MEMS IMU Based INS/GNSS Integration: Design Strategies and System Performance Evaluation

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ABSTRACT

Application of MEMS sensor in navigation is increasingly becoming important due to its advantages in terms of the quickly improving precision, robustness, high dynamic response and lower costs of development and usage. Moreover by employing the optimal estimation technique of Kalman filtering, the performance of MEMS based INS has been greatly enhanced by the integration of GNSS.

This paper focuses on the integration design of INS with GNSS based on MEMS IMU sensors. The sophisticated MEMS IMU error models are employed to evaluate the MEMS error impacts on INS performance. Through the use of the MEMS IMU error model, the MEMS IMU raw measurements can be simulated conveniently. Moreover it provides the fundamental model for the inertial sensor error compensation before INS calculation. The Kalman filter based integration configuration is also designed by combining GNSS solutions in this paper. Different experimental scenarios are designed to evaluate the performance of the proposed integration configuration by various simulation tests. The experimental results indicated that the performance of the MEMS based INS is greatly enhanced by integration of GNSS compared with its stand-alone usage and by employing the MEMS IMU error model to compensate the deterministic sensor errors.

INTRODUCTION

As an independent means of navigation, strapdown inertial navigation system (INS) providing position/velocity/attitude information via the measurements from inertial sensors has various advantages, such as totally autonomous, high dynamic response, good short-term accuracy and robust performance when exposed to interference/jamming, etc. In the last decade, as the rapid development of Micro-Electro-Mechanical System (MEMS) drastically reducing the cost of previously expensive inertial sensors, the low-cost MEMS-based strapdown INS has been a subject of great interest. However its usage as a stand-alone navigation system is limited due to time-dependent growth of the MEMS sensor bias/noises. In comparison to MEMS-based INS, the Global Navigation Satellite System (GNSS), such as GPS, GLONASS and Galileo, is capable of delivering position and velocity information ascertained with time-independent precision, while the performance becomes unreliable when the system is exposed to high dynamics, interference from communication equipment and jamming. Because of the aforementioned complementary characteristics, GNSS and INS are commonly coupled with Kalman filter technique to augment the over-all performance by overcoming the shortcomings of each individual system.

The purpose of this study is to determine the MEMS-based INS/GNSS integration design strategies by evaluating the impacts of those aforementioned issues on the integrated INS/GNSS system. Although the fundamental principle is the same, a practical design of INS/GNSS integration varies from the system requirements as well the selected IMU sensors. For example, MEMS presents the unique noise characteristics and generally containing high-level noises inherent in the output data, therefore the issues of the advanced techniques to simulate and also compensate MEMS raw measurement errors should be addressed. Firstly, to simulate the raw MEMS IMU measurements, the advanced error modelling technique is utilised by this study to estimate and evaluate the MEMS sensor noises. With the comprehensive error models, the noises of MEMS can be characterised in terms of random noise, bias, quantization error, scale factor correction and alignment error, etc. Secondly, by employing the sensor error model in INS calculation, the compensation of the deterministic noise terms from the raw MEMS measurements can be performed, such as the bias, scale factor errors, and the quality of the MEMS measurements for INS algorithm can be thus greatly improved. Finally, a loosely coupled Kalman filtering design for INS/GNSS integration is presented. Particularly, the design of Kalman filter process model which is suitable for the MEMS sensor noise characteristics is addressed in the paper. In additional, with the results from MEMS error modelling, the random noise compensation of MEMS sensors is achieved for the Kalman filter design. The structure employed in this study is to perform the theoretical analysis which provides the fundamental verification of the design strategies, followed by the experimental validations in simulation.

With its well-convinced advantages in theoretical analysis and the simplicity tuning the parameters, the simulation in Matlab is used for this study in order to validate the design and potential performances. It consists of firstly the generation of simulated GNSS and MEMS raw measurements corresponding to the reference flight trajectories. Secondly, the INS algorithm utilising the raw IMU measurements derives the navigation attitude, velocity and position solutions. Finally, the integrated INS/GNSS Kalman filter is design to deliver the optimal navigational solutions through fusing both of MEMS-based INS and GNSS data.

Experimental results indicate that mitigation of the raw MEMS IMU measurement noises by MEMS error modelling technique improves the accuracy of the INS solutions which in turn enhances the integrated INS/GNSS performance. Moreover this error model helps to achieve the more accurate statistical noise estimation of Kalman filter, which is well-known critical to the integrated Kalman filter's performance. The results also show that due to the large IMU noises in the MEMS-based INS/GNSS integration design, the formerly complicated Kalman filter dynamic model can be greatly simplified by reducing the dimension of the error state vector without degrading the performance. With using the simplified models, the processing load of Kalman filter can be greatly reduced.

MEMS IMU BASED INS/GNSS INTEGRATION STRUCTURE IN SIMULATION

It is worth mentioning that the simulation of INS/GNSS integration algorithms is a mandatory step prior to real-time implementation in order to validate the design and assess the performance [4]. The following scenario is proposed as shown in Figure 1.

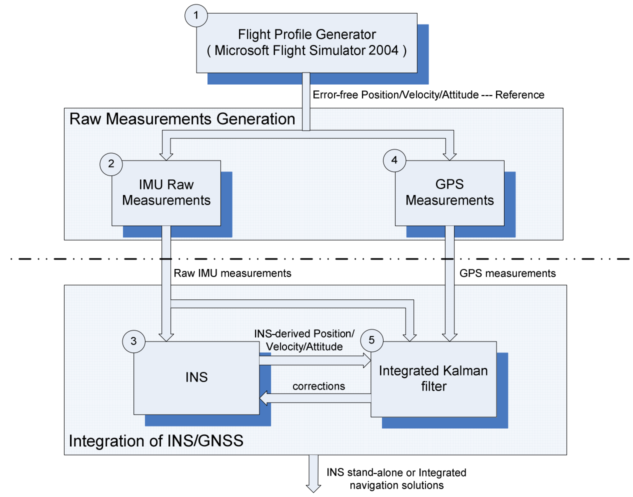


Figure 1. The structure of the integrated INS/GNSS navigation based on MEMS IMU

Flight profile Generator①: Given the flight trajectories, this software package is used to generate the flight profile typically providing detailed information such as attitude, velocity and position. In this research, a realistic flight profile simulator, i.e. Microsoft Flight Simulator™ or X-Plane is employed.

IMU Raw Measurements②: Given the inputs of flight profile, this software package generates the corresponding error-free IMU measurements, i.e. the true outputs of triad gyro and accelerometer. By modelling the inertial sensor errors, and then combining them to those error-free gyro and accelerometer measurements, the raw IMU measurements therefore can be obtained. In this study, to characterise the MEMS IMU sensor error features, a more sophisticated IMU sensor error model is employed [1], which will be detailed in the following section.

INS③: Inertial Navigation System software package is an autonomous process of computing position location by doubly integrating the raw measurements of triad gyro and accelerometer of a point, whose position is to be determined [1]. First integration is to determine a three-dimensional velocity vector and again to obtain a three-dimensional position vector. INS is indispensable in the integration of INS/GNSS, providing the INS navigation solutions for the integrated filter, system errors can be estimated and corrected by the integrated Kalman filter.

GNSS measurements④: This software generates the GNSS velocity and positioning raw measurements and solutions, in terms of velocity/position and pseudorange-rate/pseudorange corresponding to the flight profile. Optionally, it provides the GNSS shortage / blockage information.

Integrated Kalman filter⑤: Optimal estimation technology, i.e. so-called Kalman filtering, is employed through combining the navigational information from both INS and GNSS to deliver the optimal estimations of the navigational states. In the integrated INS/GNSS, the INS error equations are commonly utilised to construct the Kalman filter; hence Kalman filter's states are the navigational solution errors. Through compensating these optimally estimated navigational errors, the optimal solutions can be derived thereafter. Another obvious advantage of the integrated Kalman filter is, during the blockage/shortage of the GNSS signal, it directly forwards the INS stand-alone solutions as Kalman filtering outputs at the typical INS output rate, e.g. 100Hz. Once the GNSS signal is available again, Kalman filter corrects the INS stand-alone solutions at the typical GNSS measurement rate, e.g. 1Hz.

MEMS IMU ERROR MODEL DESIGN

Comparing with traditional IMU sensors, e.g. nuclear magnetic gyro (NMR), electrostatic gyro (ESG), Ring Laser Gyro (RLG), the pendulum accelerometers .etc., which costs rise dramatically with the increasing precision, MEMS has greatly reduced the costs therefore a mass production has been permitted. Nevertheless, MEMS fabrication process is continuously improving and its performance is always better. Whereas due to the large time-growing noises inherently existing in the MEMS IMU sensor, its applications are limited significantly, usually constrained to low-precision and short-term applications. Hence careful studies of the characteristics of MEMS IMU sensor noises are potentially beneficial to enhance the performance. In this study, a set of more sophisticated IMU sensor models [1], which is expressed respectively as Gyro and accelerometer sensor model, is employed to investigate the MEMS IMU sensor performance.

While manufacturing an inertial MEMS sensor, it is virtually impossible to control tolerances with actual production technology. However, manufactured component inaccuracies are generally stable and analytically predictable, which provides the basis for modelling the inaccuracies. The error effects of each sensor can be measured as part of manufacturing/testing operations, in turn the relative error effects will be provided in the specifications in terms of various errors/noise parameters, which are organised by a general inertial sensor model.

For example, the gyro error model is described by:

$$\underline{\omega}_{Puls} = \frac{1}{\Omega_{W_{to}}}(I + F_{Scal})(F_{\mathrm{Alg}n}\underline{\omega} + \delta\underline{\omega}_{Bias} + \delta\underline{\omega}_{Quant} + \delta\underline{\omega}_{Rand}) \tag{1}$$

Where,

$\underline{\omega}$ Error free angular rate output

$\underline{\omega}_{Puls}$, Gyro output in *pulses/second*

$\Omega_{W_{to}}$, Nominal pulse weight, i.e. scale factor

F_{Scal}, Scale factor correction matrix

$F_{\mathrm{Alg}n}$, Alignment matrix

$\delta\underline{\omega}_{Bias}$, Gyro bias vector

$\delta\underline{\omega}_{Quant}$, Quantization error

$\delta\underline{\omega}_{Rand}$, Gyro random error

Comparing with gyro error model, the similar form of the accelerometer error model can be characterised as:

$$a_{SF_{Puls}} = \frac{1}{A_{W_{to}}}(I + G_{Scal})(G_{\mathrm{Alg}n}\underline{a}_{SF} + \delta\underline{a}_{Bias} + \delta\underline{a}_{Size} + \delta\underline{a}_{niso} + \delta\underline{a}_{Quant} + \delta\underline{a}_{Rand}) \tag{2}$$

Where,

$\underline{a}_{SF}$, Error free specific force acceleration vector sensed by the accelerometer triad

$\underline{a}_{SF_{puls}}$, Accelerometer triad output in *pulses/second*

$A_{W_{to}}$, Nominal pulse weight, i.e. scale factor

G_{Scal}, Scale factor correction matrix

$G_{\mathrm{Alg}n}$, Alignment matrix

$\delta\underline{a}_{Bias}$, Accelerometer bias vector

$\delta\ \underline{a}_{anisoinertia}$, Accelerometer anisoinertial bias error

$\delta\ \underline{a}_{Quant}$, Accelerometer quantization error

$\delta\underline{a}_{Rand}$, Accelerometer random error

Using the flight profile derived from flight trajectory generation software package, IMU measurements generator outputs the inertial sensor error free angular rate and specific force vector, i.e. $\underline{\omega}$ and $\underline{a}_{SF}$ in the above models.

From the inertial sensor error models given by Eq. (1) and (2) one can conclude, most of the dominant error effects of inertial sensors are taken into account. After setting the appropriate values of each error item, i.e. the coefficients in the models, the error model outputs the raw IMU measurements which are contaminated by the various inertial sensor errors. Furthermore by setting those error items in the models, different grades of IMU sensors, e.g. MEMS IMU, commercial, tactic, navigation I, II, can be simulated in the experimental simulations. Table 1 presents some examples of the values of the error model coefficients which determine the grades of IMU sensors.

Table. 1 Grades of the IMU [14]

	Accelerometers		
Error Model Parameters	Bias [µg]	Scale Factor Error [ppm]	Noise [µg/√Hz]
Navigation II	0,1 - 10	2 - 20	1 - 10
Navigation I	10 - 300	100 - 300	50
Tactic	200 - 1000	400 - 1000	200 - 600
Commercial(MEMS)	1000 - 10000	800 - 5000	800 – 10000
	Gyro		
Error Model Parameters	Bias [deg/h]	Scale Factor Error [ppm]	Noise [deg/h/√Hz]
Navigation II	0,002 - 0,01	5 - 50	0,002 - 0,005
Navigation I	0,002 - 0,1	100 - 300	0,002 - 0,05
Tactic	1 - 50	100 - 1000	0,2 - 0,5
Commercial(MEMS)	50 - 3600	100 - 5000	0,5 - 1

As an example, one of the laboratory tested MEMS sensor is from MEMsense™ namely the AccelRate3D™. The relevant error items from the manufacturer specifications are given by table 2. When compared with table 1, one can find the MEMS sensor has much more large errors than other IMU.

Table. 2 MEMS sensor errors of the AccelRate3D™

	Accelerometers		
Error Model Parameters	Bias [µg]	Scale Factor [mV/g]	Noise [µg/√Hz]
AccelRate3D™	N.A.	1000	35 (X/Y) 65(Z)
	Rate Gyro Output		
Error Model Parameters	Bias [deg/h]	Scale Factor [mV/deg/sec]	Noise [deg/h/√Hz]
AccelRate3D™	200	12.5	180

By setting the proper MEMS IMU sensor error parameters in the model, MEMS IMU outputs can be generated in the simulation according to a specific sensor grade.

INTEGRATED KALMAN FILTER DESIGN

A state-of-the-art MEMS inertial sensor usually contains high level noise, which makes MEMS-based INS stand-alone solution fairly unreliable. According to the aforementioned various advantages the MEMS-based INS/GNSS integration is the ideal solution for MEMS practical application.

Generally there are many issues concerning the design of an integrated Kalman filter. While particularly in this study, i.e. in MEMS-based integration scenario, the high level noises contaminate the raw IMU measurements which cause the INS solution diverges quickly. How to account for this behaviour becomes the key issue of this research which should be addressed.

Related to this constraint, this section focuses on the design of the Kalman filter error state dynamic model which describes the INS error characteristics driven by MEMS noises. First of all, by defining INS attitude, velocity and position errors parameters ($\Psi, \delta V, \delta R$) in the Earth frame (i.e. ECEF, Earth-Centre Earth-fixed frame) and then transforming in the Navigation frame (in the North-slaved implementation, where Navigation frame x/y/z axis are parallel to local east/north/up direction), the complete INS error equations can be expressed as [2]:

$$\begin{aligned}
\underline{\dot{\Psi}}^N &= -C_B^N \delta \underline{\omega}_{IB}^B - \underline{\omega}_{IN}^N \times \Psi^N \\
\delta \underline{\dot{V}}^N &= C_B^N \delta \underline{a}_{SF}^B - \underline{a}_{SF}^N \times \Psi^N + \delta \underline{g}_{Mdl}^N - (2\underline{\omega}_{IE}^N + \underline{\omega}_{EN}^N) \times \delta \underline{V}^N \\
\delta \underline{\dot{R}}^N &= \delta \underline{V}^N - \underline{\omega}_{EN}^N \times \delta \underline{R}^N
\end{aligned} \tag{3}$$

Where,

$\underline{\Psi}, \delta\underline{V}, \delta\underline{R}$ Attitude, velocity and position error parameters

C_B^N Direction cosine matrix (DCM) from Body (B) to Navigation (N) frame

$\delta\underline{\omega}_{IB}^B$ Angular-rate vector error in B frame

$\underline{a}_{SF}^N, \delta\underline{a}_{SF}^B$ Specific force vector in N frame and the specific force error vector in B frame

$\delta\underline{g}_{Mdl}^N$ Plump-bob gravity error

$\underline{\omega}_{IE}^N, \underline{\omega}_{EN}^N$ Earth rotation rate vector and transport rate vector in N frame

$\underline{\omega}_{IN}^N$ Navigation frame rotation rate with respect to the inertial frame, by definition which equals to $\underline{\omega}_{IE}^N + \underline{\omega}_{EN}^N$

In some documentation, the equations (3) refer to INS ψ-angle error model. In the Kalman filter design, the INS error parameters are represented as the error states in the Kalman filter dynamic model, the computing load is determined by the number of selected error states, i.e. the dimension of the error state vector. As the MEMS noises are the dominant terms causing the divergence of INS, the complete INS error model can be simplified by deleting the negligible terms, which in turn reduces the Kalman filter error vector dimension and remarkably decreases the computing load. Finally the deleted error terms will be evaluated as the combined overall effects contributing to the MEMS error parameters. For the attitude error differential equation simplification, by considering that the main attitude error is caused by the angular-rate error, therefore it can be simplified as:

$$\underline{\dot{\Psi}}^N = -C_B^N \delta \underline{\omega}_{IB}^B \tag{4}$$

The velocity error differential equation can be simplified by deleting the contribution of the velocity error in its propagation and the gravity vector error compared to the specific force and the attitude error, which gives out:

$$\delta\dot{\underline{V}}^{N} = C_B^N \delta\underline{a}_{SF}^{B} - \underline{a}_{SF}^{N} \times \Psi^{N} \tag{5}$$

For the position error differential equation, the position errors are fairly small compared to the velocity errors, thus the position error equation can re-write as:

$$\delta\dot{\underline{R}}^{N} = \delta\underline{V}^{N} \tag{6}$$

The simplified equation set containing (4), (5) and (6) is the Kalman filter dynamic model. By discretizing it with the proper time interval, i.e. Kalman filter dynamic update rate typically in 50-200 Hz, the Kalman filter state transition matrix (Phi-Matrix) and the integrated process noise matrix (Q matrix) can be formed properly.

In the high performance INS sensor application, those deleted terms in this study become significant. A thorough study on the INS complete model is being developed to investigate the impacts of the INS error terms in presence of high grade sensors. This complete model will be discussed in future paper.

SYSTEM VALIDATION AND EXPERIMENTAL RESULTS

In this section, several tests were developed to validate the proposed design scenarios. First of all, the reference trajectory was generated by the use of Microsoft Flight Simulator^{TM} with deliberated manoeuvres. By inputting the given reference trajectory, the IMU (i.e. triad of Gyros and Accelerometers) measurements were generated corresponding to the reference trajectory. One need to mention, these generated IMU measurements are free of IMU sensor noises. The Figure 2 depicts the 3D reference trajectory.

Table. 3 Simulated MEMS sensor errors

Summit Instruments 65210A - Accelerometers	
Bias [μg]	Noise [μg/√Hz]
3×10^5	10^3
Summit Instruments 65210A – Angular Rate Output	
Bias [deg/h]	Noise [deg/√h]
10^4	1.2

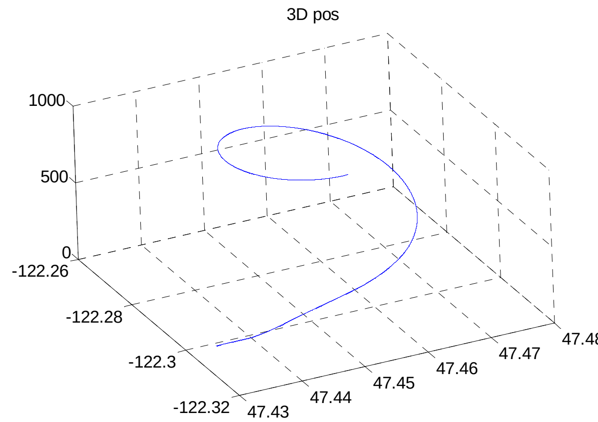


Figure 2. Reference trajectory in 3-D (meters)

The following test will first obtain the stand-alone INS solution using the MEMS raw measurements without integrating GNSS solution. Figures 3 to 5 depict the stand-alone MEMS-based INS solutions versus reference trajectory in attitude, velocity and position respectively. From those results, it can be concluded that the stand-alone INS solutions based on the raw MEMS IMU diverge dramatically because of the large sensor noises, its usage as the stand-alone INS obviously is not practical. To provide the effective MEMS-based INS solutions, it is mandatory to compensate these noises. There are various noises inherent in MEMS IMU raw measurements; mainly it consists of the deterministic and random noise terms. According to the noise analysis, the dominant terms of these two kinds of noises generally are the gyro/accelerometer bias and the white noise.

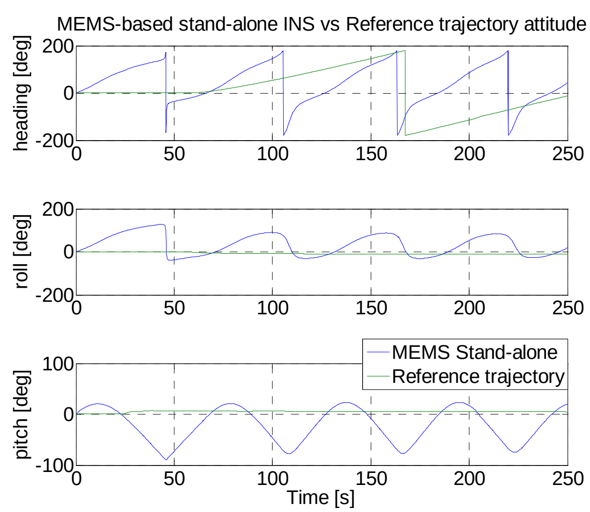


Figure 3. Attitude solution from stand-alone INS

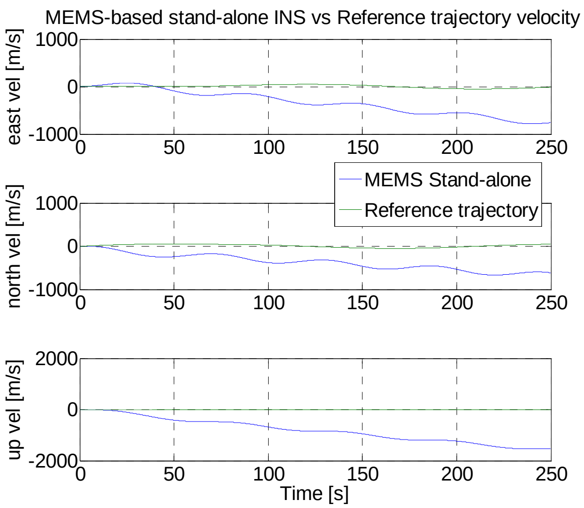


Figure 4. Velocity solution from stand-alone INS

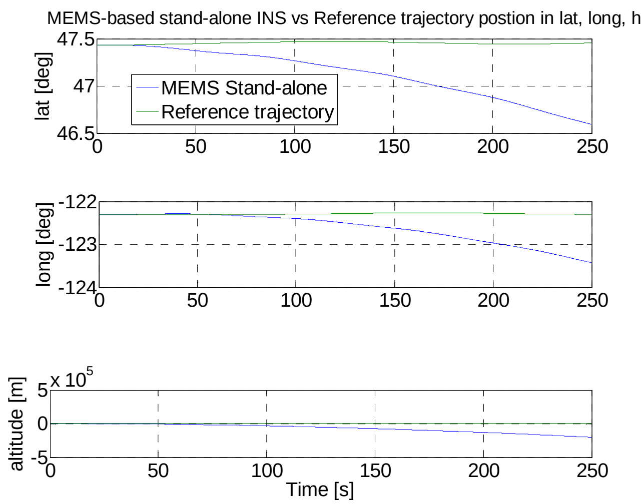


Figure 5. Position solution from stand-alone INS

To compensate the deterministic noise terms, such as the bias, misalignment, scale factor errors etc., the effective way is to employ the MEMS sensor error model to remove those deterministic noise terms prior to input them to the INS algorithm. After compensating the deterministic terms, the residual noise terms mainly are the random noises, according to the aforementioned discussion, Kalman filtering is the ideal technology to estimate and compensate the random noises. In order to validate this idea, the strategy used in this study consists mainly to compensate the random noises by Kalman filter, meanwhile keeping no compensation for the bias terms. The results of this process are depicted through Figures 6 to 10.

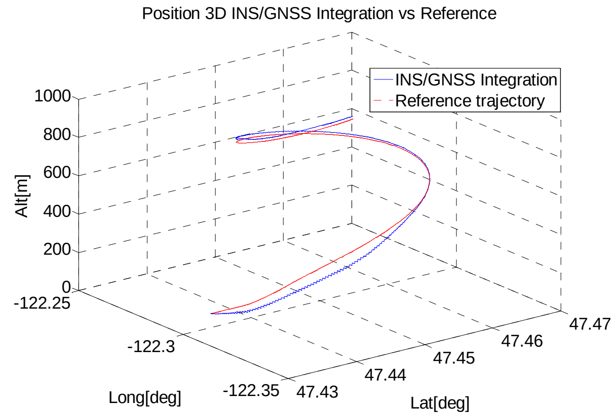


Figure 6. INS/GNSS Integration 3D-Solution without Biases Compensation

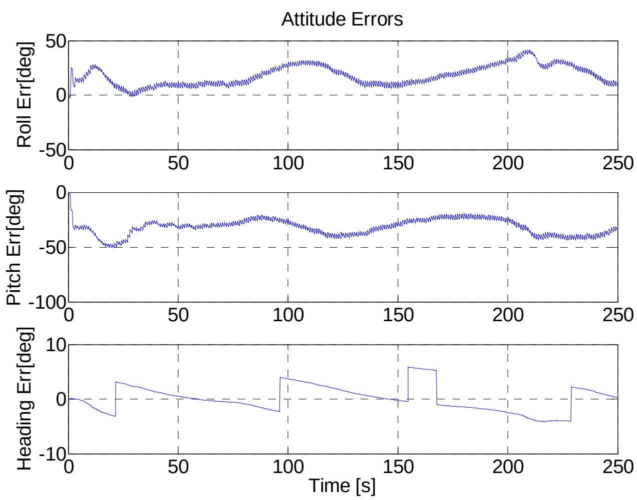


Figure 7. INS/GNSS Integration Attitude Errors without Biases Compensation

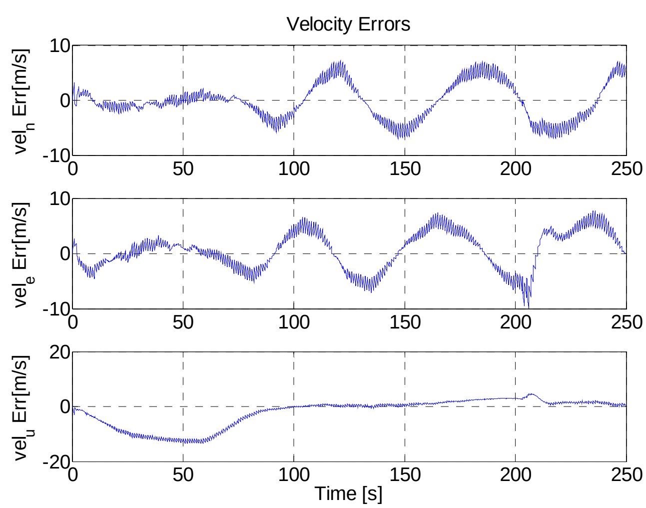


Figure 8. INS/GNSS Integration Velocity Errors without Biases Compensation

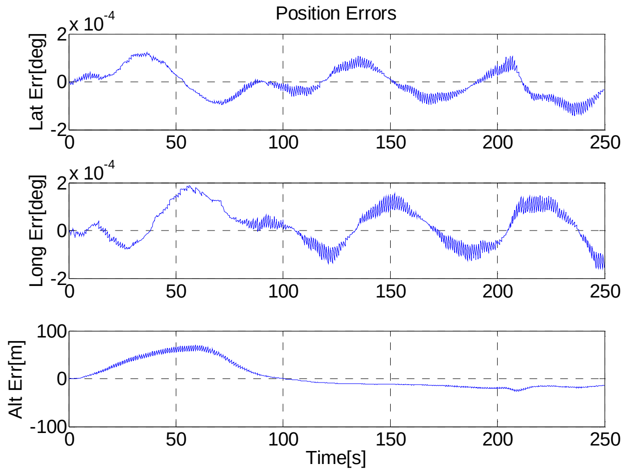


Figure 9. INS/GNSS Integration Position Errors without Biases Compensation

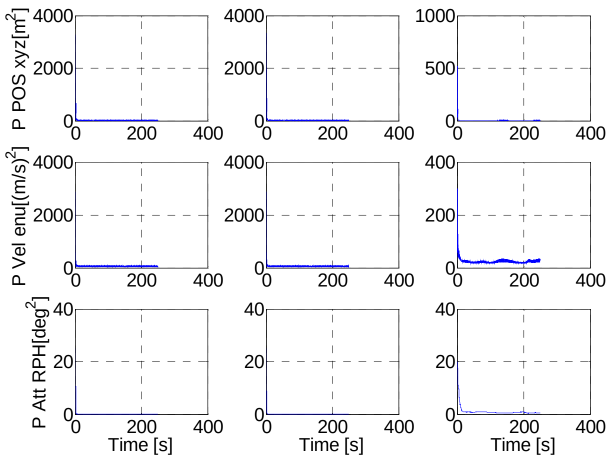


Figure 10. Attitude/Velocity/Position Estimation Errors by INS/GNSS Integrated Kalman filter

From Figure 6 one can see that the integrated MEMS-based INS/GNSS solution follows the reference trajectory with some errors, which is believed to be caused by the large gyro/accelerometer biases. Comparing to the stand-alone INS solutions, i.e. comparing Figures 7 with 3, 8 with 4 and 9 with 5, the attitude, velocity and position errors are reduced remarkably, although the errors are still too larges to provide the useful solutions. Nevertheless, Figure 10 shows that the estimation errors of Kalman filter converge quickly and the random noises are effectively estimated and compensated by Kalman filter. The improvements in attitude, velocity and position solutions also validate the random noise compensation by the integrated INS/GNSS Kalman filter.

The second step of the validation is to compensate the deterministic noises. In this study, gyro/accelerometer biases were removed by using the MEMS sensor error model from the IMU raw measurements. The 3D integrated INS/GNSS solution with the bias compensation is illustrated in Figure 11. From the figure, one can find that the INS/GNSS solution fits the reference trajectory. Figures 11 to 13 depict the attitude, velocity and position errors compared with the reference. As for figure 10, Figure 14 shows the good estimation of the random noises. Therefore after compensating the deterministic and random noises, the INS/GNSS integration is accurate enough to provide useful attitude, velocity and position solutions.

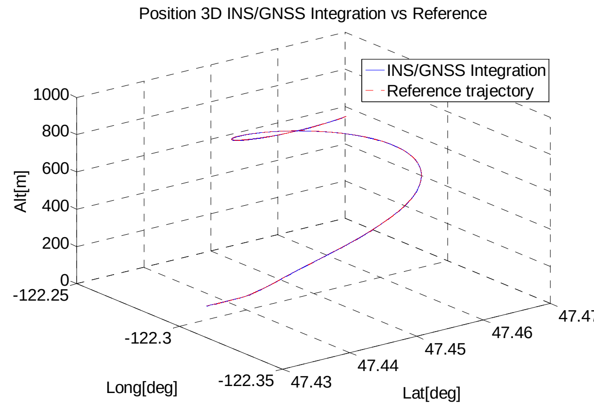


Figure 11. INS/GNSS Integration 3D-Solution with Biases Compensation

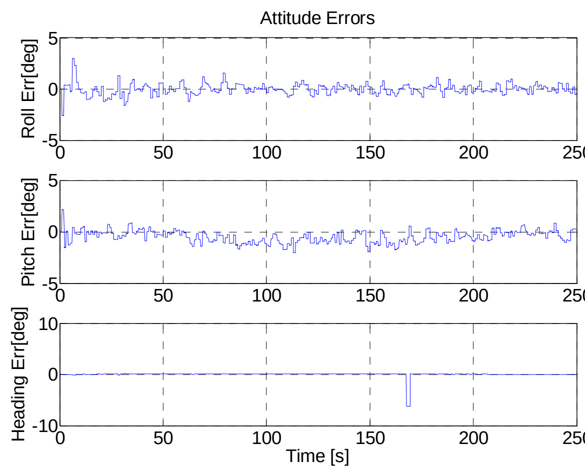


Figure 12. INS/GNSS Integration Attitude Errors with Biases Compensation

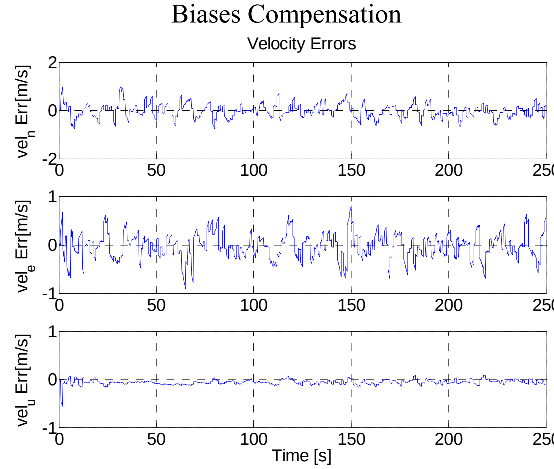


Figure 13. INS/GNSS Integration Velocity Errors with Biases Compensation

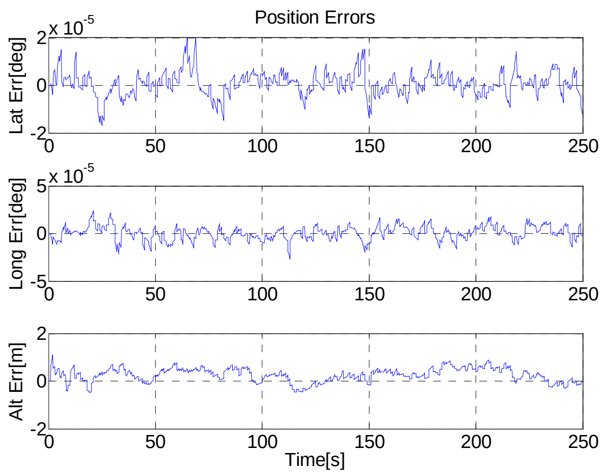


Figure 14. INS/GNSS Integration Position Errors with Biases Compensation

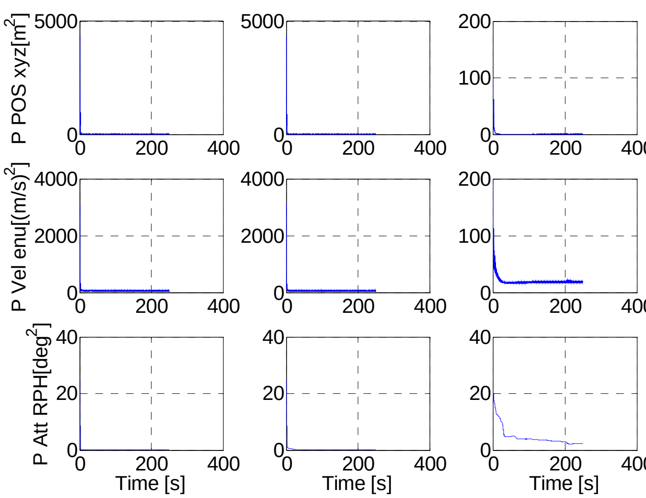


Figure 15. Attitude/Velocity/Position Estimation Errors by INS/GNSS Integrated Kalman filter

To test the functionality of the MEMS-based INS/GNSS integration, the GNSS signal (particularly GPS was utilised in this study), was blocked for the duration of 60s in the test (from 100s to 160s). Figure 16 gives out the 3D integration solution, in which it obviously can be seen that during the blockage of GPS signal, the stand-alone INS solution starts diverging. From the Figures 17 to 19, one can also find that during the GPS signal blockage, the attitude, velocity and position errors start increasing. This is due to the residuals of the biases and random noise compensation. After the time epoch 160s, with the re-acquisition of the GPS signal, the optimal estimations of the attitude, velocity and position errors from the integrated INS/GNSS Kalman filter are available again, thus the solution re-fits the reference by correcting the errors.

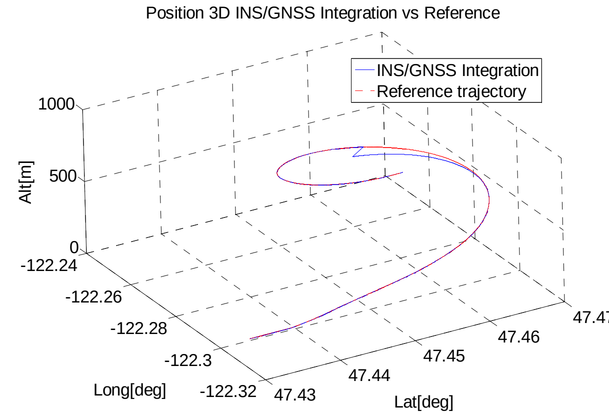


Figure 16. INS/GNSS Integration 3D-Solution with GNSS 60s Blockage

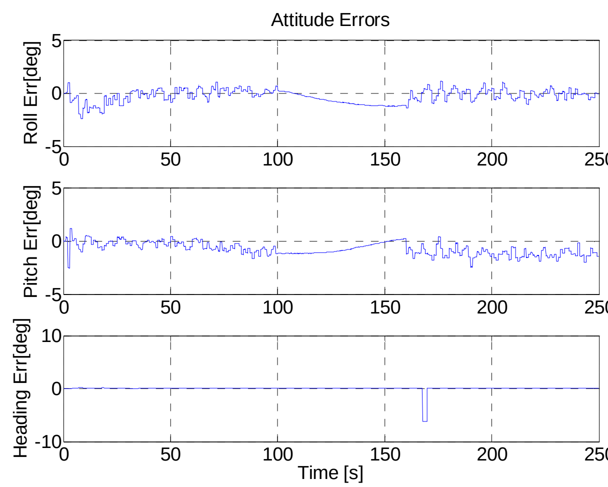


Figure 17. INS/GNSS Integration Attitude Errors with GNSS 60s Blockage

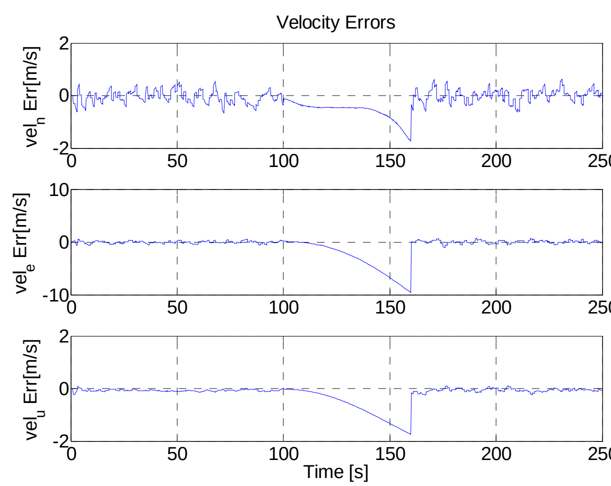


Figure 18. INS/GNSS Integration Velocity Errors with GNSS 60s Blockage

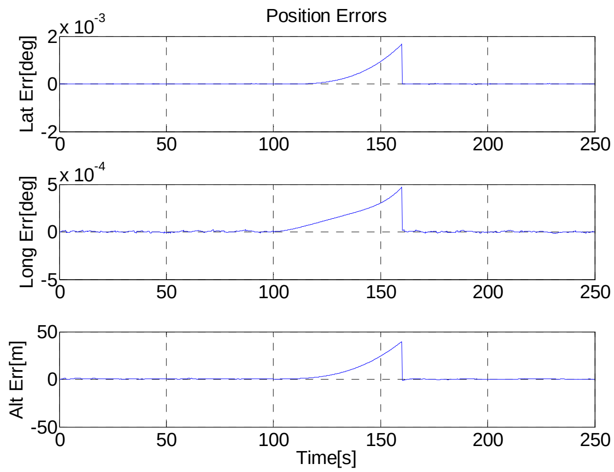
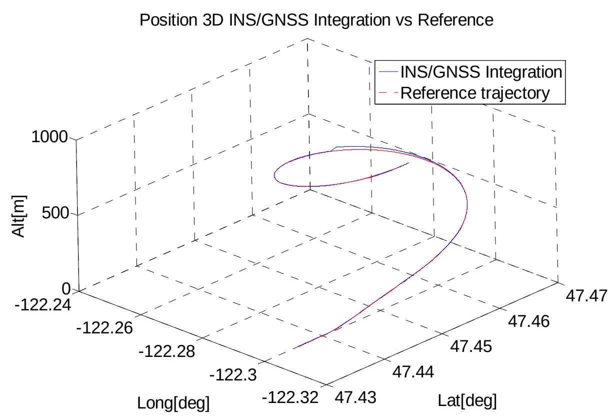


Figure 19. INS/GNSS Integration Position Errors with GNSS 60s Blockage

As a complementary explanation, GPS blockage test was repeated with a simulated tactic grade IMU sensor. Figure 20 shows the result. Due to the reduced gyro and accelerometer biases in the tactic grade inertial sensor, the divergence is barely small compared with MEMS test results in Figure 16 during the GPS blockage from 100s to 160s.



CONCLUSION

This paper focuses on the design of the integrated INS/GNSS solution based on MEMS IMU sensors. Due to the large sensor noises inherent in the MEMS sensors, first of all MEMS IMU error models are introduced to simulate the various noises in the raw MEMS IMU measurements. Moreover, the proposed models provide the fundamental structure for the compensation of raw IMU deterministic noises. Then with the purpose of obtaining the practical solution for MEMS IMU application, the integrated INS/GNSS Kalman filter is employed to deliver the optimally integrated attitude, velocity and position solutions with the aid of GNSS meanwhile compensating the random noises in the raw MEMS measurements.

In this study, various test scenarios are developed to validate the proposed design. Firstly by the stand-alone INS test, it validates that the stand-alone MEMS INS solution is unreliable due to the utilised MEMS sensor in this study having large noises. The following validation test shows that Kalman filter is able to effectively estimate/compensate the raw IMU random noises. After compensating the deterministic errors by utilising the MEMS IMU sensor error models, the integrated INS/GNSS delivers the accurate solution compared to the reference. Finally, the functionality of the integrated INS/GNSS is validated by the simulation of the loss of GNSS signal. According to the results, it can be concluded that GNSS effectively aids INS solution from divergence.

From this study, it can be concluded that low cost MEMS INS solution is able to be improved by mitigating the inherent large MEMS sensor errors with the aid of integrating GPS data. Considering its advantages of lost cost, high dynamic, etc, and with the rapid innovation in MEMS technology, the application of MEMS INS is believed as one of the INS research interests for the next decades.

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