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Article · January 2007

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Performance Improvement of MEMS-Based Sensor Applying in Inertial Navigation Systems

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***Abstract*—The demand of navigation and guidance have been urgent for many years. In fact, INS is daily used in controlling flight dynamics. Nowadays, with the strong growth of Micro-Electro-Mechanical-System (MEMS) technology, the Inertial Navigation Systems (INS) are applied widely. However, there are existing errors in the accelerometer and gyroscope signals that cause unacceptable drifts. There are two kinds of noise in the INS: deterministic and stochastic errors. The deterministic noises are usually eliminated by the carefully calibration process but the stochastic noises are always difficult to treat. In this paper, we have determined successfully the characteristics of the MEMS sensors' noise by analyzing the Allan variance of the experiment data. After characterizing the IMU errors, the information of these noises is brought to the Wavelet Multi-Resolution Analysis (WMRA) block in order to improve the sensors' signal–to-noise ratios, remove sensor errors that are mixed with motion dynamics, and provide more reliable data that is applied directly to the Noise Eliminating Block (NEB).**

Keywords: *Navigation, IMU, INS, MEMS, Allan variance, Kalman*

I. INTRODUCTION

Navigation and guidance are very important problems for marine, aeronautics and space technology. In such systems, Inertial Measurement Units (IMUs) are widely used as the core of the Inertial Navigation Systems (INS) [1]. In principle, an IMU consists of gyroscopes and accelerometers that measure angular velocities and accelerations in three dimensions. Due to the strong growth of MEMS technology, the INS is widely applied to navigation and guidance of aircraft movements. However, there are existing errors in the accelerometer and gyroscope signals that cause unacceptable drifts and bias. These errors are classified into deterministic errors and stochastic errors [2].

Kalman filter is often used for integrating Inertial Navigation System sensors with GPS measurements. In this case, the parameters of those errors must be specified. To eliminate the deterministic errors, we can specify them quantitatively by calibrating the device. It is, however, more complex in determination of the stochastic errors. In this paper, we have determined noise parameters of both deterministic and stochastic errors of MEMS based IMUs. For the deterministic errors, the calibration process is not so difficult. For the stochastic errors, we have tried two different methods PSD (Power Spectrum Density) and Allan variance. The PSD is known as a classical method to analyze signal, while Allan variance is a new method that can show more information than the PSD. In this paper, the Allan variance method was applied to give us a reliable noise model that is applied directly to the Kalman Filtering Block (KFB).

The Wavelet Multi-Resolution Analysis (WMRA) is studied and applied as a proposed tool to improve the sensors' signal–to-noise ratios, remove sensor errors that are mixed with motion dynamics, and provide more reliable data to the KF based MEMS-INS/GPS integration module.

II. MEASUREMENT AND CHARACTERIZATION

In this paper, the MICRO-ISU BP3010 (see Fig. 1) is used to measure the six degree of movement. It consists of three ADXRS300 gyros and three heat compensated ADXL210E accelerometers [3]. The measurements are synthesized by micro-controllers and transmitted out via the RS232 interface. The unit transmits output data as angular incremental and velocity incremental data in serial frames of 16 bytes at 64 Hz.

A. Deterministic errors

Deterministic errors are corrected by accelerometer and gyroscope calibrations. In the calibration procedure of the accelerometers, the earth gravity has been utilized. In this method, the IMU is initially positioned so that the Z-axis of the IMU aligned with the location level frames U-axis, the Y-axis of the IMU aligned with the N-axis and the X-axis aligned with the E-axis (Fig. 2). It means that the gravity component will affect only the accelerometer along Z-axis by an amount of $+g$ ($g = 9.8$ m/s^2). If the IMU is then rotated 180^0 around the Y-axis, a new measurement could be taken when the accelerometer along Z-axis senses the negative gravity ($-g$).

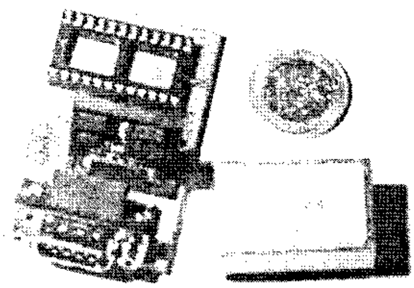


Fig. 1. The MICRO-ISU BP3010 – A MEMS unit

When the IMU with the i^{th} accelerometer aligned with the U-axis in the navigation frame, the output of the accelerometer is:

$$z^1(a_i^b) = \alpha_i + (\alpha_{ii} + 1)g \tag{1}$$

Where α_i, α_{ii} and a_i^b are accelerometer bias, accelero-meter scale factor, and accelerometer output in body frame coordinates, respectively.

Rotating the IMU 180^0 around perpendicular axis and making another measurement will give the following output of the accelerometer:

$$z^2(a_i^b) = \alpha_i - (\alpha_{ii} + 1)g \tag{2}$$

Solving set of (1) and (2) above, we can estimate of the accelerometer bias and scale factor:

$$\alpha_i = \frac{z^1(a_i^b) + z^2(a_i^b)}{2} \tag{3}$$

$$\alpha_{ii} = \frac{z^1(a_i^b) - z^2(a_i^b)}{2g} - 1 \tag{4}$$

The collecting data process is performed for about 10 minutes for each position, then the data is averaged to give $z^1(a_x^b)$ and $z^2(a_x^b)$. Two equations (4) and (5) are finally used to extract the accelerometer bias and scale factor. Calibration results showed that the accelerometer along Z-axis has bias of 0.1330 m/s^2 and scale factor of 0.0041.

The gyroscope calibration procedure is performed by using a precise rate table which contains sequence of different rates for each dimension has been used. The IMU is initially positioned in center of rate table and each rate is run approximately for 10 minutes.

The error model equation of the gyro is:

$$w_{gi} = \beta_i + (\beta_{ii} + 1)(w_j + w_{ex}) \tag{5}$$

Where w_{gj} is nominal gyro angular rate at table angular rate w_j [deg/h, rad/s].

w_j - average table angular rate for data segment j [deg/h, rad/s].

w_{ex} - sensed component of earth rotation rate [deg/h, rad/s].

β_i - gyro bias [deg/h, rad/s].

β_{ii} - gyro scale factor.

From (5), we have:

$$\beta_{ii} = \frac{(w_{g1} - w_{g2}) - (w_1 - w_2)}{(w_1 - w_2)} \tag{6}$$

$$\beta_i = \frac{w_{g1} + w_{g2}}{2} - (\beta_{ii} + 1)\frac{w_1 + w_2 + 2w_{ex}}{2} \tag{7}$$

We can then estimate gyro bias scale factor based on (6) and (7). Results showed that the Z-axis gyro has bias of 0.3172 °/s and scale factor of -0.0070.

B. Stochastic IMU errors

Some stochastic errors that affect the Initial Navigation Systems are listed as follows [4, 5].

- Quantization noise

Quantization noise is made from encoding the analog signal into digital form. This noise is caused by the small difference between the actual amplitudes of the sampled signal and bit resolution of A-D Converter. We can reduce quantization noises by improving encode methods, adjusting sample rate, or increasing bit resolution.

- White noise

White noise can be a major source of the IMU error and it has a constant power spectrum over whole frequency axis. Angle random walk (for gyroscope) and velocity random walk (for accelerometer) are caused by the white noise.

- Random walk

This is the random process of uncertain origin, possible of a limiting case of an exponentially correlated noise with long correlation time. The gyroscopes are affected by angular rate random walk, while the accelerometers are affected by acceleration random walk.

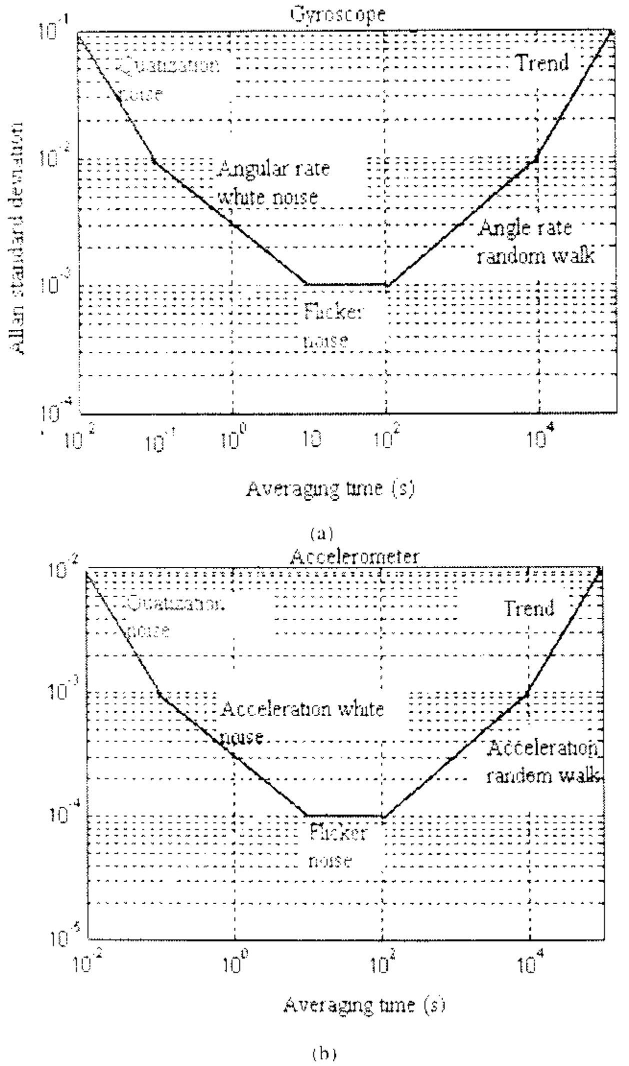


Fig 2. The standard slopes of the Allan standard deviation of gyroscopes (a) and accelerometers (b)

- Flicker noise

Flicker noise is low-frequency noise term that shows as bias fluctuations in data. This noise is caused by the electronics or other components that are susceptible to random flickering.

In order to analyze stochastic IMU errors, we have utilized the Allan variance method. It is a powerful tool for analyzing and characterizing data, and for stochastic modeling. The Allan variance technique has been originally developed for the characterization, estimation, and prediction of precision clocks and oscillators in the time domain. The different types of noise associated with inertial sensors can be revealed via Allan variance method.

The Allan variance is statistical measure to characterize the stability of a time-frequency system [6]. The PSD can only extract white noise standard deviation. In contrast, using the Allan variance, several other error parameters can be comprehensively derived.

The basic idea of the Allan variance is to take a long data sequence and divide it into segments based on an averaging time τ to process. Let give a sequence with N elements y_k, $k= 0, 1,\dots, N-1$

Then, we define for each $n=1, 2, 3,\dots, M\leq N/2$ a new sequence of averages of subsequence with length n:

$$x_j(n) = \frac{y_{nj} + y_{nj+1} + \dots + y_{nj+n-1}}{n} \tag{8}$$

Where $j = 0,1,\dots,\left[\frac{N}{n}\right]-1$

If the sampling time is Δt, the time span within an averaged sequence of length n is $\tau = n\Delta t$. The Allan variance, for a given subsequence length n, is defined as:

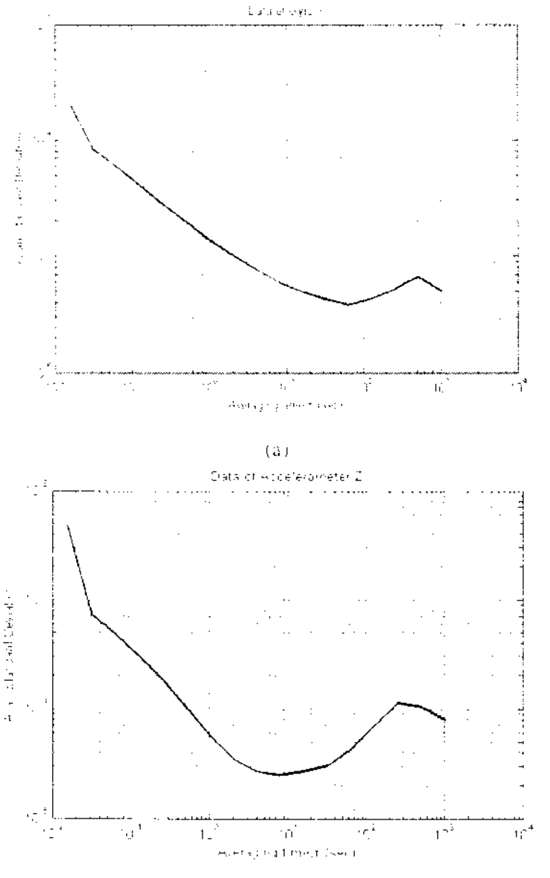
$$\sigma_a^2(\tau, N) \triangleq \frac{1}{2\left(\left[\frac{N}{n}\right]-1\right)} \sum_{j=0}^{\left[\frac{N}{n}\right]-2} (x_{j+1}(n) - x_j(n))^2 \tag{9}$$

The typical slopes of the Allan variance for the gyroscope and the accelerometers in log-log plot are shown in Fig. 3a and Fig. 3b with data collected from the IMU ISU BP3010 during an hour.

To extract the noise parameters, we need to fit the standard slopes in Fig 2. For example, if data contains white noise, the slope -1/2 will appear in the log-log plot of the Allan standard deviation.

The log-log plot of the Allan standard deviation in Fig. 3a indicates the presence of angular rate quantization noise (slope -1), angular rate white noise (slope -1/2), angular rate random walk (slope 1/2), while angular rate flicker noise (slope 0) is absent. This result is fully consistent with that obtained by the PSD.

plot.



(a)

(b)

Fig. 3. The Allan standard deviation of gyro X (a) and of accelerometer Z (b)

Table 1.Iidentified noise coefficients

Gyros	Q_Z (rad)	Q(rad/$\sqrt{s}$)	B (rad/s)	K (rad/s/$\sqrt{s}$)	R (rad/s^2)
X	$1.50*10^{-6}$	$1.37*10^{-5}$	×	$5.62*10^{-7}$	×
Y	$1.65*10^{-6}$	$1.52*10^{-5}$	$5.31*10^{-6}$	×	×
Z	$1.66*10^{-6}$	$1.53*10^{-5}$	$5.56*10^{-6}$	$4.89*10^{-7}$	×
Accel	Q_Z(m/s)	Q(m/s/$\sqrt{s}$)	B(m/s^2)	K (m/s^2/$\sqrt{s}$)	R(m/s^2)
X	$1.35*10^{-5}$	$4.73*10^{-5}$	$4.15*10^{-5}$	$1.16*10^{-5}$	×
Y	$1.40*10^{-5}$	$5.17*10^{-5}$	$4.71*10^{-5}$	$7.58*10^{-6}$	$5.07*10^{-7}$
Z	$1.34*10^{-5}$	$5.69*10^{-5}$	$4.02*10^{-5}$	$9.19*10^{-6}$	$7.40*10^{-7}$

Figure 3.b shows the log-log plot of the Allan standard deviation for the accelerometer. This shows the presence of accelerometer quantization noise (slope -1), accelerometer white noise (slope -1/2), accelerometer flicker noise (slope 0), and acceleration random walk (slope 1/2). This result is well consistent with that from the PSD plot. In addition, this shows the presence of acceleration trend (slope 1) that is unable to be indicated by only using the PSD plot.

The white noise coefficient is obtained by fitting the slope line at $\tau = 1$. Table 1 shows the estimated noise coefficients for the gyros and the accelerometers.

Character × means that the sensor lacks the error or this error is much smaller than the others. Q_Z, Q, B, K and R denote quantization noise, white noise, flicker noise, random walk and trend noise, respectively.

III. APPLICATION TO WAVELET MULTI-RESOLUTION ANALYSIS

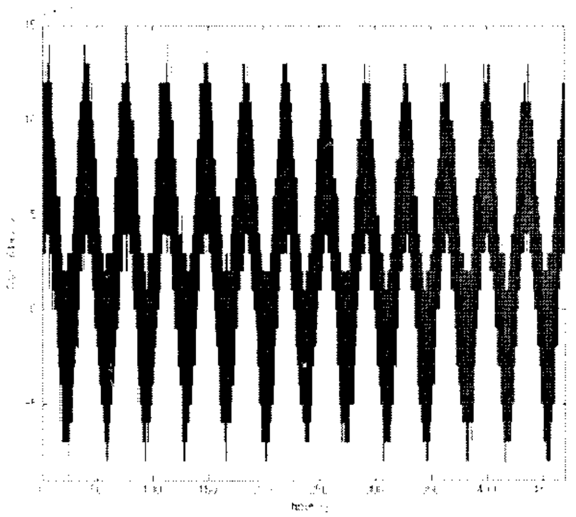


Fig. 4. Comparison of the raw measurement and WMRA: on the rate table

After characterizing the IMU errors, the information of these noises is applied to the Wavelet Multi-Resolution Analysis (WMRA) block in order to improve the sensors' signal–to-noise ratios, remove sensor errors that are mixed with motion dynamics, and provide more reliable data to the KF based MEMS-INS/GPS integration module [7, 8]. Applying WMRA to the MEMS inertial signal comprises two main steps. The first involves eliminating the high frequency sensor noise using wavelet de-noising methods. The second step then follows by specifying a proper threshold through which the motion dynamics can be separated from the short-term and long-term sensor errors as well as other disturbances.

The output data rate of both linear and angular MEMS inertial sensors was 64 Hz. After applying wavelet analysis to all inertial sensors, their measurements were processed by the KF based INS/GPS integration algorithm. The Daubechies "db8" wavelet was applied first with hard then with soft threshold criterion. Fig. 4 compares the raw measurements of the Ax accelerometer to the same measurements after applying the proposed WMRA technique in the case IMU is placed on the precise rate table of 10 ^{0}/s. Fig. 5 shows the signal obtained from Ax accelerometer when the IMU is placed on the vehicle for outside experimentation. After processing by WMRA, the short term noise is eliminated. In both Fig. 4 and Fig. 5, it can be seen that the signal was efficiently de-noised, while all sharp transition details of the true signal remain.

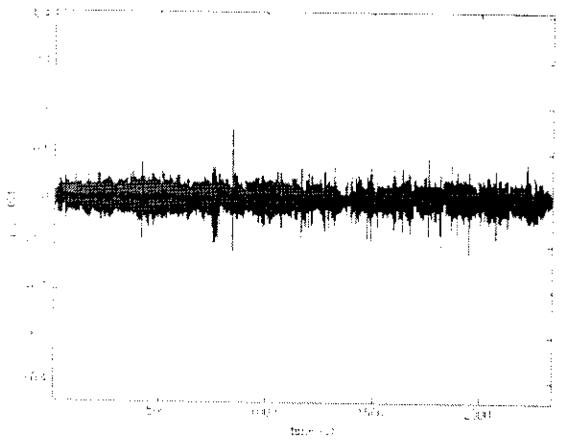


Fig. 5. Comparison of the raw measurements and WMRA: on the road

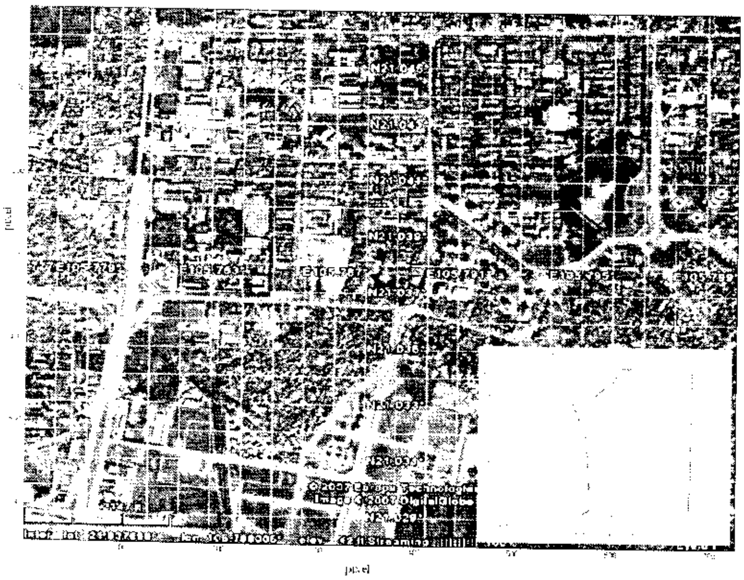


Fig. 6. Comparison of the GPS measurements and Kalman output

IV. Application to INS/GPS system

The demand of navigation and guidance has been urgent for many years. In fact, GPS have been employed widely in many applications while INS is daily used in controlling flight dynamics [9]. Recently, thank to the development of MEMS technology, the IMUs become smaller, cheaper and more precise. However, the position error of an INS increases rapidly with navigation due to the integration of measurement errors in the gyroscopes and accelerometers [10]. In order to make the corrections, there appears a new trend in navigation and guidance domain: it consists of the integration of INS and GPS altogether. Integrating these two methods can improve the performance of the system and reduce concurrently the disadvantages of both INS and GPS.

After Allan variance and WMRA processes, the more reliable data is brought to the KF based MEMS-INS/GPS integration module.

The update from the INS was taken every 0.015625s, the GPS update was taken every 1s and the KF was run every 0.5s to achieve better accuracy. Every alternate 0.5s instant, when the GPS update is not available; we have to predict the error state by using the most recent GPS update as the measurement, i.e. the GPS update is taken constant for that whole one second. This also comes in use when there are GPS outages.

For the experiment of the IMU on road [11], GPS and the data acquisition system were installed in a vehicle. The vehicle was driven for 12 minutes in a 5 km trajectory. Initially the vehicle was at rest, with the engine on, for about 45 seconds. This stationary data was used for calibration and alignment purposes.

The 2-D trajectory is presented in Fig. 6. This figure shows the position of the vehicle along North and East direction on the Earth instead of the latitude and the longitude. The reason is that we can prevent numerical instabilities in calculating the Kalman gain. It can be seen the INS/GPS trajectory supported by KF It can be seen the INS/GPS trajectory supported by KF (solid curve) follows the GPS one (dot curve) with small error for a quite long trip.

V. Conclusion

This paper has succeeded in specifying the parameters of the IMU errors, which is a necessary step when applying error-processing algorithms for the INS. Estimation of the stochastic errors is more complicated than for the deterministic ones. The Allan variance method has been used here to estimate the stochastic errors of the IMU. The extracted results will be used as the parameters in WMRA and Kalman filter for the INS-GPS integrated system. The experimental results have shown that the initial calibration and alignment is accurate enough to allow navigation with IMU sensors for extended period of time with low dead reckoning errors.

ACKNOWLEDGMENT

This work is supported by the QC-07 project of Coltech, VNUH.

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Phu Thuy Nguyen received his PhD degree in 1979 at Charles University, Prague, Czechoslovakia. Since 1980, he has been a faculty member of the Vietnam National University, Hanoi (VNUH). He has also been associated to International Training Institute for Materials Science (ITIMS) since 1992 as senior researcher. In 2005, he was nominated Dean of the Faculty of Electronics and Telecommunications, College of Technology, VNUH. He is author and coauthor of more than one hundred papers published in professional journals and international conferences. His research interests cover magnetic materials and MEMS-based sensors with applications.

Huu Tue Huynh received his Sc.D. from Laval University in 1972, where he had been a Professor of the Department Electrical and Computer Engineering since 1969. He left Laval in 2004 to become the Chairman of the Department of Information Processing of the College of Technology, Vietnam National University, Hanoi and recently nominated Rector of Bac Ha International University. He has been an invited professor at l'INSA (Lyon, France) in 1972, ENST (Paris, France) in 1980, l'Universite de Rennes (France) in 1982, Concordia University (Montreal, Canada) in 1985, Ecole Polytechnique (Montreal, Canada) in 1986, l'Universite de Sherbrooke (Sherbrooke, Canada), in 1990, CEPHAG (Grenoble, France) in 1995. In 1984, he was an invited guest of Bell Lab (Neptune, N.J. USA). He is author and coauthor of more than one hundred papers published in professional journals and international conferences; he is also coauthor of two books, "Systemes non-lineaires" (Gordon & Breach 1972) and "Simulations stochastiques et applications en Finances avec des Programmes Matlab" (Economica, 2006); the English version of the second book will be published by Wiley in 2008. His research interests cover stochastic simulation techniques, information processing, fast algorithms and architectures with applications to digital communications