IN-FLIGHT SENSOR CALIBRATION AND ADVANCED FAULT TOLERANT SCHEME FOR INERTIAL NAVIGATION FOR EXTENDED DURATION MISSIONS

***S.Sreejith[a], V.S.Vinoj[a], Vidhya.U.Menon[a] ,Umadevi P[a] and P.P.Mohanlal[a]**
[a]ISRO Inertial Systems Unit, Thiruvanthapuram – 695013, India.

Abstract

The design of space systems for long duration missions have to be superior in reliability and accuracy compared to expendable Launch vehicles. An Interplanetary mission is a typical example. In addition to the standard design techniques for reliability and accuracy, these navigation systems have to incorporate optimum strategies for sensor failure management, error correction and utilization of maximum number of sensors throughout the mission. Even in the face of imminent sensor failure, appropriate algorithms have to be employed to filter out the erroneous data so as to scavenge and utilize the sensor to the maximum extent possible. There are two main failure modes associated with an inertial sensor; total functional failure and performance deterioration. Most of the present algorithms apply a Failure Detection and Isolation (FDI) approach to isolate faulty sensors. In this paper, we propose an algorithm for filtering and reusing the data from a deteriorated sensor by applying a weighted parameter approach. Performance assessment of the algorithm for different missions is carried out using standard simulation methods and their impact on mission performance is also discussed.

Keywords: Bias drift, weighted LSE, sensor residue, scale factor, sensor error model

1. Introduction

Navigation systems form a critical part of every space transportation system, be it spacecraft or launch vehicles. They employ inertial sensors like gyroscopes and accelerometers, for attaining position, velocity and attitude information. The angular rate and linear acceleration outputs from these sensors are integrated to provide required navigation information, due to which minor errors in sensor measurements will propagate into navigation states which in turn affect the mission accuracy. Inertial sensors are prone to change in the calibration coefficients in long run due to various reasons. Therefore, redundancy schemes, intelligent error compensation algorithms and failure detection and isolation schemes become extremely important in a navigation system especially when they are envisioned for extended duration missions. INS contribution in total mission error is estimated typically as 80% or more. So any accuracy improvement in INS has a direct impact on the total mission accuracy. An in-flight estimation of sensor coefficients is proposed in this paper, which estimate and correct the sensor error during the flight. A novel technique based on weighted LSE scheme is also proposed in this paper for fine selection of FDI passed sensors for navigation parameter estimation.

2. Sensor Errors and Estimation

Any sensor is prone to performance variations due to imperfection in manufacturing, limited operating range, modelling approximations, change in operating environment etc. The accompanying sensor errors can be either deterministic or random. The general strategy in error compensation is modelling and compensation of the deterministic errors using a sensor error model. Usually first order approximation is done, and for better accuracy missions, second order approximation is also attempted. The effect of random error in sensor measurement can be reduced by employing multiple measurements using a number of sensors.

3. Classical Approach in Error Compensation and FDI

The measurement from any sensor channel is the sum of expected output, deterministic errors and un-modeled sensor errors.

$$M = HX + E + n \qquad \textbf{(1)}$$

M = Sensor measurement matrix
H = Sensor geometry matrix
X = Physical input in three orthogonal axis
E = Deterministic measurement error matrix
n = Un-modeled sensor errors

Once the measurement is compensated for deterministic errors, the equation (1) reduces to

$$M_{comp} = HX + n \qquad \textbf{(2)}$$

The effect of un-modeled error (n) can be reduced by taking the LSE from all the sensor measurements. The classical failure detection scheme analyzes compensated data for consistency in measurement. The majority voting scheme is usually adopted and those sensors, which violate the majority rule is isolated, either temporarily or permanent depending on the severity of degradation. There are only two

* Corresponding Author: email: sreejith_sreekumar@vssc.gov.in

possibilities for a sensor data; it is either usable or not usable. All the usable sensor data are given equal priority in final navigation.

4. Proposed Algorithm

This paper attempts to introduce a new philosophy of partial use of a degraded sensor, depending on the extend of degradation. So all the sensors will be used throughout the mission with a varying utilization factor which range from 0% to 100% depending on the extend of degradation. This paper also discusses a novel mechanism to estimate the deterministic error, due to sensor degradation during operation and possible correction of the same in flight instead of isolating the degraded sensors. This ensures the availability of maximum number of sensors throughout the mission.

4.1 Weighted Least Square Estimation

Existing algorithms use least square estimate to get an optimum estimate from available sensor measurements. However, it does not take into consideration the relative spread of the errors. Weighted LSE takes care of this drawback by assigning adequate weights to the different sensor measurements based on individual sensor error estimates. Figure 1 shows the algorithm for weighted LSE.

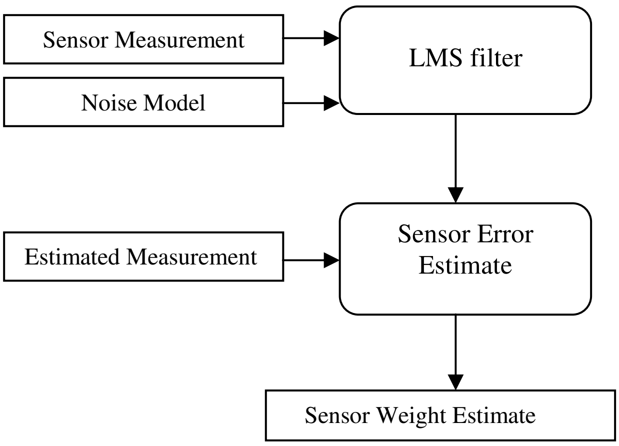

Fig1. Weighted LSE flow diagram

4.2 Coefficient estimation and update

Sensor coefficients estimated on ground through calibration procedures are loaded onboard via "initialization files" as part of pre-launch schedule. Therefore, variations accumulated in the time window from calibration to launch is unaccounted for. The proposed algorithm circumvents this by estimating the coefficient during mission and updating them on flight. It can also be helpful in cases when the mission duration is long (Ex: Interplanetary mission), during which the coefficients changes throughout the whole mission duration is taken care.

The measurement equation of INS:

$$M = H.X + E + n \qquad \textbf{(3)}$$

After compensating for systematic errors

$$M_{comp} = H.X + n \qquad \textbf{(4)}$$

The measurement M_{comp} can be resolved into vehicle body axis using LSE estimation.

$$X_{est} = [(H^T.H)^{-1}.H^T].M_{comp} \qquad \textbf{(5)}$$

Effect of n is neglected, as it will be minimized by LSE. An estimate of each sensor measurement can be derived from X as follows.

$$M_{est} = H.X_{est} \qquad \textbf{(6)}$$

Random noise in each measurement can be eliminated using an LMS filter whose inputs are the measurement and a random noise model n_{model}.

$$M_{filt} = LMS\ (M, n_{model}) \qquad \textbf{(7)}$$

An estimate of error "E" due to coefficient variation can be found out as

$$e_{Est} = M_{est} - M_{filt} \qquad \textbf{(8)}$$

We fix the measurement in a second order equation as:

$$M_{comp} = c2.m^2 + c1.m + c0 \qquad \textbf{(9)}$$

Where c0, c1, c2 are the sensor coefficients viz bias, scale factor, second order factor and m is the estimated sensor measurement M_{est}.

$$c2 = \frac{1}{2}\frac{\partial^2 M_{comp}}{\partial m^2} \qquad \textbf{(10)}$$

$$c1 = \frac{\partial M_{comp}}{\partial m} - 2.m.c2 \qquad \textbf{(11)}$$

$$c0 = M_{comp} - c2.m^2 - c1.m \qquad \textbf{(12)}$$

If the estimated values of sensor coefficients are within a predefined band, then no correction is made assuming that the difference will be due to computational inaccuracy. Similarly, if the values are beyond a limit, no corrections are made assuming the failure is so severe that it may be beyond correction; sensor will be isolated and system is configured with remaining sensors. In all other cases, the coefficients will be updated using the estimated ones. The flow diagram of this algorithm is given in Figure 3. Fig 2 gives the overall flow diagram of the proposed algorithm.

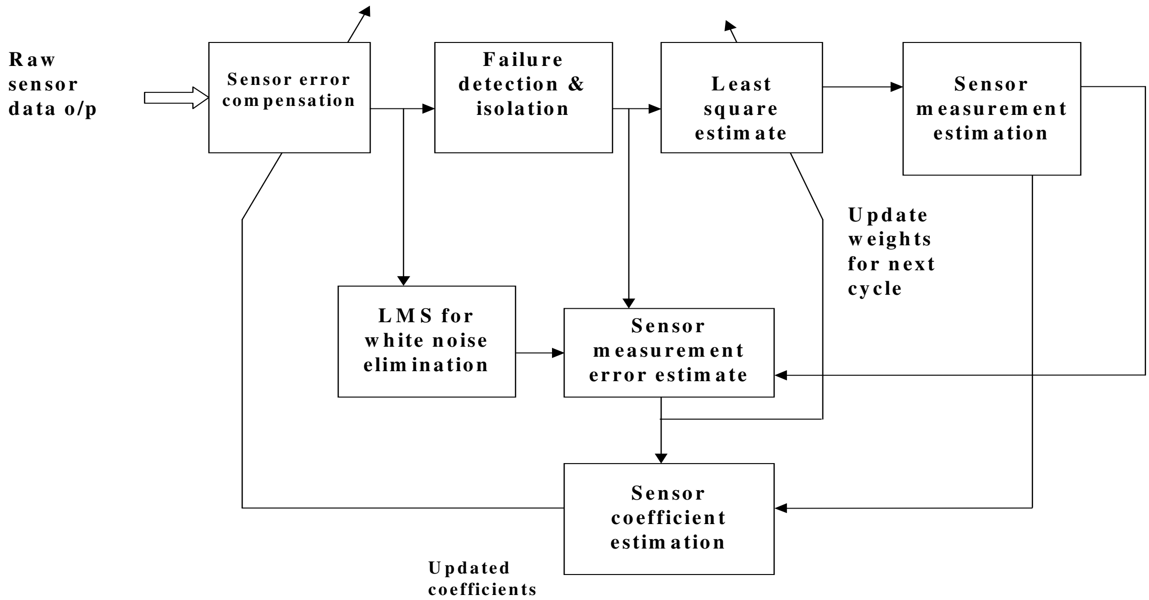

Fig 2. Overall algorithm flowchart

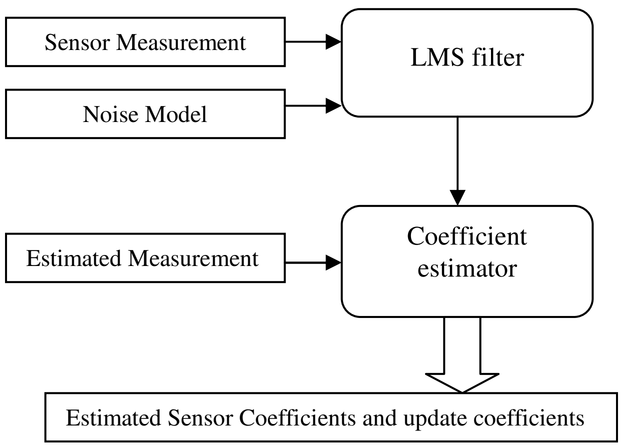

Fig 3. Flow diagram for calibration coefficient updating algorithm

5. Simulation results

For simulation studies INS configuration of six accelerometers and three gyroscopes are chosen. Accelerometers are arranged in skewed triad hexad configuration of half cone angle 54.74° and gyroscopes in orthogonal skewed geometry. Simulation studies were carried out by inducing different types of errors in one of the acceleration channels.

Simulations were carried out in typical mission trajectory and sinusoidal acceleration input profiles and error in bias and scale factor is injected. Figure 4 shows the coefficient updating done by the algorithm for an introduction of 3millig error in bias from 100 second onwards in a sinusoidal input of frequency 3Hz. Simulation with typical launch vehicle trajectory is also shown with similar results. The net gain in orbital accuracy in the mission due to in flight calibration is tabulated.

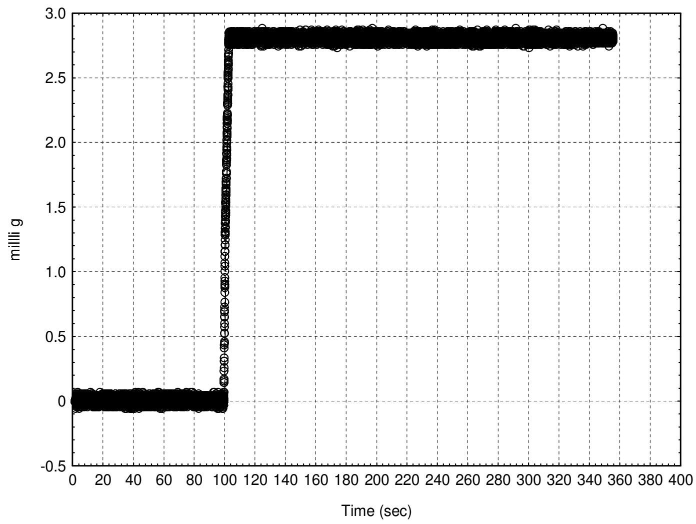

Fig 4. Bias estimation in open loop mode

5.1 Simulation in GTO launch trajectory

5.1.1 Bias error

Bias error of 10 millig is introduced in one of the sensor from time T0 + 100 s onwards for a flight of 1200s duration. Simulations were done in GTO trajectory. The simulation shows that the bias error was estimated well and was corrected during flight. The estimated bias error was shown in figure 5. Navigation parameters for the proposed algorithm and present scheme are compared and proposed scheme is found to be better. Details are given in table 1.

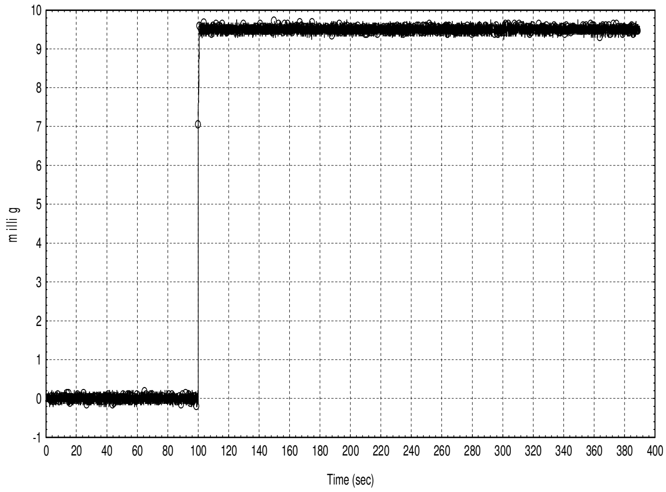

Fig 5. The bias error (Coefficient c0) estimated by proposed algorithm for GTO simulator.

Table 1: Performance of the proposed algorithm in the orbital parameters for GTO simulator

	Apogee (Km)	Perigee (Km)	Inclination (Deg)
Without in-flight calibration			
Trajectory	34153.75	165.12	19.54
INS	36025.92	170.66	19.37
INS-Traj	**1872.17**	**5.54**	**-0.17**
With in-flight calibration			
Trajectory	35884.11	172.85	19.39
INS	36013.19	170.61	19.37
INS-Traj	**129.08**	**-2.24**	**-0.02**

5.1.2 Scale factor error

Scale factor error was introduced in one of the sensor outputs and simulations were taken. Scale factor error was estimated and updated. Significant improvement was observed in Navigation parameter estimation for the proposed algorithm over the existing scheme. Figure 6 shows the scale factor error estimated by the proposed algorithm. Orbital error performance is tabulated in table 2.

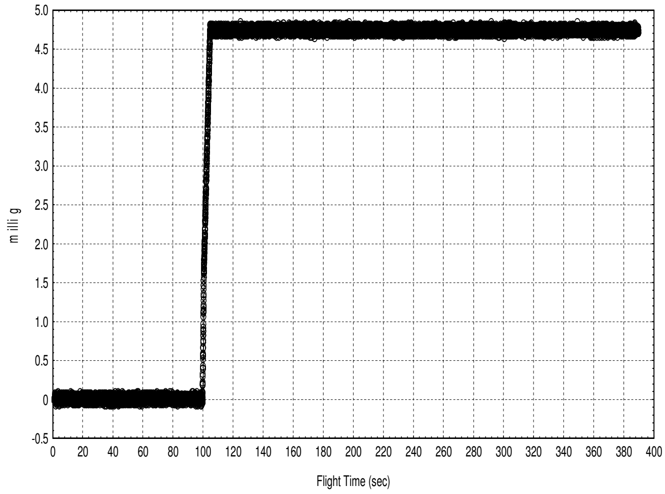

Fig 6. The scale error (Coefficient c1) estimated by proposed algorithm for GTO simulator

Table2 Performance of the proposed algorithm in the orbital parameters for GTO simulator

	Apogee (Km)	Perigee (Km)	Inclination (Deg)
Without in-flight calibration			
Trajectory	35261.80	167.29	19.38
INS	36010.83	170.43	19.37
INS-Traj	**749.03**	**3.14**	**-0.01**
With in-flight calibration			
Trajectory	35935.21	170.35	19.37
INS	35997.22	170.53	19.37
INS-Traj	**62.01**	**0.18**	**0.0**

5.2 Closed Loop Simulation: Polar traj

Simulation studies are carried out in Polar trajectory simulator with bias error of 2 millig and scale factor error of 1 millig simultaneously from 100 second onwards. The orbital error performance is summarized in table 3.

Table 3 Performance of the proposed algorithm in the orbital parameters for polar traj simulator

	Apogee (Km)	Perigee (Km)	Inclination (Deg)
Without in-flight calibration			
Trajectory	817.52	815.24	98.66
INS	828.24	823.98	98.71
INS-Traj	**-10.72**	**8.74**	**0.05**
With in-flight calibration			
Trajectory	824.79	820.05	98.69
INS	822.50	821.28	98.72
INS-Traj	**-2.29**	**1.23**	**0.03**

The INS accuracy improvement scheme using weighted LSE is simulated over the updated coefficients. The weight-age rule for simulation is given in Table 4.

Table 4 Weight rule used for studying the proposed algorithm in GTO simulator

SI No	2 second accumulated estimated error (E_{est})	Weight rule
1	E_{es} <200 µg	No correction
2	200 µg<E_{est}<300µg	Give 75% weightage compared with others
3	300 µg<E_{est}<500µg	Give 50% weightage compared with others
4	500 µg<E_{est}<700µg	Give 25% weightage compared with others
5	700 µg<E_{es}<1400 µg	Give 5% weightage compared with others
6	1400 µg<E_{es}	Isolate the sensor

Simulations are done in GTO simulator with a bias shift of 250µg on sensor 1 and 400µg on sensor 2. The simulation results are tabulated in table 5. It clearly shows that the weighted LSE scheme improves the performance of INS orbit.

Table 5 Performance of the weighted LSE algorithm in the orbital parameters for GTO simulator

	Apogee (Km)	Perigee (Km)	Inclination (Deg)
Without in-flight calibration			
Trajectory	35797.90	170.67	19.37
INS	35948.25	171.18	19.37
INS-Traj	**150.35**	**0.51**	**0.0**
With in-flight calibration			
Trajectory	35983.69	170.76	19.37
INS	35994.54	170.60	19.37
INS-Traj	**10.85**	**-0.16**	**0.0**

6. Conclusion

A novel algorithm for sensor coefficient estimation and correction was developed with INS accuracy improvement scheme. The algorithm was developed and simulated with different types of error like scale factor error, bias error and was found to be giving a better estimate compared to present scheme. Mission simulations carried out gave better orbital parameter estimates using his algorithm. Simulation studies are done for short duration missions and performance of the algorithm is satisfactory in both Polar and GTO trajectory simulator. It is evident that the INS is more prone to shift of calibration coefficients in long duration missions and hence this algorithm is highly desirable in long duration missions.

Acknowledgment

We would like to acknowledge the support and advice provided for developing the concept of this paper by Smt. S Syamala / DH,NFSD, Mr S Hemachandran / GH,CSNG, Mr J Krishnakumar / GH,NSIG and Mr A Abdul Shukoor / GD,LVIS. We are thankful to the encouragement from Mr Radhakrishna Pillai C, Dr VN Radhika also.

Reference

1. Prediction and Compensation of Errors in Inertial Navigation System, Matveev V. A. and Salychev D. *S.* Bauman Moscow Technical University Moscow, Ren Si-cong Department of Automatic control Northwqtern Polytechnical University, Xian

2. Skewed Axis Sensor Geometry for Optimal Performance, Mark A. Sturza Littol1 Systems, Inc. Guidance and Control Systems Division, California

3. Maximum Likelihood identification of Gaussian Autoregressive Moving Average Models, AkaikeH, Boimetrika Vol 60

4. Functional Requirement Document of Navigation Software / Internal document.

5. Using LabVIEW for Adaptive Noise Cancellation: http://www.ni.com