INERTIAL NAVIGATION SYSTEM DEVELOPED FOR MEMS APPLICATIONS

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Abstract

Key words: MEMS, INS/GPS integration, Kalman Filter

The purpose of this study is to validate a developed INS/GPS integration algorithm for embeddable positioning and navigation purpose using MEMS IMU (Inertial Measurement Unit) sensors. MEMS IMU sensors present unique noise characteristics and generally contain high-level noise inherent in the output data. In this paper, we investigate an advanced error modeling technique to evaluate these errors. With the proposed error models, the impacts of the MEMS noises can be characterized in terms of random noise, bias, quantization error, scale factor correction and miss-alignment errors. By employing this model in the INS calculation, the compensation of the deterministic noise terms from the raw MEMS measurements can be greatly improved. A loosely coupled Kalman filtering design for INS/GPS integration is also presented in this paper. Hence, the random noise compensation of MEMS sensors can be achieved for the proposed Kalman filter design.

Introduction

Inertial Navigation Systems (INS) provide a good short-term accuracy in terms of position, attitude and velocity estimation. As the price rises dramatically with the increase of inertial sensor precision, this technology has been confined to high precision applications, such as in aerospace or aeronautic navigation for a long time. With the emergence of MEMS based IMU sensors, inertial navigation system is becoming affordable for many applications due to its advantages in terms of quickly improved precision, robustness, high dynamic response and lower costs. However, its usage as a stand-alone navigation system is limited due to the time-dependent growth of the inertial sensor errors.

Compared with INS, GPS can provide position and velocity information via various measurements. While the precision of the position and velocity information from GPS is independent of time, its performance becomes unreliable when the system experiences high dynamics, multipath, interference, jamming and/or under undesirable operating environments such as indoors and urban canyons.

Because of the aforementioned complementary characteristics, INS and GPS can be integrated together to enhance the performance of each individual system. In this paper, a loosely coupled Kalman filtering design for INS/GPS integration is proposed. This method combines GPS measurements such as velocity and position with the INS calculations to estimate the errors. For the MEMS inertial sensor based IMU which generally provides high level noise contaminated raw measurements, a good estimation of the sensor bias is also crucial. An adapted error model is then used in the filter to estimate the gyroscopes and accelerometers bias.

The main objective of the study is to implement a robust, autonomous and precise MEMS based navigation system that could be used for embedded applications such as cell phone utility, personal navigation and location based services. This paper focuses on testing and validating the proposed INS/GPS integration design. Generally, there are two different scenarios that can be utilized for the validation, i.e. the post-processing and real-time processing mode. The post-processing mode is mainly performed in this study due to the performance analysis simplification compared with the real-time processing. After the proposed INS/GPS design is validated in the post-processing, the real-time application will be implemented as the next step and presented in future publications. To evaluate the MEMS performance, a navigation solution based on NovAtel SPAN™ Technology is employed as the reference. Results from this study show that the use of the proposed MEMS error model in the MEMS based INS/GPS integration system improves significantly its overall performance.

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Sensors Main Characteristics

There are two types of sensors used in this study, the Honeywell HG1700 tactical grade IMU (Utilized by NovAtel SPAN™ Technology) and the low-cost nIMU MEMS sensor from MEMSense. Both sensors have their specific properties and characteristics. The tactical grade HG1700 sensor consists in an assembly of three Ring Laser Gyro (RLG) and three accelerometers mounted in the referential axes X, Y and Z [1]. Because of its stability and reliability, the navigation solution obtained from NovAtel SPAN™ Technology which is calculated by the DL-4 plus GPS receiver is used in the study as the reference. The low-cost nIMU sensor from MEMSense provides 3D accelerometers, gyroscopes and magnetometers data at a sampling rate of 150 Hz [2]. Compared with the Honeywell sensor data, measurements from the nIMU are subject to higher noise, bias and scale factor errors as shown in the Table 1 and Table 2.

nIMU Sensor Components	**Dynamic Range**	**Noise**	**Nonlinearity**
Accelerometer	±2 (g)	4.87 (mg)	±0.4 (% of FS)
Angular Rate Sensor	±300 (°/s)	0.56 (°/s)	0.1 (% of FS)
Magnetometer	±1.9 (Gauss)	5.6×10^{-4} (Gauss)	0.5 (% of FS)

Table 1: MEMS IMU Characteristics

SPAN IMU HG1700	**Dynamic Range**	**Noise(Random Walk)**
Accelerometer	±50(g)	58(μg/√Hz)
Angular Rate Sensor	± 1000 (°/s)	0.125(°/√hr)

Table 2: SPAN IMU Characteristics

Figure 1 and Figure 2 show the raw accelerations and angular rates in the X, Y and Z axes for SPAN and MEMS IMU which have been logged in static mode for the duration of 15 minutes approximately.

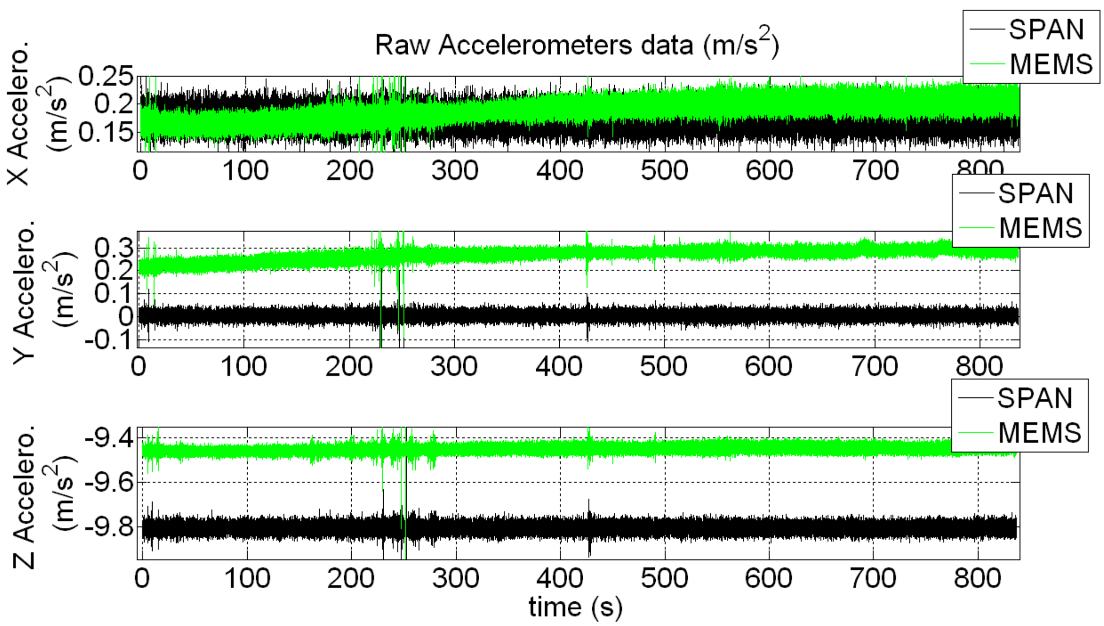

Figure 1: Raw Accelerations Data

According to the Figure 1 the specific force raw measurement data show a significant bias for all three axes of the MEMS accelerometers. We can also see that the MEMS accelerometers bias is non-constant and drifting by time.

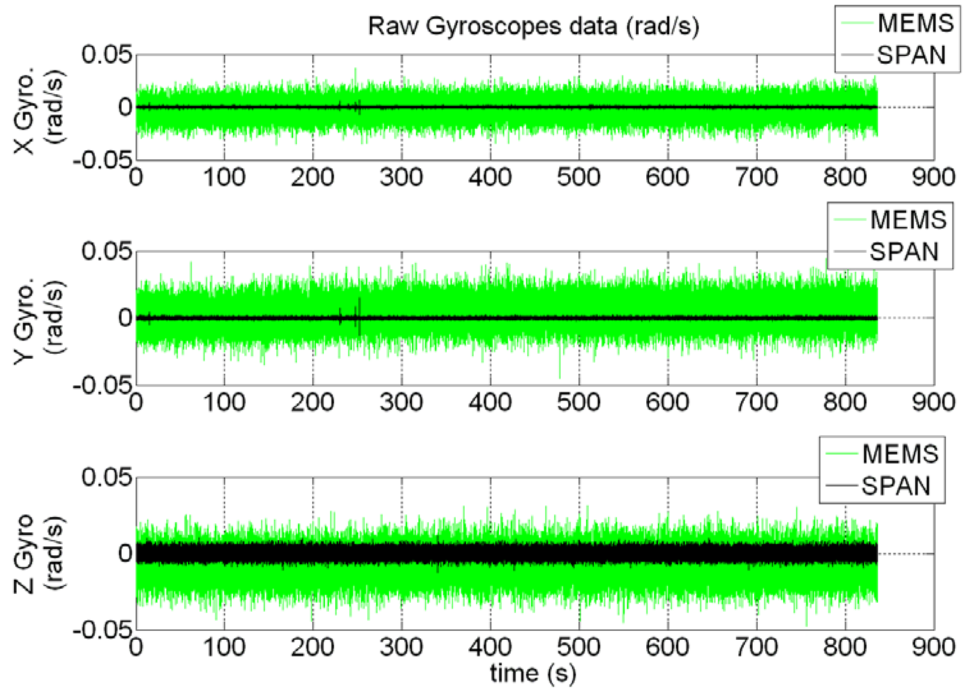

Figure 2: Raw Angular Rates Data

The angular rate raw measurement data show an important difference between the SPAN and MEMS. According to figure 2 the data provided by the MEMS sensor is subject to a very large noise characteristic and also present a small bias which is also non-constant in time. According to the inertial navigation theory, this is the principal reason degrading the performance of MEMS based inertial solution.

Results confirmed that the raw measurements provided by the MEMS sensor are subject to higher noise and bias characteristics than SPAN measurements. For this reason a MEMS adapted error model is required to be implemented in the INS calculation to estimate and correct these errors.

MEMS Based Attitude Determination for Initial Alignment

The basic of INS consists in the integration of attitude, velocity and position rate equations which must be first initialized. In most applications this initialization can be done under quasi-stationary conditions when the mobile is subject to very slow attitude and position variations [3]. By assuming that the fixed position is known well (e.g. derived from a GPS receiver) and by setting the initial velocity to zero, the problematic is simplified as the determination of the attitude initials. Wahba's problem (first published in 1965) proposed an attitude determination by matching two non-zero vectors that are known in one coordinate frame and measured in another under only angular movement condition [5],[6].

The attitude initials can therefore be determined by using three accelerometers and three magnetometers to measure the components of the gravity and of the earth magnetic field in the Body frame (B-frame). These values are known and constant for the given position in the Local Level frame (L-frame). The quaternion representing the attitude relates the gravity and earth magnetic vector measurements in B-frame to those known values in the L-frame. The MEMS attitude can then be estimated by using a complementary Kalman filter to converge the quaternion components [7].

Under quasi-stationary conditions the obtained quaternion should be constant and can be used directly to initialize the attitude calculation in the navigation system software. The attitude quaternion relating B-frame to L-frame is defined as [3]

$$q_B^L = \begin{bmatrix} a & b & c & d \end{bmatrix}^T \quad (1)$$

The definition of attitude components are from the "four-vector" [3]

$$u = a + bi + cj + dk \quad (2)$$

where a is scalar component of q_B^L, b, c, d are vector component of q_B^L and j, j, k are unit vector along coordinate frame axes.

The Direction Cosine Matrix (DCM) C_B^L, i.e. the attitude matrix for the transformation from the B-frame to LL frame is a function of this attitude quaternion and its expression is given by [3]

$$C_B^L = \begin{bmatrix} (a^2+b^2-c^2-d^2) & 2(bc-ad) & 2(bd+ac) \\ 2(bc+ad) & (a^2-b^2+c^2-d^2) & 2(cd-ab) \\ 2(bd-ac) & 2(cd+ab) & (a^2-b^2-c^2+d^2) \end{bmatrix} \quad (3)$$

The error state vector of the complementary Kalman filter consists of attitude quaternion components *a*, *b*, *c* and *d*. The body frame measured gravity vector and earth magnetic field vector are directly employed as the observations in the Kalman filter. The Kalman filter measurements are calculated by the measurement models using the estimated attitude quaternion to transform the known constant L-frame gravity and earth magnetic field vector to the body frame. By comparing the observations and measurements, the Kalman innovations are derived then to compensate the inaccuracy in the estimated quaternion components. After sufficient number of iterations, the estimated quaternion components should converge and could be utilized as the attitude initials [7].

INS Algorithm adapted for MEMS

This section focuses on presenting a digital strapdown INS integration algorithm [3] for MEMS application. The algorithm has already been validated in previous study [8] for SPAN IMU application. However, the approach for MEMS IMU is somehow different due to MEMS sensor's high level noise characteristics. In this version of the INS algorithm the raw IMU data are corrected before being utilized by the INS algorithm. This correction is made by the removal of the raw sensor noise, which is estimated by the use of an adapted error model in the proposed Kalman filter. The data is then processed by the two-speed digital INS algorithm at the 150 Hz rate corresponding to the IMU data rate. The structure of the INS algorithm utilized in the study is shown in the Figure 3.

The basic of this INS algorithm is to use the corrected sensors output to calculate the wanted PVA (Position, Velocity and Attitude). The structure of the INS represented by the Figure 3 is divided in different blocs. First, the angular rates are used to calculate the attitude which can then be used to convert the specific forces from the B-frame to the navigation frame (N-frame). Once the specific forces are represented in the N-frame, a gravity model is used to remove the gravity and the coriolis components to obtain directly the acceleration of the mobile. Finally, by doubly integrating this acceleration the velocity and then the position can be obtained.

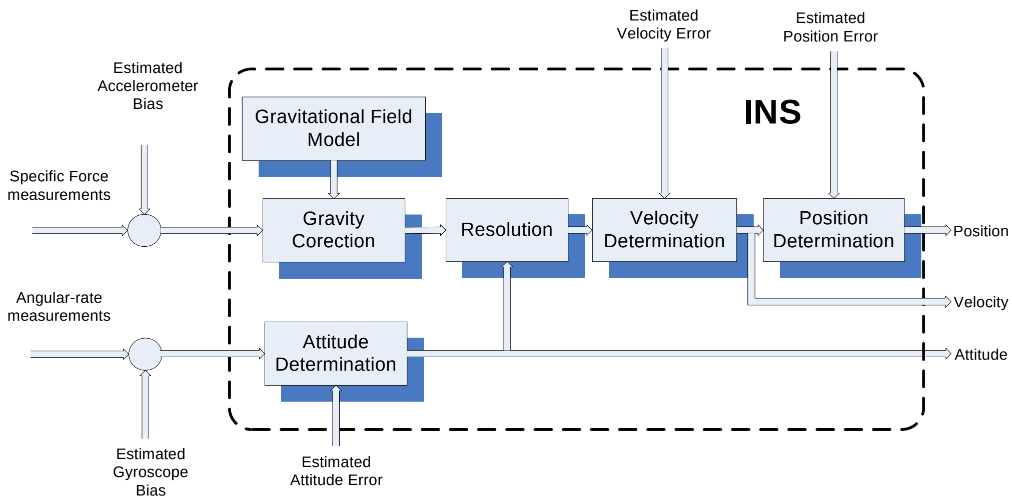

Figure 3: INS Digital Integration Structure

Loosely Coupled INS/GPS Integration Algorithm Adapted for MEMS

As we aforementioned, the navigation filter implemented in this study consists in a loosely coupled INS/GPS integration algorithm. This Kalman filtering design has also been validated in a previous research [8]. Since this filter is applied in the preset work for MEMS integration purpose, some important modifications have to be introduced to estimate the low-cost MEMS accelerometers and gyroscopes constant biases. To perform this estimation, an inertial sensor error model has been implemented in the filter. Therefore the fifteen states Kalman filter error state vector can be described as [7]

$$\overline{X} = \begin{bmatrix} \delta V_{3x1} \\ \delta R_{3x1} \\ \delta \psi_{3x1} \\ \delta a^B_{SF_{3x1}} \\ \delta \omega^B_{IB_{3x1}} \end{bmatrix} \tag{4}$$

where $\Psi, \delta V, \delta R$ are respectively the errors in attitude, velocity and position parameters measured in the Earth frame (E-frame) and expressed in Navigation frame (N-frame). The other components $\delta\omega^B_{IB}$ and δa^B_{SF} are respectively the angular rate and specific force constant bias vectors expressed in the B-frame.

The angular rate and specific force noise vectors can be generally modeled as [3]

$$\delta\omega^B_{IB} = \delta\omega^B_{IB_{Bias}} + w_\omega \tag{5}$$

$$\delta a^B_{SF} = \delta a^B_{SF_{Bias}} + w_a \tag{6}$$

where $\delta\omega^B_{IB_{Bias}}$ and $\delta a^B_{SF_{Bias}}$ are the bias vectors and w_ω and w_a are the random noise vectors.

The accelerometer and gyroscope biases are then modeled as a constant value in this study. Hence the process model can be derived from the following definition

$$\delta\dot{\omega}_{IB_{Bias}}^{B} = \delta\dot{a}_{IB_{Bias}}^{B} = 0 \tag{7}$$

The bias error vectors $\delta\omega_{IB_{Bias}}^{B}$ and $\delta a_{SF_{Bias}}^{B}$ are included in the Kalman error state vector. As we aforementioned early, MEMS bias is then used in the feedback control by the INS algorithm to correct its measurements.

Low-cost MEMS Testing Results and Performance Analysis

Several tests have been done to evaluate the performance of the algorithm in a realistic environment. For the real data post-processing validation scenario which is highlightened in this paper, the raw IMU data is acquired directly from the MEMS IMU sensor at a data rate of 150 Hz and the GPS position and velocity data are logged simultaneously at a rate of 5 Hz. The data are post-processed by the INS algorithm and then integrated with GPS data in the proposed Kalman filter. For the proposed scenario, NovAtel best PVA solution (logged via the OEM4 receiver), is also recorded as the true reference to evaluate the MEMS IMU solution. The road test scenario presented in this paper was conducted in a parking lot in Angrignon Shopping Mall, Montréal, Canada on the 3rd April 2008, where a good acquisition of GPS signal is generally available. Figure 4 shows the complete 2-D trajectory of this test in terms of latitude and longitude.

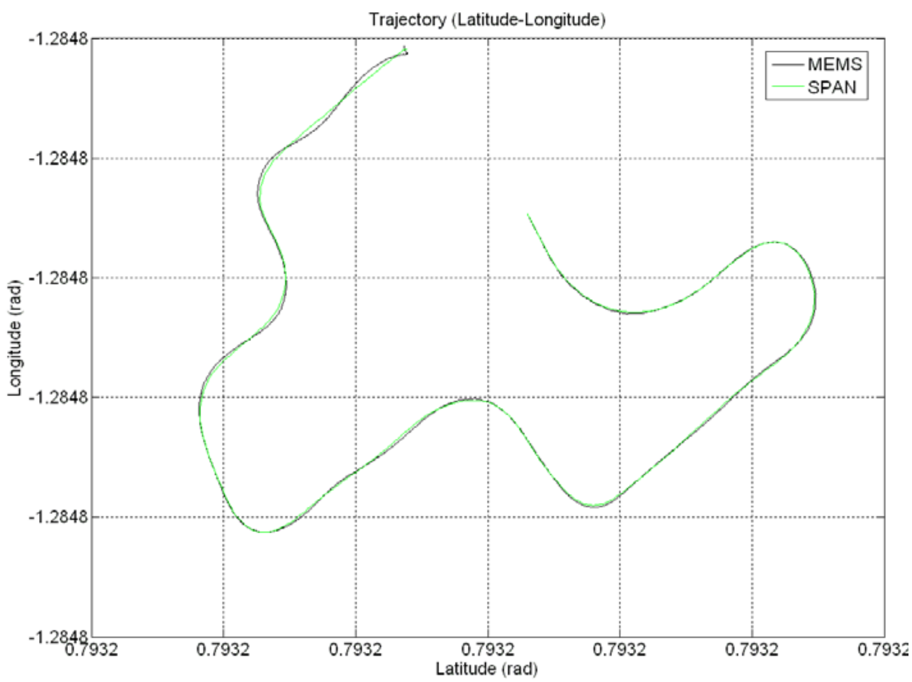

Figure 4: Test trajectory (Longitude vs Latitude)

By comparing the MEMS solution with NovAtel's, the overall performances of the proposed algorithm in this study can be measured in terms of position, velocity and attitude errors shown respectively in Figure 5, Figure 7 and Figure 8.

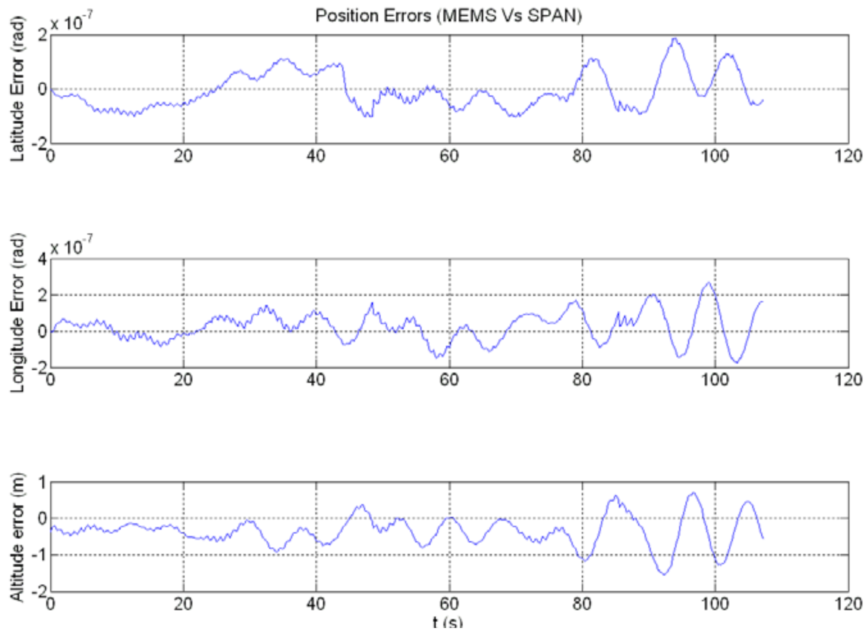

Figure 5: Geographic Position Errors (latitude, longitude and altitude) (MEMS vs SPAN)

According to Figure 5 the position errors between the MEMS solution and the reference can be characterized by a maximum error of approximately 3×10^{-7} radians in geographic coordinates (latitude and longitude) which correspond to approximately a 1.5 meter error in Cartesian coordinates (X, Y and Z) as shown in Figure 6. The program for the conversion (from Geographic to Cartesian coordinates) is accomplished by utilizing the algorithm from chapter 4.1 [9]

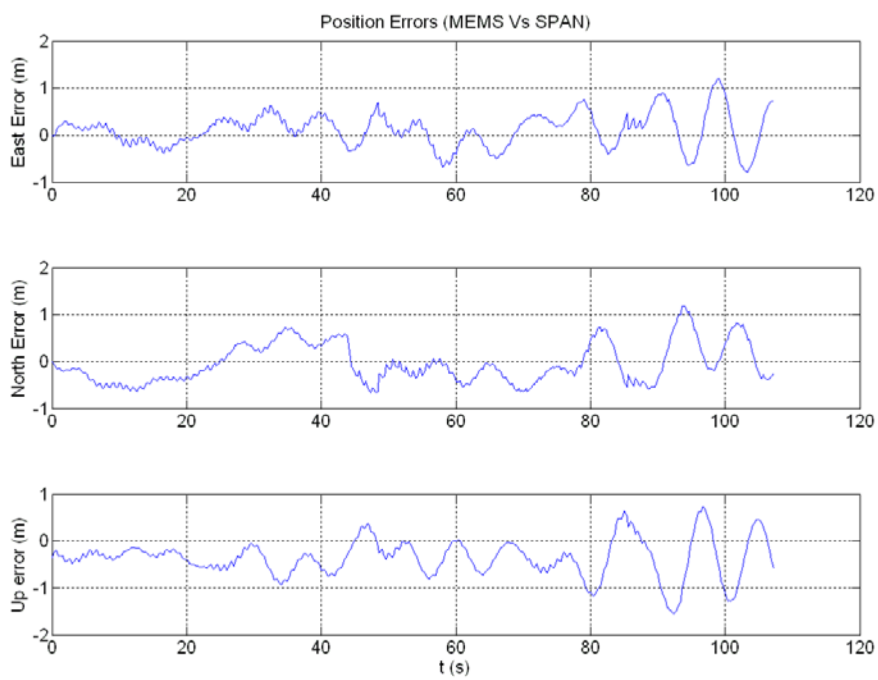

Figure 6: Cartesian Position Errors (latitude, longitude and altitude) (MEMS vs SPAN)

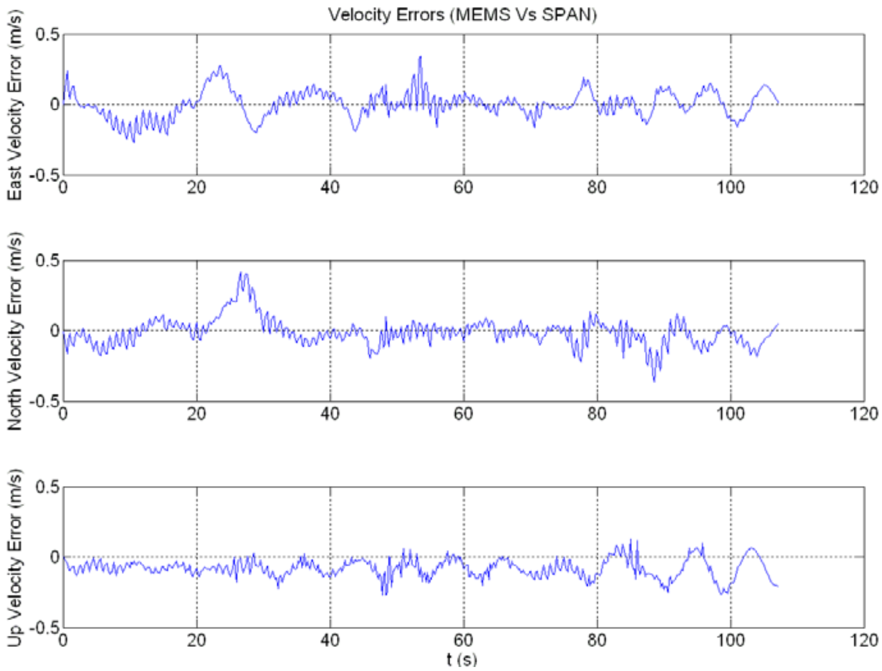

Figure 7: Velocity Errors (East, North and Up) (MEMS vs SPAN)

The attitude errors in terms of roll, pitch and heading angles represented by Figure 8 show a very small roll and pitch errors of approximately 0.05 radians but a heading error which trends to be diverging with time. This difference in terms of errors between the roll/pitch and the heading depend on the dynamic of the trajectory where the gyro outputs of X and Y axes are almost null comparing to the Z gyro outputs. This time dependant growth reflects the effect of a non-constant bias inherent in the raw gyro outputs, which has been shown in figure 2. The error model used in the Kalman filter is used to estimate the assumed constant bias of the sensors. A more deliberately designed error model should then be utilized in future work to get a better estimation of this non-constant bias, e.g. performances of Markov model or random walk model will be investigated.

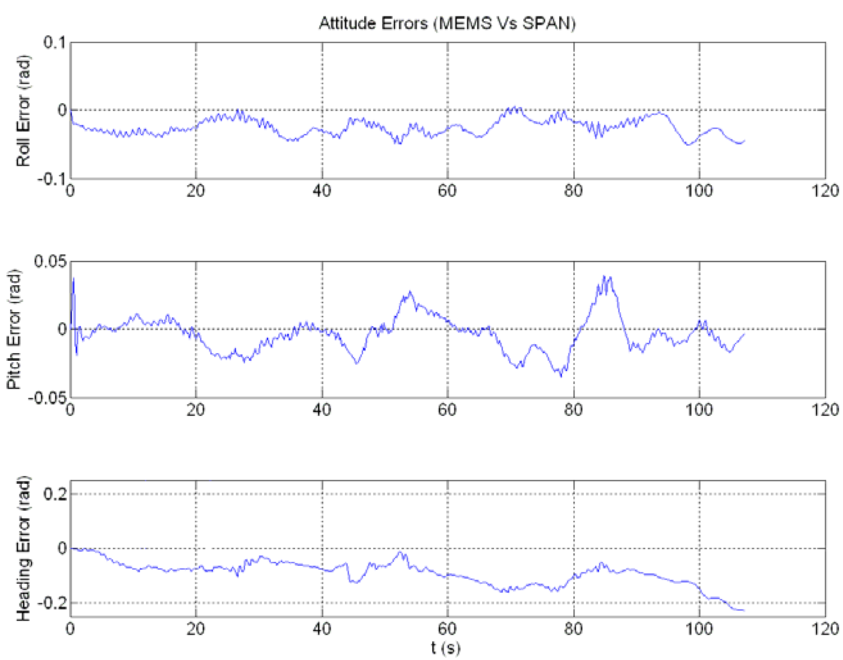

Figure 8: Attitude Errors (Roll, Pitch and Heading) (MEMS vs SPAN)

Conclusion

The purpose of this paper was to validate the proposed INS/GPS integration algorithm for MEMS applications. The results have shown very good overall performances of the algorithm for short duration trajectory with a maximum error observed of approximately 1.5 meter. However, time growing errors in the attitude (0.2 radians after two minutes) due to the non-constant bias of the MEMS sensors could be an important source of errors for longer trajectories or high dynamics situations. In this case a quasi-stationary calibration should be re-performed sometimes during the trajectory using the initial alignment process to reinitialize the attitude and null the time-dependent growth.

This study is a first step in the development of this MEMS based INS/GPS integration algorithm. Future work will be performed to test and validate the proposed design in real-time data processing for autonomous embedded application e.g. personal navigation, location based services, cell phone/PDA utility, and so on. With its well-convinced advantages in the real-time application and its stability the C Language-based programming method will be utilized to implement the algorithm for the real-time processing. Before that, the implementation of a new error model will be investigated to be able to get a better estimation of the sensor bias and then get a more precise attitude determination. A method using the UTC time tag will also be investigated to have an automatic synchronization of the raw MEMS IMU data and the GPS data.

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