Statistical scheme for fault detection using Arduino and MPU 6050

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***Abstract*—Unmanned Aerial Vehicles (UAVs) are widely used for various civilian, security and military applications. UAVs are equipped with a number of sensors such as accelerometers and gyroscopes, the measured data reliability of these sensors is critical and data obtained from these sensors must be accurate. Sometimes, sensors are prone to damage because of various electric/communication problems. This paper proposes a statistical scheme for catering real-time experimental results of fault detection for inertial measurement unit sensors (accelerometer and gyroscope) by using statistical analysis measures. The objective is to detect sensor bias fault, total sensor failure and drift or additive type fault in gyroscope and accelerometer measurements by processing their data via statistical measures. The scheme of processing the sensor data aims to suggest best statistical measures for fault detection in a multiple-sensor setting, after graphical signal analysis (comparison of the graphs of signal overture of all sensors) has been completed. This scheme can be helpful in diagnosis and subsequent isolation of sensors with fault in high-reliability applications where accuracy of data is critical.**

Keywords- Fault; Arduino; MPU 6050; variance; RMS; kurtosis

I. INTRODUCTION

Nowadays, sensors are playing key critical part for modern systems to furnish their maximum potential of economy and efficiency. However, sensor faults have continued to be one of the biggest impediment for systems in achieving efficacy of health management. The systems in modern times have turn out to be more dependable but sensors are still infamous for causing failures because of being prone to faults.

Fault detection is the process responsible for highlighting the existence of fault and approximating the frequency of repetition of it for a system. Fault isolation is the next step in line which detects the fault-prone components and the nature of fault associated with them. The next procedure is of fault identification which is delineated as the method of determination of the extent and the time variant response of the error. Most of the previous studies for detecting sensors errors used complicated techniques such as neural networks, fuzzy, and Kalman filters to enhance the accuracy of the detection. However, these techniques are not suitable for use in the sensor systems equipped with low performance microprocessors.

Bansal [1] discusses the distinction between system and sensor faults; the experimental setup uses electro-mechanical actuator for collection of sensor data. Common sensor faults were injected for evaluation of experimental results. Avram [2] considers fault detection, with focus on sensor bias fault, using a sliding mode observer method to obtain data value through which a diagnostic algorithm is created. Oh [3] discusses a simple sensor fault detection algorithm in a multiple sensor

978-1-7281-0860-5/19/$31.00 ©2019 IEEE

setting in which comparison of individual sensor values is made against a set threshold. Xu [4] discusses an FDI approach based on inter observer-based method. The paper discusses independent components of residuals being defined to ensure corresponding fault sensor fault relation. Further, it is proposed to conduct research on mathematical methodology for FDI underpinning the discussed method. Marzat [5] discusses in the review article about various methods and filters basing his work on model based fault diagnosis. Various advantages and disadvantages have been discussed of assorted methods. Preference of residual generation and parameter estimation approaches of model based methodology for appropriate applications have also been discussed. [6][7] describe a pool of estimators that have been implemented which make use of information redundancy. This is considered as complementary behavior of sensors for detection of faults in an IMU setting. Residuals are computed as the difference of the observed and expected results. Heredia [8] describes a structure for sensor and actuator fault detection in autonomous helicopters of small size. The detection of the actuator fault has been achieved for stuck actuator type fault. Avrutov [9] discusses scalar method for fault analysis of the inertial measurement unit (IMU). This method is based on quality monitoring and diagnostics. Xu [10] proposes a sensor fault detection and diagnosis (FDD) method to cater linear state-space models when outliers are present. Using this approach the cause of fault is approached by observing the variations on measured unwanted noise covariance.

The proposed scheme in this paper uses statistical measures for fault detection in a multiple-sensor setting, after receiving, comparing and analyzing the graphical results of the sensor values. This technique can be helpful in critical applications where accuracy of data is of high value.

II. Components

A. Arduino

Arduino is in use for constructing various types of electronic circuits by making use of a physical programmable circuit board with a microcontroller and a program code running on computer with a USB connection between the computer and Arduino device. In this project Arduino Uno R3 has been used. Arduino Uno is considered as start-point board for electronics and coding as it has a robust nature.

B. MPU 6050

MPU6050 sensor module is a complete 6-axis 'Motion Tracking Device'. It has 3-axis gyroscope, 3-axis accelerometer and 'Digital Motion Processor' combined in a small package. The sensor also boasts an additional feature of a Temperature sensor on-board. The module of MPU 6050 is shown in Fig. 1 with the input/output pins mentioned.

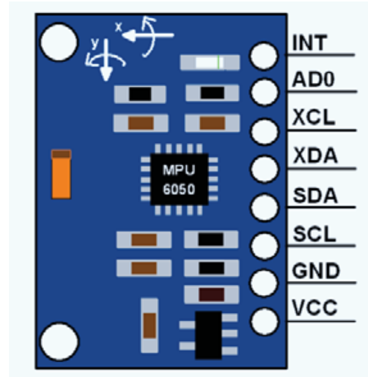

Figure 1: MPU 6050 Module

The MPU 6050 also consist of 3-axis Gyroscope based on Micro Electro Mechanical System (MEMS) technology. It detects rotational velocity along the X, Y, Z axes.

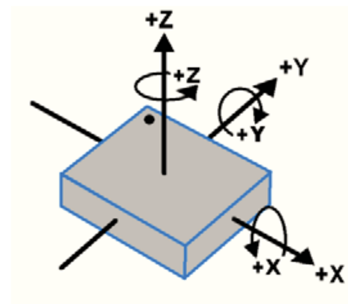

Figure 2. MPU 6050 Orientation and Polarity of Rotation

The MPU6050 also consists of 3-axis Accelerometer with MEMS technology. It detects angle of tilt or inclination along the three axes. The axes and polarities are shown in Fig. 2 for the accelerometer in MPU 6050.

The movable mass is deflected because of acceleration along the axis. This destabilizes the differential capacitor which generate a sensor output signal. Output amplitude is proportionate to acceleration.

The in-built Digital Motion Processor (DMP) is used for the computation of motion processing protocols. Data from gyroscope, accelerometer and other sensor for instance magnetometer is fed into it for processing. Data of angles of yaw, roll and pitch, and portrait sense etc. is received. Thus, effort of host in the computation of the motion data is minimized. The output data is read through the DMP registers.

Analog-to-Digital converter is used to digitize the output of the Temperature sensor, already built-in on the MPU 6050 board. The output data is read through the data registers of the sensor.

III. Experimental Setup

The experimental setup is presented in Fig. 3 and shows the bread-board with MPU 6050 sensors, Arduino device and the interface with the computer system:

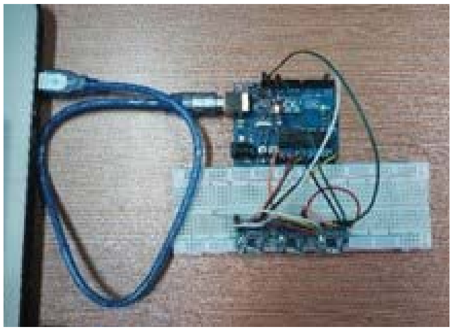

Figure 3. Component connections

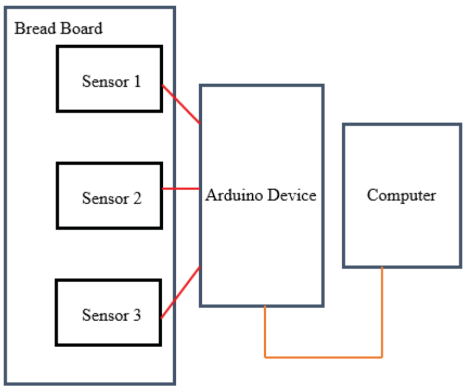

Figure 4. Block Diagram

Three IMU 6050 sensors are used in the experimentation of fault detection in the sensors. The sensors were fixed the on the bread board using the connecting wires for the electrical communication between the sensors and Arduino device. Different color wires facilitated the differentiation of the ports of the different sensors. Then the Arduino device was connected to the computer. At each instant of data collection, only one sensor was connected and the resultant values noted for a period of 20 seconds. Sensor 1 and sensor 2 were chosen to be the fault free sensors therefore, their values were noted only once and used in all successive calculations for comparison. Sensor 3 was chosen to be the faulty sensor and faults were injected successively to record readings for a period of 20 seconds. Output of all the sensors was displayed on the computer screen and comparison was plotted against sensor 1 and sensor 2 with sensor 3 in all fault types. Faulty sensors show different behavior than the other sensors from where we observed/ detect the fault. After that, the data collected from each sensor is used to calculate variance, RMS and kurtosis using MATLAB to establish statistical inference. A block diagram of the setup is presented in Fig. 4.

IV. Sensor Results

A. *Accelerometer Faults*

The faults for accelerometer are presented in Fig. 5. Fig. 5 (a) shows the result for total sensor failure where sensor 3 stops responding at t=11 sec. due to fault while other two sensors keep displaying values. Fig. 5 (b) displays the values for the three sensors where because of constant bias failure sensor 3 attains a constant value at t=11 sec. and display a 'stuck' value afterwards, while other two sensors kept responding accordingly. Fig. 5 (c) presents results for drift / additive type fault because of variation of temperature as sensor 3 shows a drift in values and the values keep moving away from the mean as a result of the injection of fault from t=11 sec.

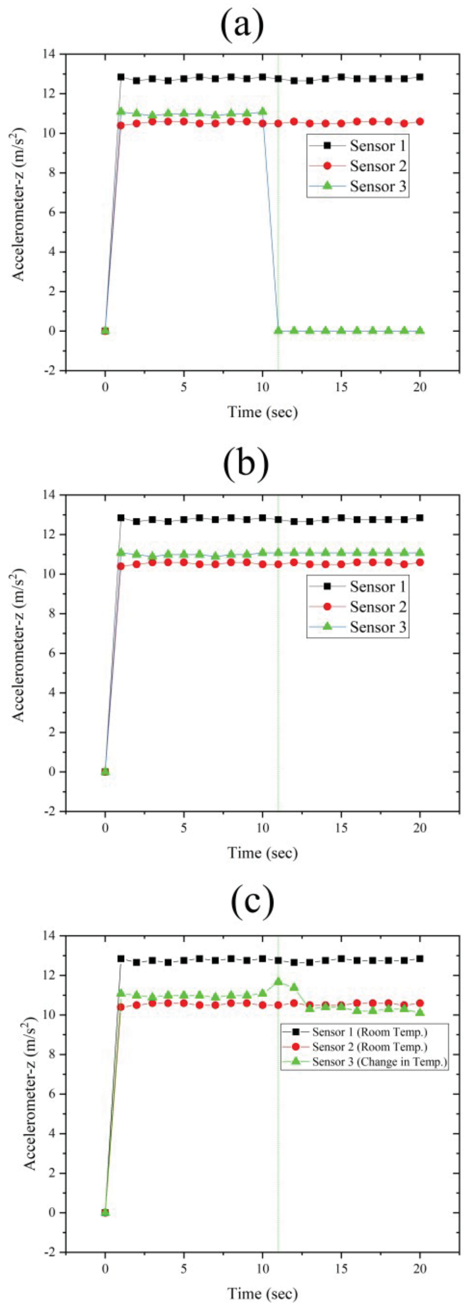

Figure 5: Accelerometer Faults: (a) Total Sensor Failure, (b) Constant Bias, (c) Drift Fault

B. Gyroscope Faults

The faults for gyroscope are presented in Fig. 6. Fig. 6 (a) shows the result for total sensor failure where sensor 3 shows a null value from t=11 sec. after injection of fault while other two sensors keep displaying varied results. Fig. 6 (b) display the values for constant bias fault where sensor 3 shows a constant value at t=11 sec. and furthermore, is stuck to this value till the end.

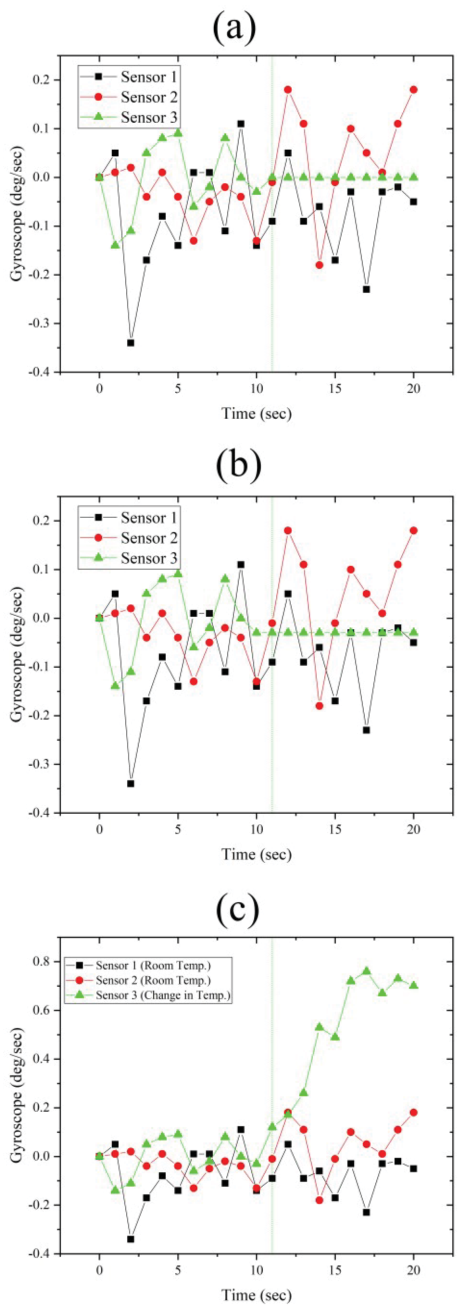

Figure 6: Gyroscope Faults: (a) Total Sensor Failure, (b) Constant Bias, (c) Drift Fault Failure

Other two sensors displayed varying results. Fig. 6 (c) presents results for drift / additive type fault because of variation of temperature as sensor 3 shows a diverging behavior from the mean value from t=11 sec. as fault is injected.

V. POST PROCESSING

A. Tools

The following statistical measures were used for analysis of the recorded values of the three sensors:

1) Variance: is a measurement of spread between values in a dataset. It measures how far values are from the mean in a dataset.

$$\sigma^2 = \frac{\sum_{k}^{n}\left(x_k - \overline{x}\right)^2}{n} \tag{1}$$

where $\overline{x}$ is the mean value of the signal.

2) RMS: The RMS (Root Mean Square) value of a set of data is the normalized, single value of the second statistical moment of the signal (standard deviation):

$$RMS = \sqrt{\frac{1}{n}\sum_{k}^{n}\left(x_k\right)^2} \tag{2}$$

3) Kurtosis: is the normalized fourth statistical moment of the signal.

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{k}^{n}\left(x_k - \overline{x}\right)^4}{\sigma^4} \tag{3}$$

This measure provides an estimate of the impulsive nature of the values of signal; indexing the signal to the 'fourth' power effectively magnifies the isolated peaks in the values of the signal. Higher kurtosis is the result of infrequent extreme deviations.

B. Analysis

The analysis of the statistical measures are presented next:

1) Accelerometer

a) Total Sensor Failure

VARIANCE

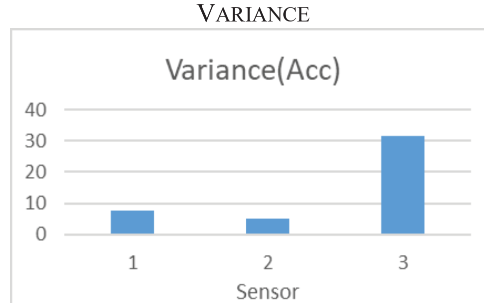

Figure 7: Variance of Sensors' Values

RMS

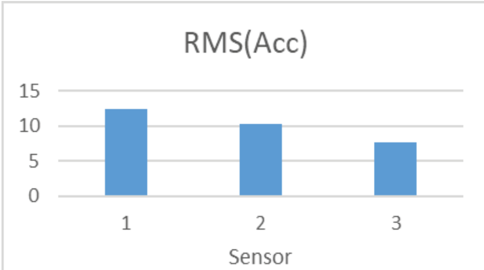

Figure 8: RMS of Sensors' Values

KURTOSIS

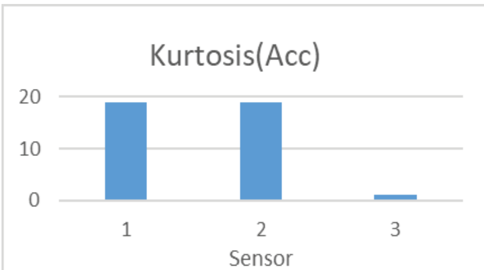

Figure 9: Kurtosis of Sensors' Value

The measure of Variance in Fig. 7 and Kurtosis in Fig. 9 are most affected by Total sensor failure and therefore, are suggested as better detector of this fault. The huge discrepancy in the data of sensor 3 augments a lot to the variance as the spread of values from the mean value is great. The very low value of Kurtosis is an indicator that shift of values to "0" renders the data values no more as 'infrequent deviation', rather deals with them as a continued trend afterwards.

b) Constant Bias

VARIANCE

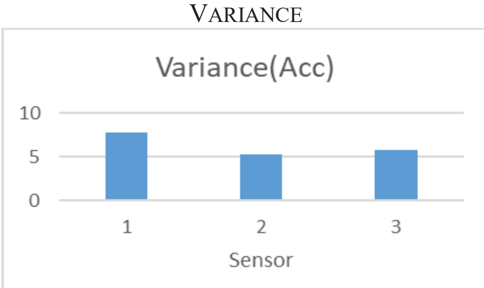

Figure 10: Variance of Sensors' Value

RMS

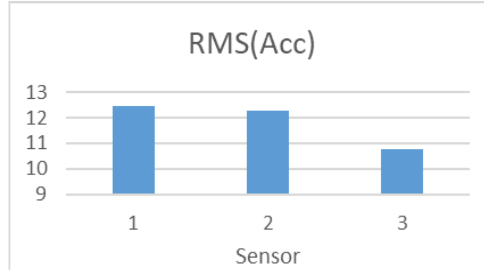

Figure 11: RMS of Sensors' Value

KURTOSIS

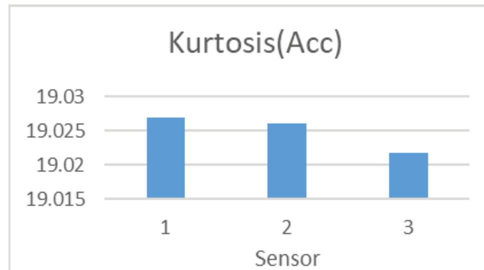

Figure 12: Kurtosis of Sensors' Value

RMS in Fig. 11 and kurtosis in Fig. 12 are better estimates of the constant bias fault as the low value of second statistical moment in comparison to sensor 1 and sensor 2 are evident as the values of sensor 3 being stuck. The kurtosis also highlights this with a low value in comparison to the other two sensors as the frequent trend of deviation is the usual case here hence, low value of kurtosis. The variance in Fig. 10 is still not a good detector as the mean value is close to the constant value therefore, deviations are not appreciable.

c) Drift/ Additive Type

VARIANCE

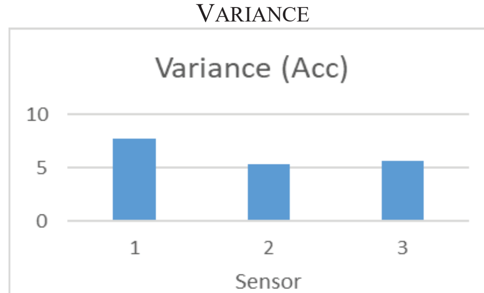

Figure 13: Variance of Sensors' Value

RMS

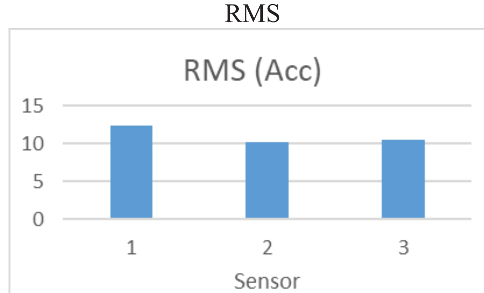

Figure 14: RMS of Sensors' Value

KURTOSIS

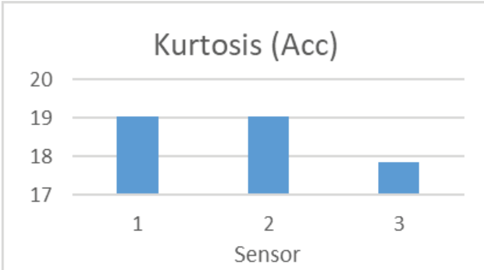

Figure 15: Kurtosis of Sensors' Value

Kurtosis in Fig. 15 is a better estimate of additive type fault as its value is most affected by the temperature change. Variance in Fig. 13 and RMS in Fig. 14 do not lead to conclusion as the deviations from mean value is present in all three sensors.

2) Gyroscope

a) Total sensor failure

VARIANCE

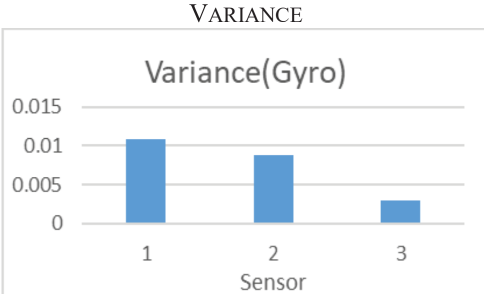

Figure 16: Variance of Sensors' Value

RMS

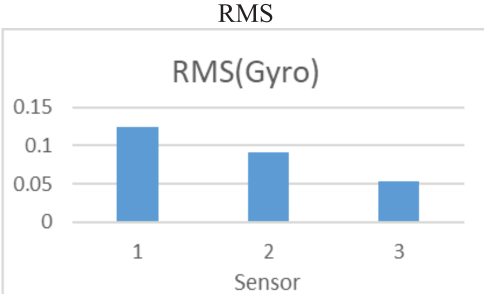

Figure 17: RMS of Sensors' Value

KURTOSIS

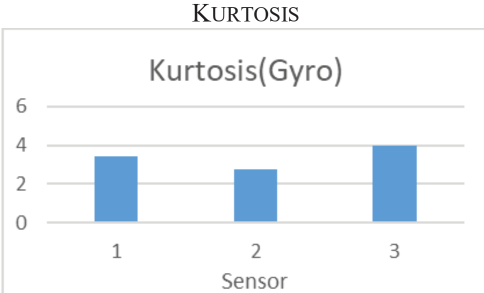

Figure 18: Kurtosis of Sensors' Value

The measure of variance in Fig. 16 is most affected by the total sensor failure with a minimum value being the representation. The gyroscopic data is fluctuating between either axes, therefore the values after failure are all very close to the mean and results in low value of variance unlike in sensor 1 and sensor 2. The values of RMS in Fig. 17 shows a similar trend but the difference of values of different sensors is not appreciable as the magnitude of values is very small. The values of Kurtosis in Fig. 18 are affected by infrequent deviations in all three sensors therefore, are not a good indicator of fault in this case.

b) Constant Bias

VARIANCE

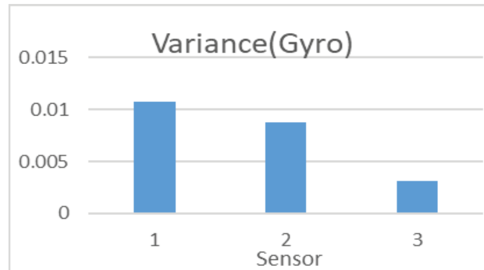

Figure 19: Variance of Sensors' Value

RMS

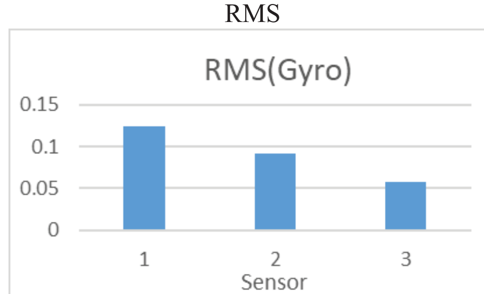

Figure 20: RMS of Sensors' Value

KURTOSIS

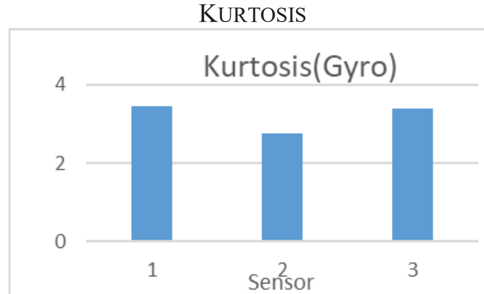

Figure 21: Kurtosis of Sensors' Value

Variance in Fig. 19 is a good indicator of constant bias fault in gyroscopic data as the low value in comparison to the other two sensors shows the values attained a constant deviation from the mean, which according to the values is close to mean because of the fluctuating nature of gyroscopic data in this case. However, the other two sensors show considerable deviations from the mean. The RMS in Fig. 20 also in this case shows the similar pattern but the values are small to mark a considerable difference between other sensor results. The fourth statistical moment shown in Fig. 21 also does not show a conclusion as other sensors also present similar effect because of infrequent deviations.

c) Drift/Additive Type

VARIANCE

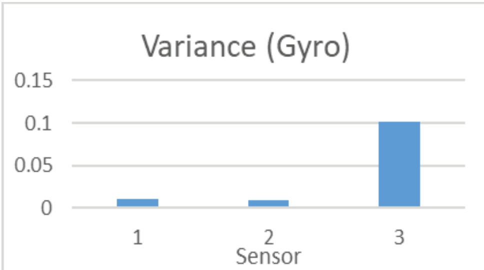

Figure 22: Variance of Sensors' Value

RMS

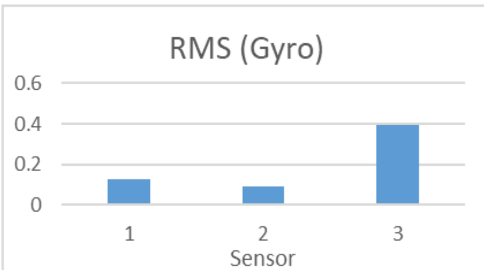

Figure 23: RMS of Sensors' Value

KURTOSIS

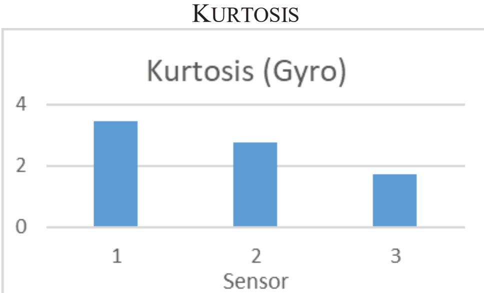

Figure 24: Kurtosis of Sensors' Value

Variance in Fig. 22 and RMS in Fig. 23 are better detector of additive type fault in gyroscope as it shows marked difference in the spread of value in the case of Sensor 3. The graph of values of sensor 3 also underpins the Variance and RMS value as a drift in values is evident. Kurtosis in Fig. 24, though shows a similar pattern of identification, is still not appreciable because of infrequent deviations in data of other sensors limiting the distinction.

CONCLUSION

In this paper the multi-sensors structure for increasing reliability using statistical analysis has been proposed. Three faults are under consideration, namely: total sensor failure, stuck with constant bias and drift or additive type sensor failure. The statistical measures of variance, RMS and kurtosis have been used to evaluate the signal values of the three sensors with sensor 3 having fault. The process has enabled to suggest better estimates of detecting faults statistically and also to highlight which statistical measure(s) plays an important role in which type of fault. The analysis furnishes statistical trend for the detection of the mentioned faults in sensor outputs. The technique used in [3] has been compared and further developed in form of better statistical measures for the evaluation of failure. The framework hence proposed, delivers a robust methodology for fault detection. An advantage of the proposed statistical measures is the simplicity with which they could be applied to sensor data for detecting faults.

Further work is still needed in this field with residual based methods in cognizance with statistical methods appearing to be a path of future research. Also, comparison of various model based fault detection with statistical analysis measures is under the process of evaluation, to be discussed in research later.

ACKNOWLEDGMENT

The authors give special thanks to MEMS lab of the faculty of School of Aeronautical Engineering of Northwestern Polytechnical University, Xi'an, China, for experimentation facility.

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