Low-cost MEMS Sensor-based Attitude Determination System by Integration of Magnetometers and GPS: A Real-Data Test and Performance Evaluation

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Abstract **– Attitude determination systems utilizing low cost MEMS sensors are increasingly becoming important due to its advantages in terms of the quickly improved precision, robust, high dynamic response and more significantly inexpensive costs of development and usage. However the large noises inherent in low cost MEMS sensors degrade the derived attitude precision if utilized through the conventional methods, e.g. initial alignment, strapdown inertial navigation mechanization. Therefore the novel application approach suitable for MEMS needs to be investigated. This paper describes an attitude determination system that is based on low cost MEMS inertial sensor, a triad of magnetometers and a commercial GPS receiver. Two main issues are addressed in the paper; firstly determination of the attitude initials, the algorithm is based on a quaternion formulation, a representative of attitude, of Wahba's problem, whereby the error quaternion becomes the estimated state and is corrected by two observations of the earth magnetic field and gravity respectively. After the estimates converge, the derived attitude parameters are employed to initialize the inertial navigation calculations. Due to the large noises in MEMS sensor, there is a demand for external velocity and/or position corrections in the MEMS navigation calculations when system experiences translational motions. Hence secondly, GPS solutions are integrated in a Kalman filter by providing external velocity and position observations. A Kalman dynamic model is designed appropriate for MEMS sensor noise characteristics. The bias and drift are estimated by the integrated Kalman filter, which enables the online calibrations of MEMS sensor. The proposed approach has been developed and its efficiency is demonstrated by various experimental scenarios with real MEMS data and they are compared with Novatel SPAN-IMU reference.**

I. INTRODUCTION

Attitude determination is a requirement for most navigation and control problems. Traditionally, this issue has been well solved by the so-called Attitude and Heading Reference System (AHRS) (Crossbow, 2000). However a successful AHRS requires very expensive sensors that have exceptional long term bias stability. The sensor cost limits such kind of attitude determination to very expensive applications [2]. Meanwhile low cost Micro Electro Mechanical Sensors (MEMS) are experiencing rapid improvements in terms of precision, robust, size, high dynamic response and so on. With the rapid growth in demand, such as in applications of general aviation, unmanned automotive vehicle, personnel localization, mobile mapping systems, athletic training monitoring and computer games, .etc, it has become viable to construct low cost attitude determination systems.

Today's MEMS sensors are still much less precise than expensive accurate inertial sensors, such as tactic or navigation grade IMU which measurements are able to be directly used by inertial system self-alignment and strapdown inertial navigation algorithm. However, if applied by modern MEMS sensors, these standard inertial calculation procedures are not practical, or in another word, the solutions diverge quickly. For example, it takes approximately 5 minutes for the inertial self-alignment process to converge in quasi-stationary environment. The large MEMS noises cause this regular inertial self-alignment process to diverge within a few seconds. Similarly, the stand-alone use of MEMS sensors in strapdown inertial navigation system could deliver kilometre-level positioning errors for the applications of several seconds duration. Therefore as aforementioned, there are two critical issues which should be solved in order to apply MEMS sensors in attitude determination system, which are firstly to determine the attitude initials, and secondly to have MEMS based inertial solution errors bounded in time.

Recently there has been a considerable amount of effort paid at developing low cost MEMS based systems for attitude

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determination [1], [2], [3]. As first published in 1965, Wabha proposed an attitude solution by matching two non-zero vectors that are known in one coordinate frame and measured in another [2], [4]. Many solutions to this method of attitude determination have been proposed and implemented. However Wabha's problem of attitude determination is under the condition where there is no translational movement in the platform hosting MEMS sensors. Therefore the acceleration, velocity or position corrections should be introduced into the MEMS based attitude determination system in exists of any translational movement. Commonly INS and GPS are two complimentary technologies that can be integrated by Kalman filtering to provide reliable velocity and positioning information.

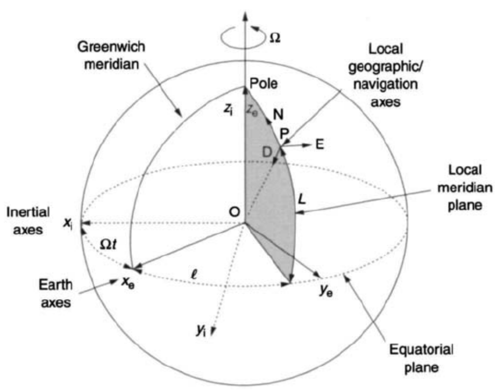

Fig. 1 Navigation coordinates

This paper presents an approach of applying low cost MEMS sensor for attitude determination system in dynamic environment, i.e. with both angular and translational movements. This system consists of a low cost MEMS sensor which includes a triad of angular rate sensors, a triad of accelerometers, a triad of magnetometers and a commercial GPS receiver. First of all, the proposed system is fixed to a known position with no translational but only angular movements, three accelerometers and three magnetometers measure components of the gravity and earth magnetic field in Body frame (B-frame). Because these values are known and constant for a given position in the Local Level frame (L-frame), there exists a quaternion, a representative of attitude, relating the gravity and earth magnetic field measurements in B-frame to those known values in L-frame depicted in Fig. 1. The components of quaternion are able to be estimated by a complementary Kalman filter. The converged quaternion represents MEMS attitude. When there is neither translational nor angular movement, the estimated quaternion is constant which hence can be used as attitude initials for the following navigation calculations. Then, an integrated INS/GPS Kalman filter is developed to deliver the navigation solutions when there exist both of translational and angular movements. Strapdown INS mechanization and INS error equations based Kalman filter are specially designed considering MEMS large noise characteristics. Moreover, inertial sensor error modelling is employed in the integrated Kalman filter to estimate MEMS sensor errors which enables MEMS sensor in-motion calibration. The test of the proposed approach is conducted via real data experiments. The raw MEMS IMU data is acquired at a data rate of 150Hz. Attitude, velocity and position solutions are delivered at the same rate but corrected by GPS data at a rate of 5 Hz in the Kalman filter. The system performance is validated in the test with deliberated attitude manoeuvres.

II. ATTITUDE INITIAL DETERMINATION

The basic computational process of the inertial sensor based navigation system consists of the integration of attitude, velocity and position rate equations which must first be initialized at the beginning of the navigational calculation [5]. The problematic discussed in this paper confines to the determination of initials under quasi-stationary conditions, which represents many of the inertial navigation applications. The quasi-stationary conditions in this study are described as having bounded attitude and velocity movements with known and fixed position where the platform hosting MEMS sensors. By setting the initial velocity to zero, the problematic of initializing MEMS sensor based attitude determination system is simplified to the determination of the attitude initials. As aforementioned, Wahba's problem proposed an attitude solution by matching two non-zero vectors that are known in one coordinate frame and measured in another under only existing angular movement condition.

To determine the attitude initials, three accelerometers and three magnetometers measure components of the gravity and earth magnetic field in B-frame. These values are known and constant for the given/fixed position in L-frame. The attitude quaternion relates the gravity and earth magnetic vector measurements in B-frame to those known values in L-frame. The converged quaternion components estimated by a complementary Kalman filter represents MEMS true-attitude. When under quasi-stationary conditions in this study, i.e. there is neither translational nor angular movement; the derived quaternion is constant and therefore can be used as attitude initials. The transformation between the vector $\underline{v}$ as expressed in B-frame and L-frame is

$$\underline{v}^L = C_B^L \underline{v}^B \tag{1}$$

The Direction Cosine Matrix (DCM) C_B^L transforming the vectors from B-frame to L-frame is function of the attitude quaternion q. The DCM is expressed in terms of quaternion q as

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

Where the attitude quaternion relating the B-frame to non-rotation L-frame is defined as

$$q_B^L = \begin{bmatrix} a & b & c & d \end{bmatrix}^T \tag{3}$$

The definition of attitude quaternion components are from the “four-vector”

$$u = a + bi + cj + dk \tag{4}$$

Where a is a scalar component of q, b, c and d are vector component of q_B^L , i, j and k are unit vector along the coordinate frame axes. For example, the N, P and E unit vector in Fig. 1.

The equation (1) is used to get the attitude initials in this study. Due to the fact that the observed vector $\underline{v}^B$ is contaminated by MEMS sensor noise, it is ideal to utilize Kalman filtering to estimate the attitude quaternion. The error state vector of the complementary Kalman filter consists of attitude quaternion components a, b, c and d. The B-frame measured gravity vector and earth magnetic field vector are directly employed as the observations in the Kalman filter. The linearized equation (1) constructs the Kalman measurement models which generate B-frame gravity/earth magnetic field vector measurements by use of the estimated attitude quaternion to transform the known/constant L-frame gravity/earth magnetic field vector to B-frame. By comparing the observations and measurements, the Kalman innovations are derived then to compensate the inaccuracy in the estimated quaternion components. The process model of Kalman filter is derived from the quaternion rate of change equation

$$\dot{q}_B^L = \frac{1}{2} q_B^L \omega_{IB}^B - \frac{1}{2} \omega_{IL}^L q_B^L \tag{5}$$

Where ω_{IB}^B is the B-frame expressed angular rate vector from B-frame to I-frame, i.e. the measurement from the gyro triad. Since there is no translational movement for MEMS sensor, therefore L-frame rotation rate ω_{IL}^L expressed in L-frame is simplified and equal to the earth rotation rate ω_{IE}^L , which is constant, i.e.

$$\omega_{IL}^L = \omega_{IE}^L \tag{6}$$

After sufficient number of iterations, the estimated quaternion components should converge and can be utilized as the attitude initials. According to the quasi-stationary conditions, the initial velocity is zero and the initial position is a known constant.

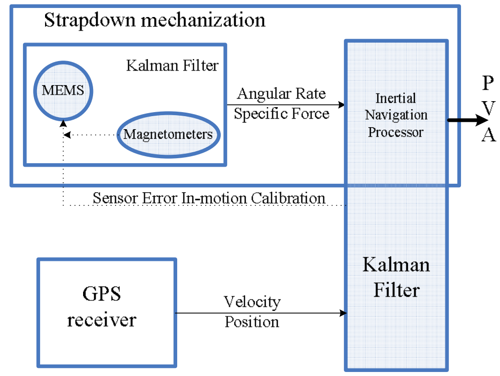

Fig. 2 Attitude Determination

III. ATTITUDE DETERMINATION

The navigation calculation in this study consists of two indispensible parts, i.e. the strapdown mechanization and a GPS integrated Kalman filter, which is depicted in Fig. 2. There are many solutions constructing strapdown mechanization for MEMS attitude determination system. Those solutions are divided into two categories, i.e. a multi-speed digital processing design including accurate coning and sculling compensations for attitude and velocity calculation, and a simplified single speed design without any attitude and velocity compensation algorithm [5] and [6]. Both of these two algorithms have been implemented and investigated in [8]. According to the results from [8], due to the large noise characteristics of MEMS sensors, the errors generated by different strapdown mechanizations, i.e. the calculated coning and sculling compensation terms are much smaller than the errors generated by MEMS sensor noise. Therefore different strapdown mechanization implementations reach the same precision when MEMS sensor applied. Moreover, the complexity and computing load vary significantly in these two implementations referring to [1]. Hence the simplified single speed design is applied in this study to construct strapdown mechanization. The attitude, velocity and position solutions are derived by solving the rate equations

$$\begin{aligned} &\dot{C}_B^L = C_B^L(\omega_{IB}^B \times) - (\omega_{IL}^L \times) C_B^L \qquad \omega_{IL}^L = C_N^L(\omega_{IE}^N + \omega_{EN}^N) \\ &\dot{v}^N = a_{SF}^N + g_P^N - (\omega_{EN}^N + 2\omega_{IE}^N) \times v^N \qquad g_P = g - \omega_{IE} \times (\omega_{IE} \times R) \\ &\dot{C}_N^E = C_N^E(\omega_{EN}^N \times) \qquad \dot{h} = v_\perp^N \end{aligned} \tag{7}$$

Where C_B^L is the attitude matrix, $(\omega_{IB}^B \times)$ is the skew-symmetric matrix of the angular rate vector in B frame, $(\omega_{IB}^B \times)$ is the skew-symmetric matrix of the angular rate vector caused by the translational motion in L frame, ω_{EN}^N is the angular rate of N frame relative to E frame, v^N is the velocity vector, a_{SF}^N is the specific force vector, g_P is the Plumb-bob gravity, g is the standard gravity and R is the position location vector from the earth centre. As a demonstration example, the

Matlab implementation of the attitude solution is depicted in Fig. 3.

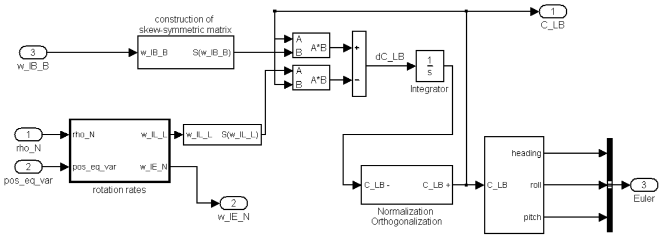

Fig. 3 Implementation of Attitude solution

When the translational movement exists in the application, due to large MEMS noise characteristics, stand-alone MEMS navigation solutions diverge quickly, generally in few seconds, therefore external velocity and/or position correction must be introduced. Most commonly utilized method is the integrated INS/GPS Kalman filter. In this study, key issues become how to account for the high level noises contaminated raw MEMS measurements through the Kalman filter design. Two topics are addressed in the following, firstly the design of the Kalman filter process model, which is to propagate the estimated errors in attitude, velocity and position. Secondly the design of MEMS sensor error model, which is utilized in the in-motion calibration of MEMS raw measurements.

The INS error model is commonly employed by the design of Kalman process model. Many different INS error models are available in [5], which are actually equivalent. In the present proposed system, the so-called psi-angle error model is applied, which defines errors in attitude, velocity and position parameters ($\Psi, \delta V, \delta R$) in the Earth frame (i.e. ECEF, Earth-Centre Earth-fixed frame) and then transformed to the Navigation frame (N-frame, in the North-slaved implementation, where Navigation frame x, y and z axis is parallel to local east, north and up direction, depicted in Fig. 1), i.e.

$$\begin{aligned}
\dot{\Psi}^N &= -C_B^N \delta\omega_{IB}^B - \omega_{IN}^N \times \Psi^N \\
\delta\dot{V}^N &= C_B^N \delta a_{SF}^B + a_{SF}^N \times \Psi^N + \delta g_{Mdl}^N - (2\omega_{IE}^N + \omega_{EN}^N) \times \delta V^N \\
\delta\dot{R}^N &= \delta V^N - \omega_{EN}^N \times \delta R^N
\end{aligned} \tag{8}$$

Where, $\Psi, \delta V, \delta R$ are errors in attitude, velocity and position parameters, C_B^N is the DCM from B-frame to N-frame, $\delta\omega_{IB}^B$ is the angular-rate error vector in B-frame, $a_{SF}^N, \delta a_{SF}^B$ are the specific force vector in N-frame and the specific force error vector in B-frame, δg_{Mdl}^N is the plump-bob gravity error, $\omega_{IE}^N, \omega_{EN}^N$ are the earth rotation rate vector and transport rate vector in N-frame, and ω_{IN}^N is the N-frame rotation rate in I-frame. In the Kalman filter design, the error parameters in attitude, velocity and position are represented as the error states which are propagated in the Kalman filter by the process model. As MEMS noises generate the main contribution in the attitude, velocity and position errors, i.e. many error terms in the INS error model are negligible when compared with raw measurements errors δa_{SF}^B and $\delta\omega_{IB}^B$. Therefore those negligible terms can be removed from the error model which in turn reduces the Kalman filter error vector dimension and remarkably decreases the computing load. Furthermore, the deleted error terms are equivalently re-evaluated as the overall contribution by the MEMS bias/drift error model. For the attitude error differential equation, according to the aforementioned discussion, it can be simplified as

$$\dot{\Psi}^N = -C_B^N \delta\omega_{IB}^B \tag{9}$$

The velocity error 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 errors and the attitude error, which gives out

$$\delta\dot{V}^N = C_B^N \delta a_{SF}^B + a_{SF}^N \times \Psi^N \tag{10}$$

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

$$\delta\dot{R}^N = \delta V^N \tag{11}$$

The simplified equation set containing (9), (10) and (11) constructs the Kalman filter process model. According to the 150 Hz MEMS raw data rate in this study, by taking advantage of the maxim data rate of MEMS sensor, this continuous-mode Kalman process model is descretized at 150 Hz to build the Kalman filter state transition matrix (Phi-Matrix) and the integrated process noise matrix (Q matrix) facilitating Kalman filter implementation in a small digital processor.

Due to MEMS sensor's high level errors, an effective way to mitigate the errors in attitude, velocity and position parameters is to model/estimate MEMS sensor errors in Kalman filter. In this study, MEMS errors are assumed and estimated to be additive noise. The angular rate noise is modeled in this study as

$$\delta\omega_{IB}^B = \delta\omega_{IB_{Bias}}^B + w_\omega \tag{12}$$

Where $\delta\omega_{IB_{Bias}}^B$ is the bias vector and w_ω is the random noise vector. The bias vector is modeled as a constant value; the process model can be derived from the following definition, i.e.

$$\delta\dot{\omega}_{IB_{Bias}}^B = 0 \tag{13}$$

The bias error vector $\delta\omega^{B}_{IB_{Bias}}$ is included in the Kalman error state vector; whereas the random noise vector w_{ω} is treated as a Gaussian process noise, which effect is evaluated in the Q matrix. The estimated MEMS bias is used in the feedback control, i.e. MEMS bias are directly used to calibrate the raw MEMS measurements at the end of each error state estimation update iteration and then the bias estimate vector is reset at the end of each correction update iteration. The accelerometer error model is derived in the same form. The error estimates are applied also in the feedback control.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Real data test is performed to validate and evaluate the proposed approach. The MEMS sensor used in the test is from MEMSense™'s nano Inertial Measurement Unit (nIMU) series product, which provides serial digital outputs of 3D acceleration, 3D rate of turn (rotational), temperature sensors and 3D magnetic field data. Digital outputs are factory configured to the I^2C or RS422 protocols and custom algorithms provide high performance, temperature compensated 3D data in real time [10]. The navigation solutions (NovAtel SPAN™ Best PVA) derived from a tactic grade IMU are employed to provide the reference due to its better performance vs. MEMS in terms of the long term bias stability. The inertial devices are shown in Fig. 4 and specs are provided in Table I. The testing assembly comprising the reference IMU, nIMU, GPS receiver, laptop computer and power supply is shown in Fig. 5. The test is made outside ETS University building with a good GPS signals visibility.

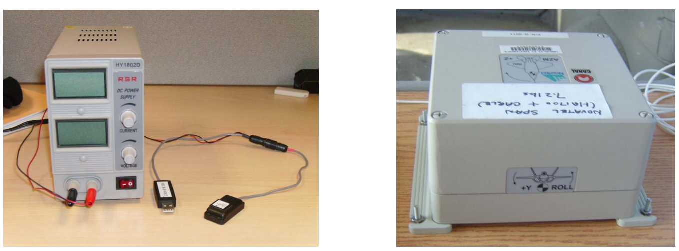

Fig. 4 nIMU MEMS sensor and SPAN IMU

Table I nIMU MEMS Sensor Specs

nIMU Sensor Components	Dynamic Range	Noise	Nonlinerity
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)

Fig. 5 Testing Device Units and Setup

The procedure of the test is first, before starting the dynamic manoeuvres; the low cost MEMS system remains static for calculating the attitude initials for 30 seconds. After the attitude calculation converges with the aid of the embedded magnetometers, the results can be used as the attitude initials for the following dynamic test. Meanwhile, the velocity initials can be set to zero. Then, dynamic trajectory is made to validate the proposed design and it consists of a series of deliberate manoeuvres in attitude.

The trajectory is depicted in Fig. 6. The duration of the test is 34 seconds. The green curve is the reference, i.e. derived from the SPAN best Position, Velocity and Attitude solutions. The black curve is the MEMS sensor integrated solution. It can be seen that MEMS integrated solution starts to diverge from the reference at the end of the test due to MEMS noises growing much faster than SPAN IMU sensor.

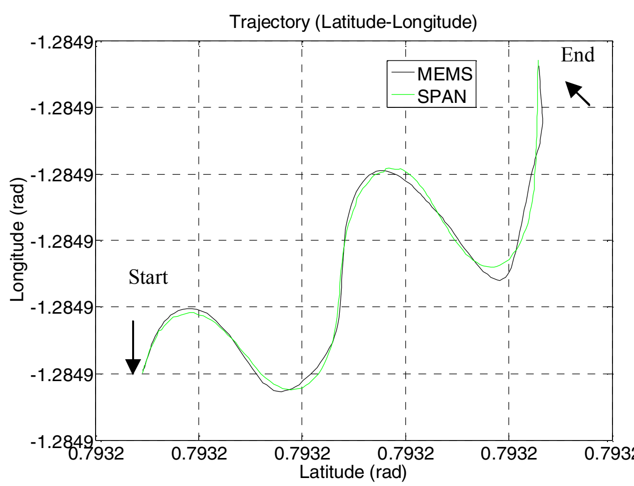

Fig. 6 Trajectory obtained with MEMS vs. SPAN

Compared with the reference, the maximum position solution errors derived from MEMS integrated solution are about 5×10^{-7} radian shown in Fig. 7; which represents 1 to 2 meters in Cartesian coordinates in Fig. 8.

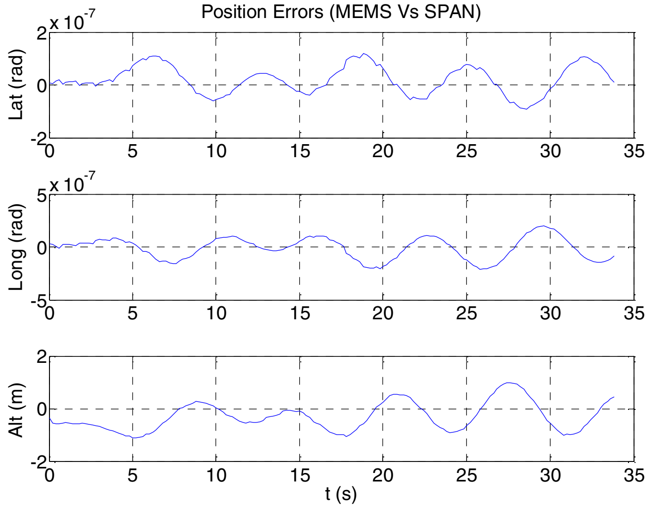

Fig. 7 Position solution errors (in radian)

The velocity solutions are shown in Fig. 9 while the velocity solution errors are depicted in Fig. 10. It can be seen that north and east velocity solutions fit the reference well; the errors remains small except up velocity starts to diverge at the end of the test. One of the reasons causing this divergence is the time growing bias/noise in MEMS accelerometer raw measurements. It can be seen that the raw specific force measurements of MEMS's are much more noisy than those of the reference IMU's in Fig. 11. Compared with the reference IMU, MEMS raw specific force measurement errors are shown in Fig. 12.

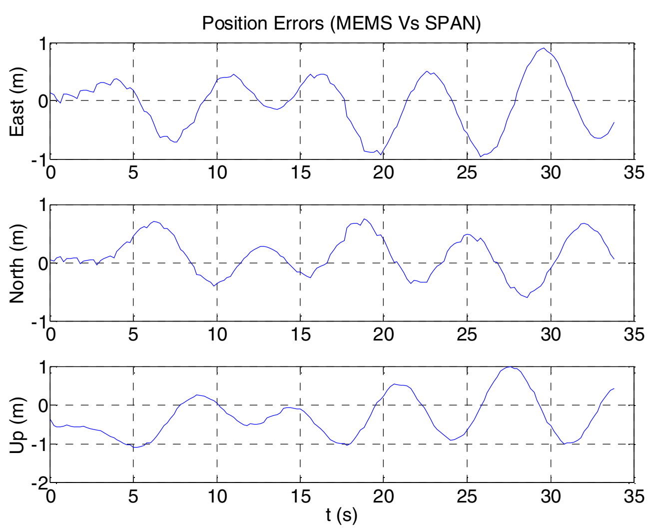

Fig. 8 Position solution errors (in meters)

From the Figure 11, one can clearly see that each accelerometer measurement error consists of a constant bias and the random noise. Moreover, the Z axis raw measurement is much more noisy compared with X and Y axis. Since Z axis accelerometer measures the major component of the up direction translational movement according to the initial attitude setup utilized in this test, the up velocity solution is degraded by the large Z axis accelerometer noise.

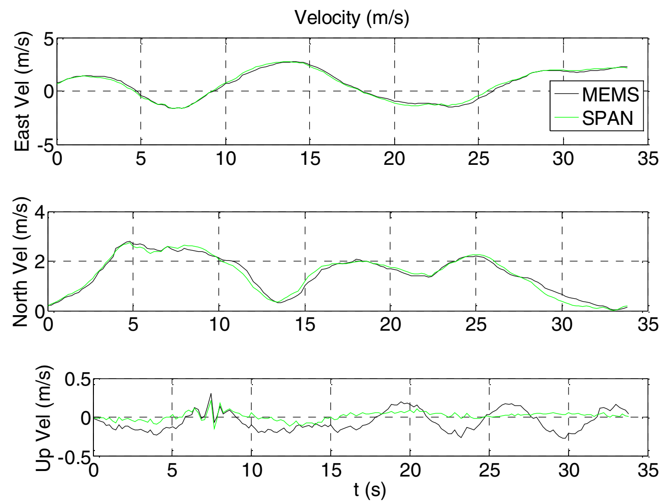

Fig. 9 Velocity solutions

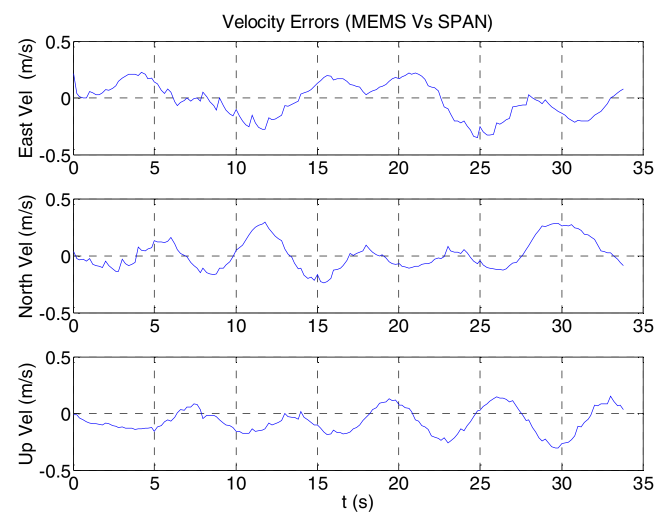

Fig. 10 Velocity solution errors

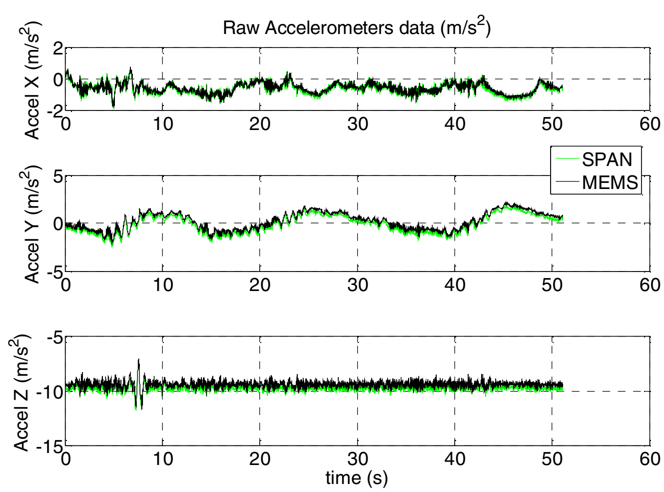

Fig. 11 Raw specific force measurements MEMS vs. SPAN

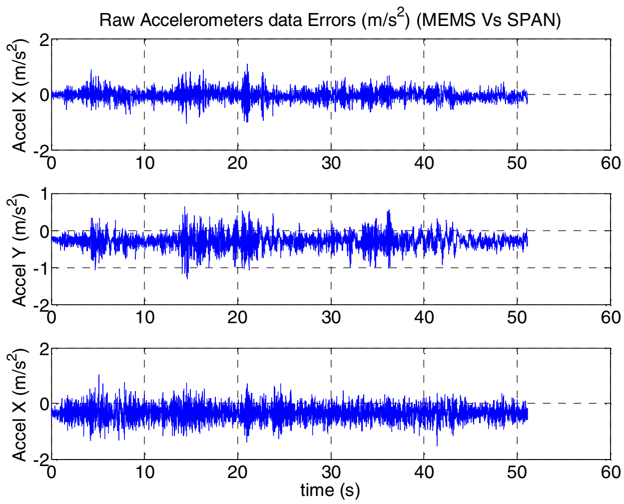

Fig. 12 Raw specific force measurement errors

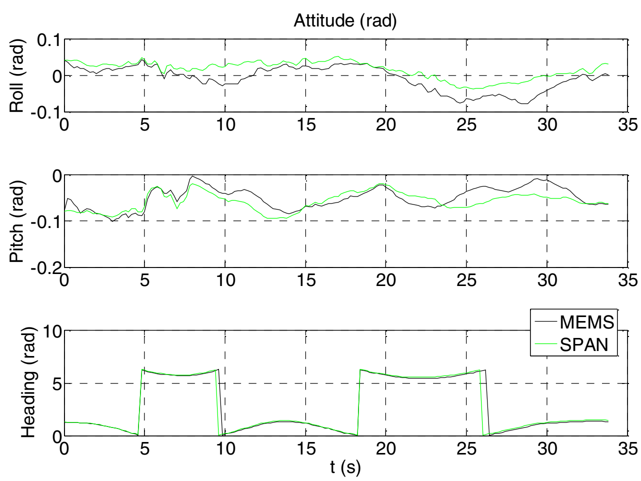

Fig. 13 Attitude determination solutions

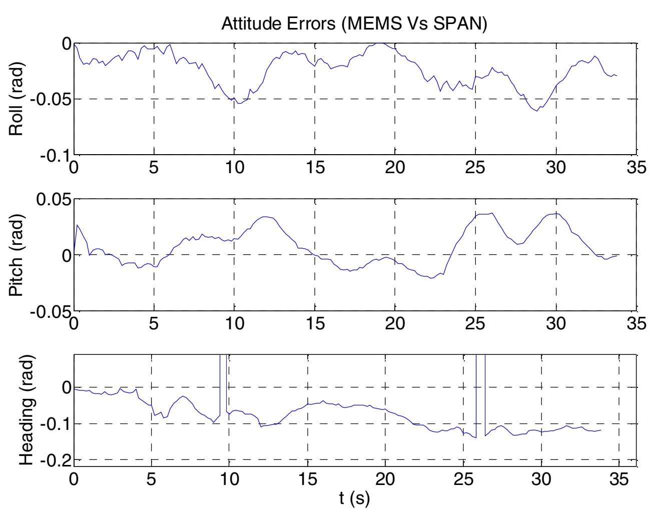

Fig. 14 Attitude determination solution errors

The attitude solutions are depicted in Fig. 13, from which we can see that attitude solutions derived from MEMS based attitude determination system are able to follow the reference. Due to the large noises contaminating MEMS raw angular rate measurements, there are distinct errors in the MEMS attitude solutions compared with the reference attitude. Similar to the velocity solutions, the attitude solutions start to diverge at the end of the trajectory.

The attitude errors compared with the reference are 2.9º, 2.7º and 11º respectively in roll, pitch and heading angle as shown in Fig. 14. From this figure, one can see that the heading error is growing with time. Referring to inertial navigation error equations (8), the attitude error is the essential reason causing the divergences in velocity and position solutions as seen in Fig. 10. The two big errors spotted in the heading are caused by the time synchronization errors, i.e. the slight time delay between MEMS and reference solutions. This type of errors becomes significant when the calculated heading angle changes from 2π to 0 or from 0 to 2π where 0 and 2π represent the same heading. During the test, GPS observation is available every 200ms. Therefore the attitude solution derived from MEMS is updated at 5 Hz rate by GPS.

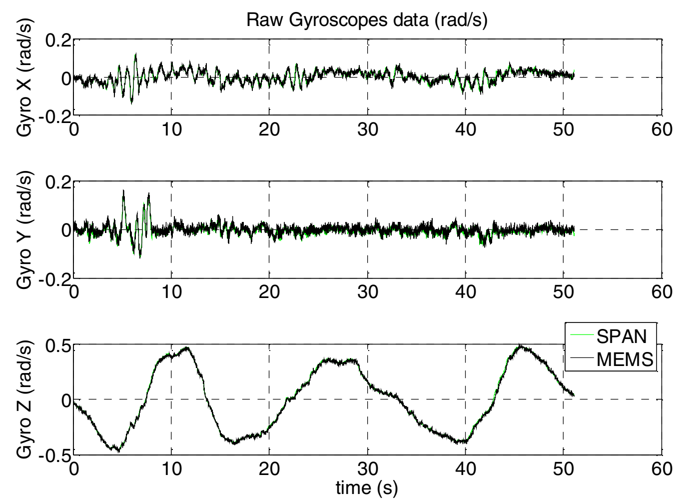

Fig. 15 Raw angular rate measurements MEMS vs. SPAN

Similarly the raw angular rate measurements from MEMS and reference IMU are depicted in Fig. 15. Although measuring the same angular motion, the raw angular rate measurements of MEMS' are much more noisy than those of the reference IMU's. The errors between MEMS and the reference IMU are shown in Fig. 16. Similar to specific force measurements, the dominant components of the raw angular rate errors consists of the constant bias and the random noise.

From those attitude, velocity and position results, it can be concluded that the proposed low cost MEMS inertial sensor based integrated navigation solutions have impressively mall errors compared with the tactic grade IMU-based navigation solutions. Specifically when the system experiences the dynamic movement, i.e. there is no direct attitude observation available in the navigation filter, the attitude solutions errors able to remain acceptable, i.e. 2.9º, 2.7º and 11º respectively in roll, pitch and heading angle in 34-second duration in this test. In consideration of the low cost utilized in the test, this validates the proposed design architecture and strategy.

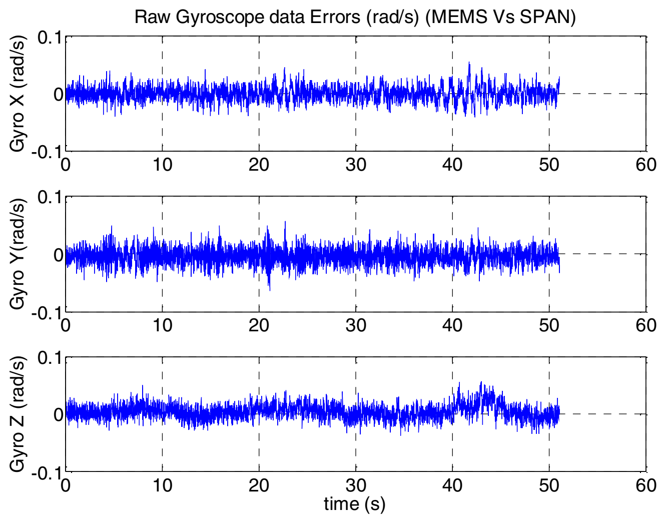

Fig. 16 Raw angular rate measurements errors

V. CONCLUSIONS

This study focuses on the design of an approach applying low cost MEMS sensor integrated by magnetometer and GPS in attitude determination system in dynamic environment. Due to the large errors, it is not practical to employ MEMS sensors in the conventional algorithms, such as the initial self-alignment or stand-alone inertial navigation calculations. Therefore, the problematic of MEMS inertial sensor based attitude determination system becomes the determination of navigational parameter initials (attitude, velocity and position) and bounding the calculation errors in time. The approach proposed in this paper is first to utilize the magnetometer compensated attitude solution as the attitude initials, which are constant under quasi-stationary conditions. Meanwhile the velocity initials can be set to zero under the same conditions. Furthermore, with the position parameters which are generally known in quasi-stationary conditions, the inertial calculation can be initialized. Second, an integrated INS/GPS Kalman filter is developed by utilizing GPS velocity/position data as observations. Navigation solution errors are limited in time by the proposed Kalman filter when the translation movement exists. Strapdown INS mechanization and INS error equations based Kalman filter process model are specially designed considering MEMS large noise characteristics. Moreover sensor error model is employed in the integrated Kalman filter to estimate MEMS sensor bias/drift which enables the in-motion calibration of MEMS sensor errors.

The dynamic test is developed to validate the proposed design. The navigation solution errors derived from this low cost MEMS system are small compared with the reference. Specifically, the advantages of this design can be seen that, since there is no direct attitude observation available for the integrated Kalman filter when the system experiences the translational motion, the attitude solutions errors are acceptable and generally stable in the short duration which validates the design. From this study, it can be concluded that low cost MEMS attitude determination system 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 response, etc, and with the rapid innovation in MEMS technology, the application of MEMS is believed as one of the attitude determination research interests for the next decades. Moreover the future work of this study will be concentrated on improving performance of the integrated MEMS/magnetometer Kalman filter in terms of computing load, design complexity and filter stability.

ACKNOWLEDGMENTS

This research is supported by a GEDEX™ and NSERC (Natural Sciences and Engineering Research Council of Canada) Research Project.

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