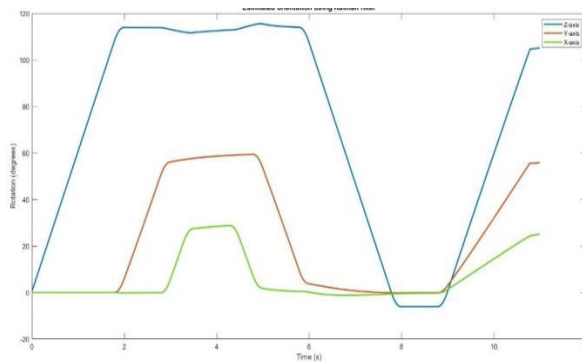


Figure (7) : Orientation estimated using the Kalman filter

The 3rd graph shows the orientation estimated using the Kalman filter

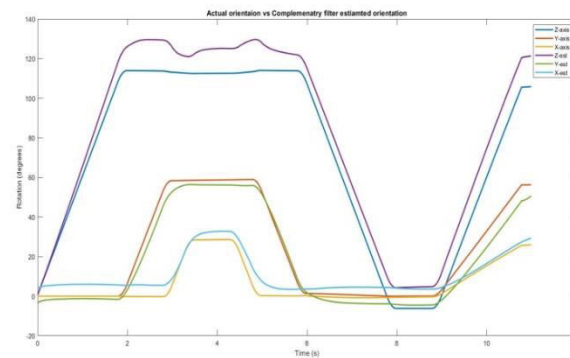


Figure (8) :Comparison between the actual input and the estimated orientation using a complementary filter

The 4th graph shows the comparison between the actual input and the estimated orientation using a complementary filter. From the comparison it is clear that a complementary filter is able to estimate the orientation with less accuracy. Although a complementary filter is computationally less expensive, its accuracy is low when disturbances are introduced into the system. Its accuracy is reasonable under the absence of disturbances.

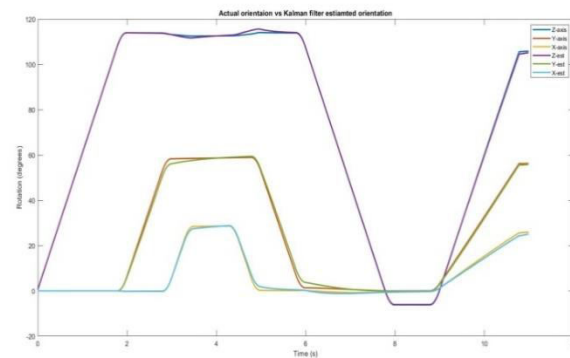


Figure (9) : Orientation estimated using the Kalman filter

5th graph shows the comparison between actual input and estimated orientation using Kalman filter. From the graphs we can conclude that a Kalman filter is highly accurate even in the presence of disturbances. Although Kalman filter is computationally complex, it is able to estimate the orientation with high accuracy with only an error of about 2 to 4 degrees at most.

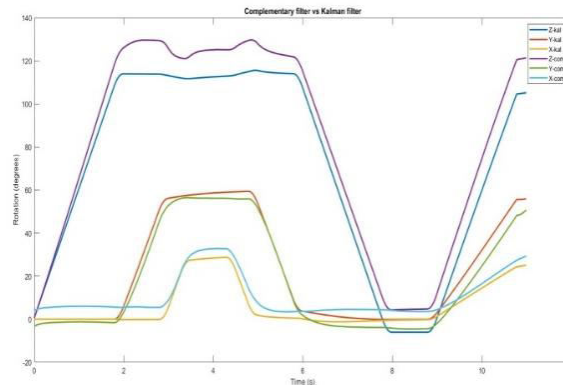


Figure (10) : Shows the comparison of estimated orientation using each filter

The 6th graph shows the comparison of estimated orientation using each filter. From the graph we can conclude that a Kalman filter is more accurate than a complementary filter and the error between the two filters is more 15 degrees which is considerable in an application which requires high accuracy.

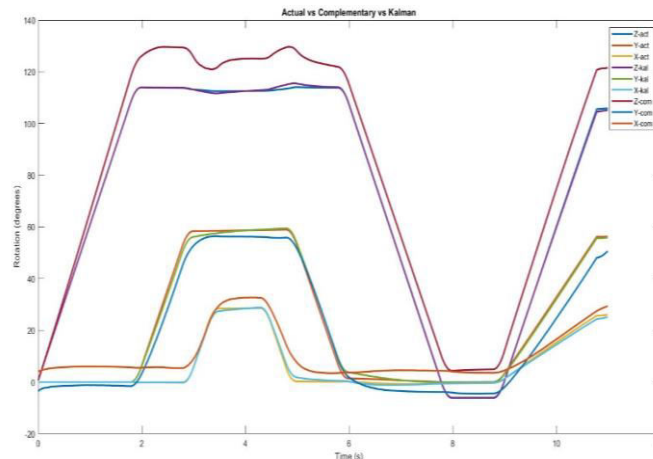


Figure (11) : Actual orientation against estimated orientation using complementary filter and Kalman filter

7th graph shows actual orientation against estimated orientation using complementary filter and Kalman filter. From here it is clear that Kalman filter is highly accurate and closely following the actual orientation whereas complementary filter is losing accuracy due to the disturbances.

VIII. CONCLUSION

Complementary filter is computationally simple and can be used in application where external disturbances are low and which requires less accuracy whereas Kalman filter is computationally expensive and can be used even when there are large disturbances and in applications which requires high accuracy.

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