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Intelligent Calibration Method of low cost MEMS Inertial Measurement Unit for an FPGA-based Navigation System

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Abstract: Based on a small, lightweight, low-cost high performance inertial Measurement Units(IMU), an effective calibration method is implemented to evaluate the performance of Micro-Electro-Mechanical Systems(MEMS) sensors suffering from various errors to get acceptable navigation results. A prototype development board based on FPGA, dual core processor's configuration for INS/GPS integrated navigation system is designed for experimental testing. The significant error sources of IMU such as bias, scale factor, and misalignment are estimated in virtue of static tests, rate tests, and thermal tests. Moreover, an effective intelligent calibration method combining with Kalman filter is proposed to estimate parameters and reduce the effect of IMU dynamic errors that can degrade the system performance. The efficiency of proposed approach is demonstrated by various experimental scenarios.

Keywords: MEMS IMU; Intelligent Calibration Method; Kalman Filter; FPGA; Navigation

1. Introduction

In recent years, a promising technology, micro-electro-mechanical systems (MEMS)-based inertial sensors, has been developed which can provide a low-cost navigation solution. MEMS systems are commonly fabricated using silicon, which possesses significant electrical and mechanical advantages over other materials [1, 2]. 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 [2, 3].

In addition to advances in MEMS fabrication techniques, one of the primary drivers behind the phenomenon of high performance MEMS inertial sensors is the skill and ability of the MEMS integrator to package these devices into an Inertial Measurement Unit (IMU) [4]. Today's MEMS sensors are still much less precise than expensive accurate inertial sensors, such as tactic or navigation grade IMU whose measurements are able to be directly used by inertial system self-alignment and strapdown inertial navigation algorithm. In principle, an IMU consists of Tri-axis MEMS gyroscopes and accelerometers which measure angular velocities and accelerations in three dimensions. However, if applied by modern MEMS sensors, these standard inertial calculation procedures are not practical, or in other words, the solutions diverge quickly. The large MEMS noises cause the standalone use of MEMS sensors in strapdown inertial navigation system (INS) to deliver kilometer level positioning errors for the applications of several seconds duration [3]. Therefore, there is a critical issue which focuses on finding the solution to improve the performance of IMU based MEMS sensors.

IMU errors include misalignment errors, biases, and scale factor errors, etc [5]. Low cost sensors, such as MEMS sensors, are quite large, and their repeatability is typically poor because of environment factors, especially temperature, which makes frequent calibration a necessity. Different calibration techniques developed by many authors differ mainly in the proposed sensor output model, the used instrumentation, and the thermal compensation.

Bekkeng [5] carried out a calibration analysis of gyroscopes. Gyro parameters had been estimated through kalman filter. Aggarwal [6] proposed a standard testing/calibration procedure for MEMS inertial sensors and a linear thermal model is developed to compensate for the effects of errors due to the temperature variation. Fang [8] analyzed the dynamic thermal error induced by accelerations of MEMS gyroscope. Other researchers [10, 11] proposed the linear interpolation, 3rd order polynomial, generic hysteresis model, and characteristic thermal error compensation methods.

Most previous works only focus on thermal compensation of IMU in reference to static environment. Sometimes the compensation is indispensable in applications where there are no static periods. Therefore, the variation of real-time biases, scale factors in low cost MEMS sensors should be taken into account in the integration of dynamic rate and temperature variation simultaneously. Moreover, there is a need for compensating dynamic noise in addition to the static noise considering the effect of temperature variation in low cost MEMS IMU.

This paper focuses on the analysis and compensation of low cost and accuracy IMU error induced by dynamic environmental variation of temperature and rate. Due to the variation of IMU errors irregularly present in dynamic environment, such as dynamic bias with time, scale factor, the conventional compensation approaches are not effective to improve the compensation accuracy of low cost MEMS IMU. An intelligent calibration approach based on combination with fuzzy control, artificial neural net work with a Kalman filter is proposed. Taking advantage of the integrated compensation method, the thermal error in static test is compensated by measuring the temperature. On the other hand, the random error, time-varying bias in rate test is estimated by Kalman filter on line. The accuracy of inertial sensors can significantly be improved by performing precision calibration of each sensor. In this way, the performance of calibrated MEMS IMU is improved and can be used for stabilization, guidance and inertial navigation.

The paper is organized as following: a standard calibration and testing method is developed to determine errors. Furthermore, according to the MEMS IMU and INS/GPS technology, a prototype based on FPGA development board, dual core processor's prototype of integrated system is developed and researched for conventional navigation. The platform integrating MEMS IMU/GPS/INS provides superior performance than any of the methods operating alone. The System-On-chip Circuitry (SOPC) implementation was developed with VHDL language into an FPGA, so as to be easy to evaluate the customized IMU error compensation and implement the navigation algorithm.

The proposed intelligent calibration method uses measurement results to estimate parameters and eliminate the effect of IMU errors in various temperatures and rates. The temperature compensation is performed to remove the thermal sensitivity of the MEMS IMU. Experimental results are afforded and evaluated.

2. Calibration method and validation

2.1 Inertial sensor error model

Traditionally, the inertial sensor errors can be divided into two parts, deterministic (systematic) errors and random errors [6, 7]. The random errors include bias-drifts or scale factor drifts. These errors change with time and dynamic rates. These random errors have to be modeled stochastically. The deterministic error sources include bias, non-orthogonality or misalignment errors and scale factor errors which can be removed by specific calibration procedures in a laboratory environment. It is demonstrated that the deterministic error is temperature dependent [8].

An inertial sensor error model is developed in this section. It is a unified model because it applies to the both accelerometers and rate gyros. A general model for the error of a single inertial sensor is as follows:

$$s_m = K \cdot s_t + b(t) \tag{1}$$

where s_m is the measured quantity at the sensor output and s_t is the true value of the quantity that sensor measures. The term K represents scale factor and $b(t)$ is the output bias.

The total output bias $b(t)$ is the residual output when no input is applied. Thus, it can be measured when the sensor is static. The total bias represents an additive error and consists of several components in (2),

$$b(t) = b_0 + b_r(t) + b_w(t) \tag{2}$$

where b_0 is a constant null-shift, $b_r(t)$ is a slow time varying component called the bias drift, and $b_w(t)$ is the random component known as noise. It is straight forward to determine numerical values for the error terms b_0 and $b_w(t)$. The noise $b_w(t)$ can be modeled as a band-limited white noise. A numerical value for $b_w(t)$ can be determined by computing the standard deviation of the sensor's output over a short period of time when no input is applied. The time varying component of the output error, $b_r(t)$, is characterized by a stochastic time series. Characterizing this slowly varying process by a single number would be overly conservative in the short term and would not adequately model the longer term error variation [7].

This suggests modeling the time varying bias component will be modeled as a first order Gauss-Markov process. This process can be described by a first order differential equation.

$$b_r = -\frac{1}{\tau} b_r + b_g \tag{3}$$

Where τ is the correlation time constant and b_g is a Gaussian white process with variance $E[{b_r}^2(t)] = {\sigma_r}^2$ and time constant τ have the following properties, Exponential autocorrelation

$$R_x(\tau) = {\sigma_r}^2 e^{-\frac{t}{\tau}} \tag{4}$$

In lab, we developed a MEMS IMU which consists of three ADXR150 gyros and three ADXL210 accelerometers. The constructed MEMS IMU, the unit dimensions are $(3.3 \times 3.3 \times 4)$cm in Figure 1.

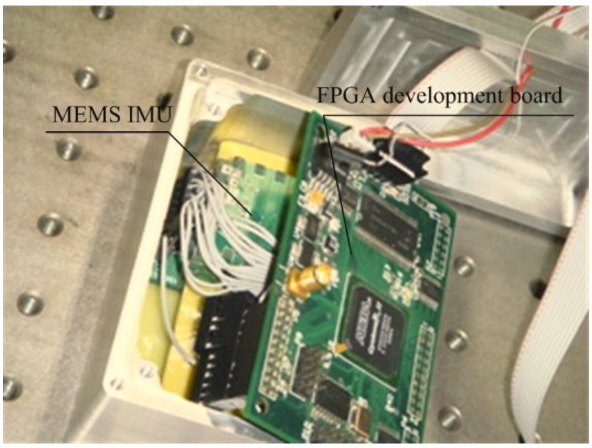


Figure 1 Photograph of MEMS IMU and FPGA prototype

The Allan variance method [9] can be used to determine $b_r(t)$ in (2). By constructing the Allan variance plot, the slow varying process corrupting a sensor output can be characterized. For stochastic inertial error, the Allan variance log-log plots for gyro and accelerometer are shown in Figure 2 and Figure 3.

Figure 2 shows the Allan variance plot constructed for the device ADXR150 gyro output. The analyzed data set consists of gyro measurement at a sampling frequency of 400 Hz. The Allan variance has an approximate slope of -1/2 for the first 35 seconds. This indicates that the angular random walk(ARW) is the dominant noise term. After 35 seconds, the Allan variance has a slope of +1/2 which implies that the velocity random walk (VRW) is the dominant noise term.

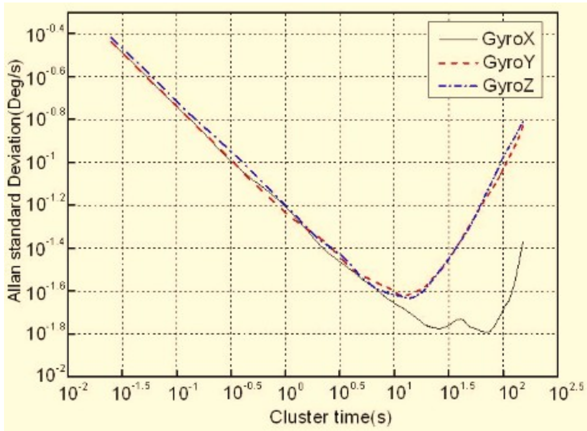


Figure 2 AV result for the device ADXR150 gyro

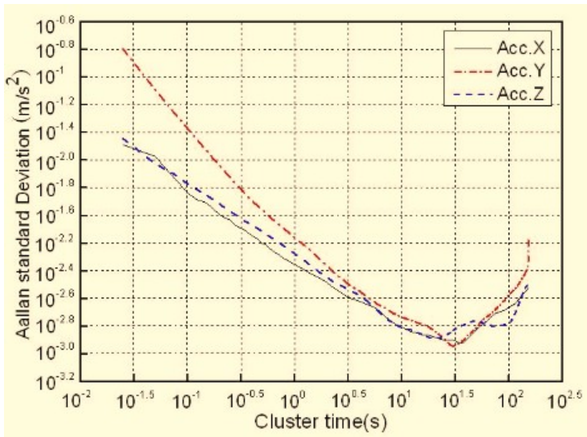


Figure 3 AV result for the device ADXL210 accelerometer

The VRW and ARW values are calculated. These parameters are required for design the process noise matrix Q to be used in Kalman Filter algorithm in the integrated navigation systems. The same analysis process in Allan variance plot is constructed for the device ADXL210 accelerometer output.

2.2 MEMS gyro and accelerometer model in lab

Gyroscopes fabricated by micro electromechanical system (MEMS) technology offer revolutionary improvements in cost, size, and ruggedness relative to fiber-optic and spinning mass technologies. The gyro model is used for calibration process in MEMS IMU in lab. It is a little different with the unified inertial sensor error model in Equation (1).

Three orthogonally mounted ADXR150 rate-gyros in order to measure angular rates around the sensitivity axes. Practically, the sensors are not precisely mounted orthogonally due to imperfections during the IMU construction process. Therefore, there will be a small angular position differences between inertial sensors sensitivity axes and the IMU frame or platform in which inertial sensors are mounted, which is called misalignment errors or non-orthogonalities as shown in Figure 4.

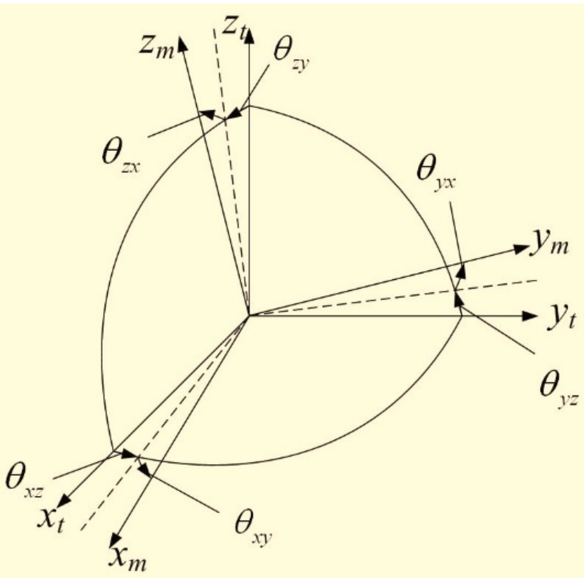


Figure 4 IMU platform coordinate axes, inertial sensor sensitivity axes

The stabilized platform $(x_t y_t z_t)$ coordinates can be defined to be the orthogonalized sensor input axis coordinates. The coordinate frame $(x_m y_m z_m)$ represents the non-orthogonalized frame of actual sensitive axes of MEMS IMU. The offset θ implies the transformation from the non-orthogonal sensor input axis cluster to the platform orthogonal coordinates with the same origin. $\theta_{ij}(i,j=x,y,z)$ is the rotation of i-th sensor sensitivity axis around j-th platform sensitivity axis. In matrix form the output of a triad of gyro sensors can be represented as follows:

$$\begin{bmatrix} \omega_{mx} \\ \omega_{my} \\ \omega_{mz} \end{bmatrix} = \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} + \begin{bmatrix} d_{xx} & d_{xy} & d_{xz} \\ d_{yx} & d_{yy} & d_{yz} \\ d_{zx} & d_{zy} & d_{zz} \end{bmatrix} \cdot \begin{bmatrix} f_{mx} \\ f_{my} \\ f_{mz} \end{bmatrix} + \begin{bmatrix} K_{\omega x} & 0 & 0 \\ 0 & K_{\omega y} & d_{yz} \\ 0 & 0 & K_{\omega z} \end{bmatrix} \cdot \begin{bmatrix} C_{xz}C_{xy} & S_{xz}C_{xy} & S_{xy} \\ S_{yz} & C_{yx}C_{yz} & S_{yx}C_{yz} \\ S_{zy}C_{zx} & S_{zx} & C_{zy}C_{zx} \end{bmatrix} \cdot \begin{bmatrix} \omega_{tx} \\ \omega_{ty} \\ \omega_{tz} \end{bmatrix} \tag{5}$$

where $\omega_{mj}(j=x,y,z)$ is gyro sensor measurement; $\omega_{tj}(j=x,y,z)$ is the true value of the quantity that gyro sensor measures; $b_j(j=x,y,z)$ is the bias output of gyro; $d_{ij}(i,j=x,y,z)$ is the gyro drift parameters depending on acceleration; and $K_{\omega j}(j=x,y,z)$is the scale factor. The terms $\cos\theta=C$,$\sin\theta=S$ are substituted in formula (5), which represents the misalignment errors.

The approximate derivation process is used in MEMS accelerometer model. In matrix form the output of a triad of accelerometer sensors can be represented as

$$\begin{bmatrix} \omega_{mx} \\ \omega_{my} \\ \omega_{mz} \end{bmatrix} = \begin{bmatrix} K_{ax} & 0 & 0 \\ 0 & K_{ay} & 0 \\ 0 & 0 & K_{az} \end{bmatrix} \cdot \begin{bmatrix} C_{xz}C_{xy} & S_{xz}C_{xy} & S_{xy} \\ S_{yz} & C_{yx}C_{yz} & S_{yx}C_{yz} \\ S_{zy}C_{zx} & S_{zx} & C_{zy}C_{zx} \end{bmatrix} \cdot \begin{bmatrix} f_{tx} \\ f_{ty} \\ f_{tz} \end{bmatrix} + \begin{bmatrix} b_{ax} \\ b_{ay} \\ b_{az} \end{bmatrix} \tag{6}$$

where $f_{mj}(j=x,y,z)$ is accelerometer sensor measurement; $f_{tj}(j=x,y,z)$ is the true value of the quantity that accelerometer sensor measures; $b_{aj}(j=x,y,z)$ is the bias output of accelerometer; $K_{aj}(j=x,y,z)$ is the scale factor. In accelerometer model, the accelerometer drift parameters depending on rotation are not considered in most cases.

2.3 IMU calibration testing method

The calibration of IMU is required to reduce the errors in the INS derived position, velocity and attitude of moving platforms. To get rid of the inertial error as much as possible, the modified methods used for calibrating IMU were primarily designed for static and rate tests. The improved calibration method combining with a static test, the dynamic rate test and thermal testing is implemented.

The standard six-position test method [6] requires the inertial system to be mounted on a fixed surface with each sensitivity axis pointing alternately up and down. In our tests, besides the above experiments, additional four positions are considered. Especially, the IMU is mounted on inclined plane in precise fixed angle in static test in Figure 5. It is called ten-position static method.

Figure 5 The constructed MEMS IMU in inclined plane

In order to find the scale factor and the bias at least two pairs of points of the calibration procedure are needed. Accelerometers are sensitive to gravity acceleration, so when each one of its sensitivity axes is placed parallel to gravity in both positive and negative senses, the measured accelerations will be 1g and -1g respectively. Therefore, two pairs of points are obtained for each axis just by placing the IMU on a fix surface leaning on the two perpendicular sides to the gravity axis, i.e, a 180° rotation is done along the three accelerometer axes.

In the lab, the adopted ten-position static test comprises following steps. The sensitivity axes of $IMU(x, y, z)$ is placed in the upward-vertical direction of the local level frame alternately. Later these sensitivity axes of IMU are rotated 180° around upward-vertical axis of the local level frame alternately. Through the above procedures, six static positions are located for IMU. Furthermore, among sensitivity axes of IMU, any axis is placed in the downward-vertical direction of the local level frame and it is rotated 180° around downward-vertical axis of the local level frame to choose two static positions. The two different sensitivity axes of IMU are placed with 30° inclined angle for the last two positions. There are ten position of IMU altogether.

By placing the IMU in reference to standard up-down four position method, the accelerometers measurement f_m will be

$$\begin{bmatrix} +g \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ +g \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ +g \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} \tag{7}$$

In order to estimate the bias, scale factor, non-orthogonalities parameters in gyro error model, not only static position test, but also rate test for gyro is indispensable. Rate tests are typically done using a precision single-axis rate table. The rate test for MEMS IMU is shown in Figure. 6.

In static test, the true value of quantity $\omega_{tj}(j = x, y, z)$ for gyro is determined as follows:

$$\begin{bmatrix} \omega_{tx} \\ \omega_{ty} \\ \omega_{tz} \end{bmatrix} = \begin{bmatrix} \omega_{i\varepsilon} \cos\varphi \sin\psi_n \\ \omega_{i\varepsilon} \cos\varphi \cos\psi_n \\ \omega_{i\varepsilon} \sin\varphi \end{bmatrix} \tag{8}$$

where the term φ is the local latitude; the term ψ_n is the angle between y-axis of IMU and north direction in inertial navigation coordinate system. The biases of the gyroscope can be estimated using the same principle as the elimination method of symmetrically aligned position. For example, if the y axes of IMU are rotated 180° around upward axis of the local level frame, the value of ψ_n would be changed. The corresponding relationship would be obtained as follows:

$$\sin(\psi_n + 180) = -\sin(\psi_n), \cos(\psi_n + 180) = -\cos(\psi_n) \tag{9}$$

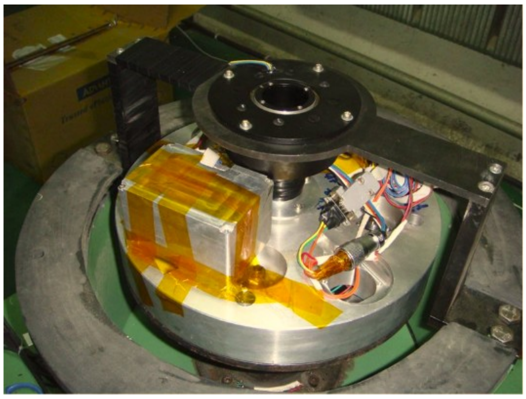


Figure 6 Rate rest for MEMS IMU

In rate test, the true value of quantity $\omega_{tj}(j = x, y, z)$ for gyro is as follows:

$$\begin{bmatrix} \omega_{tx} \\ \omega_{ty} \\ \omega_{tz} \end{bmatrix} = \begin{bmatrix} \omega_{i\varepsilon} \cos\varphi \sin(\psi_n + \omega_{rx} \cdot t) \\ \omega_{i\varepsilon} \cos\varphi \cos(\psi_n + \omega_{ry} \cdot t) \\ \omega_{i\varepsilon} \sin\varphi \end{bmatrix} + \begin{bmatrix} \omega_{rx} \\ \omega_{ry} \\ \omega_{rz} \end{bmatrix} \tag{10}$$

where $\omega_{rj}(j = x, y, z)$ is the defined rotating rate of rate platform. The t is running time of rate table. The IMU is mounted on a rate table of single. Each sensitivity axis of IMU is placed in direction rotating axis of rate table alternately. The term will be

$$\begin{bmatrix} +\psi_j \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ +\psi_j \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ +\psi_j \end{bmatrix}, \begin{bmatrix} -\psi_j \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -\psi_j \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ -\psi_j \end{bmatrix} \tag{11}$$

where, ψ_j is the numerical value of at the jth rotating rate. The positive and negative rate tests are accomplished through an amount of different defined angle rates in both the clockwise and counter clockwise directions. According to the test data, the scale factor and non-orthogonality parameters are decoupled and estimated through combination the static and rate test calibration method. The estimation techniques of least squares and cyclic iteration are developed to solve the coupling of scale factor and non-orthogonality in Equation (5). Simultaneity, combining the rate test with static test, the adverse infection of the earth rotation rate could be eliminated in solving the equation, considering the reason that low grade MEMS sensors suffering from bias instability, which can completely mask the earth's reference signal. Table 1 lists the main calibration results in Gyro ADXR150.

Table 1 Gyroscope deterministic errors for ADXR150

Axis	Gyro Deterministic error in indoor Temperature	
	Biases (°/s)	Scale factor
Gyro x	19.81	0.988
Gyro y	15.469	1.019
Gyro z	13.7	1.027

Figure 7 The circuit of FPGA Navigation computer ($9 \times 6 \times 2cm$)

Figure 8 Thermal testing for MEMS IMU

2.4 FPGA based navigation prototype

The testing platform of IMU is a prototype GPS/INS integrated navigation system, built on an Altera's FPGA development board. The prototype aims at a low-cost, small-size, and portable navigation system for guidance application. The integrated navigation system based on FPGA is shown in Figure 7.

The hardware's core of FPGA board is dual NIOSII system, which consists of two NIOSII processors. Among the two processors, the main processor is responsible for customized navigation program design and calculation task, and the coprocessor guarantees the communication ability of I/O processor and MEMS IMU/GPS, calibration module, etc. The System-on-chip circuitry (SOPC) implementation was developed with VHDL language into an FPGA, so as to be easy to compensate the MEMS IMU error and implement the navigation algorithm. Calibration testing experiments are implemented to improve the performance of prototype integrated system based on FPGA. Not only data processing in system, but also real-time of communication are realized.

Some experiments are implemented to test the performance of prototype GPS/INS integrated system based on FPGA. The processor read the data of signal of inertial sensor at 10ms sampling time. It costs 10∼15ms to accomplish the computation of INS navigation. The corresponding parameters could be transferred to PC terminal or other utilities in 10ms.

3. Intelligent calibration method combining Kalman filter

3.1 Intelligent thermal calibration method

Bias drift is probably the most crucial of the inertial errors. In inertial sensors even in the absence of any input (acceleration or angular velocity) the output is non-zero. This offset, which is usually referred to as bias, is added to the actual measured signal. This initial deterministic IMU error calibration does not guarantee proper measuring during all the time the MEMS IMU is activated since start-up. Unluckily MEMS IMU has a strong temperature dynamic bias, which means the bias will vary when temperature changes. There is a need for the development of accurate, reliable and efficient thermal models to decrease the effect of these temperature variations on IMU errors [6]. To investigate thermal effect of sensors and to evaluate piecewise local temperature drift compensation models, thermal testing for IMU is performed in thermal chamber in static environment. It is shown in Figure 8.

In most cases, the main source of temperature variation is not ambient temperature but circuit selfheating. Such biases are separated into two parts. One is stabilized bias with a fixed temperature, the other is a small time varying bias.

In order to evaluate the stabilized biases and the scale factor values for the accelerometer and gyroscopes, a local linear interpolation was performed [11]. Considering the variation largely of bias in MEMS IMU in full temperature, this method will be less reliable. In allusion to the defect of descension of thermal compensation method mentioned above, an intelligent thermal compensation combining the artificial neural network and fuzzy control(F-NN) is proposed in this paper. Thermal compensation experiments for stabilized biases are implemented in temperature chamber in static environment.

By virtue of the measurement data of IMU in full temperature on line, the characters and variation rules of stabilized biases in full temperatures is established through an offline training of feed-forward neural network. After that the adaptive neural network is implemented for online compensation of affection of these errors. During the process of training and learning, the learning rate of Network is regulated by fuzzy logic rules in order to accelerate the converging process of learning and improve the ability of adaptation. The back propagation update rule for the weights with a momentum term is as follows:

$$\Delta w_{ij}(k+1) = \eta \cdot G(k) \cdot \zeta + \alpha \Delta w_{ij}(k) \qquad (12)$$

where η is the learning rate of neural network, α is the momentum coefficient and $G(k)$ is the negative gradient, Δw_{ij} is weights of adjusting, ζ is output of neuron.

The input of NN is the value of temperature of the thermal chamber, the output of NN is the corresponding variation of stabilized biases in full temperature testing. The non-linear relation between temperature and stabilized bias is determined based on NN. Moreover, the learning rate of NN is adjusted in training process. Define the Standard deviation of NN is E, and the change of Standard deviation is EC. The input to the fuzzy controller is the Standard deviation E and the change of Standard deviation EC, which represents the magnitude of error of desired and actual output of NN, and its output is the learning rate η .

The following tuning rule is constructed for the learning rate η . When Standard deviation E and its change EC vary largely, larger changes of the learning rate must be considered to fasten the learning speed and decrease the error of training as much as possible. Thus η should tend to its maximum value, i.e. 1. On the other hand, when the Standard deviation E and its change EC are both small, in this situation the NN system is close to a steady state, adjusting of the learning rate must be scaled down, it should tend to constant value or small value. According to the above analysis, a set of fuzzy rules to adjust the learning rate η can be produced. Meanwhile, the improving measures such as additive momentum in virtue of determination of momentum parameter reasonably has been taken, and better application result is acquired. The NN is three layers feed-forward network. The number of input of NN is one; the number of hidden layer is 15 nodes and the number of output is also one node. The times of training are reached to 200. Certainly, the higher accuracy of training could be attached by increasing the training epoch, but this will cost longer calculation time. The method proposed in this paper is implemented to compensate the measured stabilized biases for Gyro X, Y, Z at different temperatures respectively. The fuzzy control rules make the selection of networks structure and learning rate η more reasonable. It exhibits a fast tuning process to reduce the error of NN converging process.

The measurement data are read into a MATLAB program for preprocessing. Later F-NN calibration program after training is stored in memory of FPGA navigation system and applied online in experimental system. In this way, the real-time of the FPGA navigation system is guaranteed in software.

The calculated values over the temperature range are changed from -20°C to 40°C in steps of 5°C. Each fixed temperature point is kept for ten minutes. A total of 14 different temperatures are considered in this experiment. The 3rd order polynomial thermal compensation method [11] and combination of fuzzy and neural network(F-NN) thermal method proposed in this paper are both implemented to compensate the measured biases for Gyro X at different temperatures respectively. The variations of stabilized biases with temperature are shown in Figure 9.

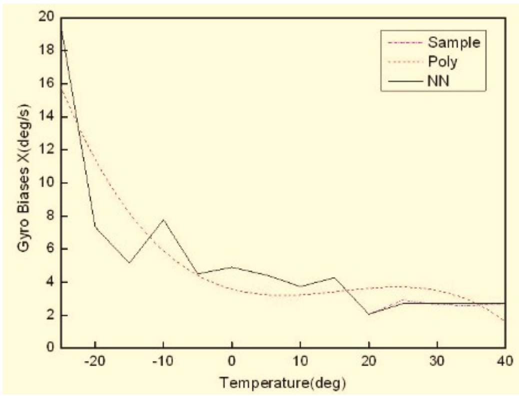


Figure 9 Gyroscope biases with temperature

As observed from Figure 9, the biases of gyroscopes vary significantly with temperature. The maximum biases can reach 20 deg/s over the entire temperature range. Hence there is a need for designing an accurate thermal calibration model for low cost MEMS sensors to compensate accurately for these bias drifts with temperatures. In Figure 9, the black dash-dotted line is the measured biases with temperature, which is sampling data of output of IMU in calibration process. The red dash line is the compensation result with 3rd order polynomial thermal compensation method. The black solid line is the compensation result with F-NN method. Comparing the three kinds of lines, we can see that the thermal calibration method in F-NN is better than thermal method in 3rd order polynomial.

Considering IMU is used for attitude and position calculation process, the F-NN compensated method could eliminate the non-zero bias from raw data in MEMS IMU according to the feedback signals of temperature sensor. The compensated precision in virtue of 3rd order polynomial method is within [-6, 6] deg/s. However, the precision with on the entire temperature in F-NN thermal method is within [-0.5 0.5] deg/s. The above analysis indicates an almost perfect compensated result in elimination of more than 90% of bias.

3.2 Combining with Kalman filter calibration method

Dynamic Bias drift is a complex phenomenon which is a combination of time, temperature and acceleration dependent behaviors. The dominant stabilized bias values are compensated in F-NN method with different temperatures in static test.

A Kalman filter is utilized to estimate the dynamic bias, random error as unknown rest calibration coefficients. In order to implement Kalman filter in calibration procedure, the simplified MEMS sensor Equation (5) are considered in calibration procedure. In most cases, the misalignments are assumed small. The simplified formula $\cos\theta_{ij} \approx 1$ is applied in (5). The term $\lambda_{fi}(i = x, y, z)$ is the 3-D vector of gyro scale factor errors, $\delta_{ij}(i, j = x, y, z)$is the 6-D vector of misalignment error, and $\delta_{ij} \approx S_{ij}(i, j = x, j, z)$ is misalignment angles expressed in radians. Higher order indefinite small terms, such as $\lambda_f \cdot \delta \approx 0$, $d \approx 0$ are adopted, in (5). The misalignment (including cross-coupling) and scale factor error matrix N is given by

$$N = \begin{bmatrix} \lambda_{fx} & \delta_{xz} & \delta_{xy} \\ \delta_{yz} & \lambda_{fy} & \delta_{yx} \\ \delta_{zy} & \delta_{zx} & \lambda_{fz} \end{bmatrix} \tag{13}$$

Therefore, the misalignment and scale factor matrix K is given by

$$K = 1 + N = \begin{bmatrix} 1+\lambda_{fx} & \delta_{xz} & \delta_{xy} \\ \delta_{yz} & 1+\lambda_{fy} & \delta_{yx} \\ \delta_{zy} & \delta_{zx} & 1+\lambda_{fz} \end{bmatrix} \tag{14}$$

Taking MEMS gyro model as example, the measured angular rate ω_m in body frame in (5) is as follows:

$$\omega_m = (I + N) \cdot \omega_t + b_r + \beta = \omega_t + \Delta \cdot \Gamma + b_r + \beta \tag{15}$$

where ω_t is true angular rate in body frame, b_r is the bias drift of time varying component,β is the gyro bias which comprises the null shit bias b_0 and the random component b_g as the Gaussian White noise in Equation (3).

$$\Delta \cdot \Gamma = N \cdot \omega_t \tag{16}$$

with

$$\Gamma = \begin{bmatrix} \lambda_{fx} & \lambda_{fy} & \lambda_{fz} & \delta_{xz} & \delta_{xy} & \delta_{yz} & \delta_{yx} & \delta_{zy} & \delta_{zx} \end{bmatrix}^T \tag{17}$$

$$\Gamma = \begin{bmatrix} \omega_{tx} & 0 & 0 & \omega_{ty} & \omega_{tz} & 0 & 0 & 0 & 0 \\ 0 & \omega_{ty} & 0 & 0 & 0 & \omega_{tx} & \omega_{tz} & 0 & 0 \\ 0 & 0 & \omega_{tz} & 0 & 0 & 0 & 0 & \omega_{tx} & \omega_{ty} \end{bmatrix} \tag{18}$$

In Kalman filter, the 12-element state vector is defined as follows:

$$X = [\Gamma \;\; \xi] \tag{19}$$

where Γ is the misalignment and scale factor error vector in (17), and ξ is the three-element bias drift of time varying component b_r in (15).

$$\xi = [b_{rx} \;\; b_{ry} \;\; b_{rz}]^T \tag{20}$$

The equation of state space process model becomes

$$\dot{X} = AX + W \tag{21}$$

where

$$A = \left[0 \quad diag(-\frac{1}{\tau})_{3\times 3} \right]_{12\times 12} \tag{22}$$

Reference [12] shows that temperature impact on scale factor is not important as on zero bias of gyroscope. This is a likely model for the misalignment parameters. Assuming that the scale factors are little affected by the expected temperature changes, as observed by testing, this model should also be sufficient for the scale factor error parameters. The stabilized bias with fixed temperature is compensated by F-NN algorithm. However, the time-dependent gyro bias (gyro drift) is estimated in Kalman filter. The estimated error would be subtracted from the raw data of the gyroscope and accelerometer.

The measurement signal Z is defined to be the difference between the commanded reference rate in rate table and the measured rate of sensors, as follows:

$$Z_k = \omega_m - \omega_t = H_k X_k + \nu_k \tag{23}$$

where the 3×12 measurement matrix H is given by

$$H = [I_{3\times 3} \quad \Delta]^T \tag{24}$$

The matrix Δ is given by (18), and ν is the zero-mean Gaussian white noise vector and null-shift bias compensated in F-NN. The Kalman filter is implemented in Figure 10.

The Kalman filter equations are used to determine the estimate $\widehat{X}$ and its covariance. The approximate method is applied in compensating the accelerometer in MEMS IMU.

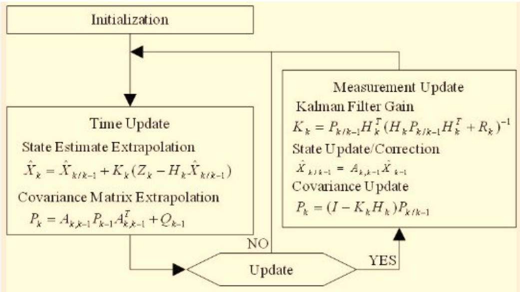


Figure 10 Kalman filter algorithm

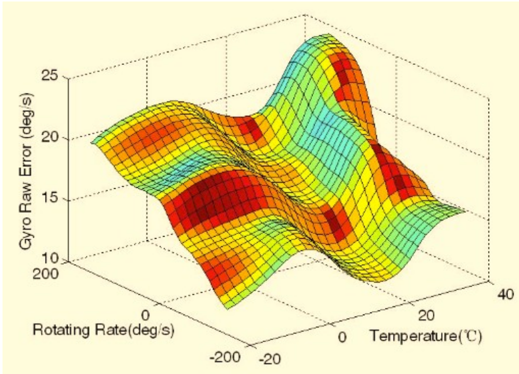
3.3 Experimental result and analysis

Corresponding experiments are implemented in single-axis rate table with thermal chamber. Concrete testing is executed as follows. Firstly define the fixed temperature in thermal chamber. Meanwhile, the commanded rate in single axis rate table are given from -150°/s to 150°/s in steps of 10°/s for 30 minutes. Later the temperature of the thermal chamber is varied to next defined value. The full temperature is changed from -20°C to 40°C in steps of 5°C. The same steps are applied in rate table in reference to different temperature defined values. In this experiment, a total of 13 different temperatures are considered and 31 different rate data are obtained.

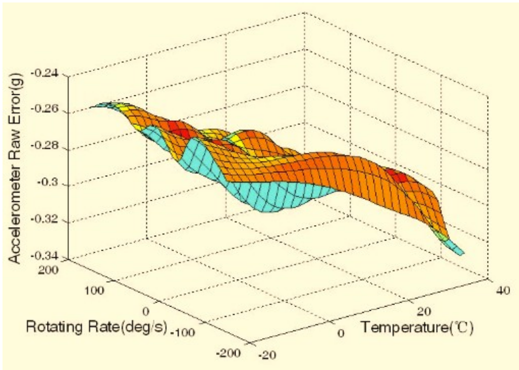
The experiment testing results of raw IMU error data, which comprise bias, misalignment and scale factor errors are shown in variance rotating rates and temperatures are in Figure 11.

As observed from Figure 11, the raw IMU errors are measured in dynamic rate test and thermal test simultaneously. It is evident to see that the raw errors of gyroscopes vary significantly with variance temperatures and rotating rates. The maximum error can reach 23 deg/s over the testing range for ADXR150 gyro X in Figure 11 (a) and 300mg for ADXL210 accelerometer X in Figure 11 (b). Among these errors, the dominant error is the bias drift. Hence there is a need for implementing an effective compensation method of MEMS IMU accurately for these bias drifts. The position and attitude error in strapdown navigation system would occur without calibration and compensation of IMU error.

Considering the variation of IMU error induced by different dynamic range in rate test and temperature variation, the input of F-NN is two dimension vectors, which comprise the value of temperature of the thermal chamber and dynamic range of MEMS gyro or accelerometer; the output of F-NN is the corresponding IMU bias drift in full temperature testing and dynamic test. Similar adjusting principle is utilized in



(a)



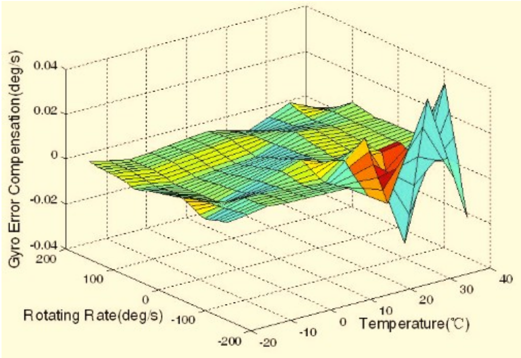
(b)

Figure 11 Raw MEMS IMU error in real measurement

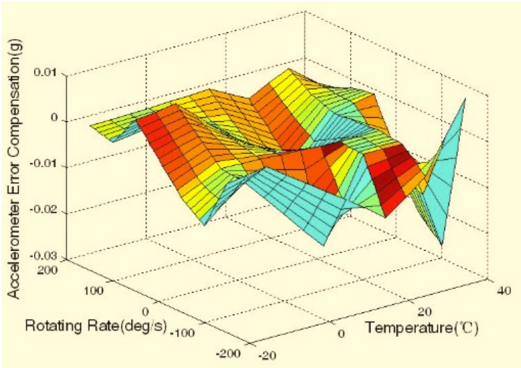
F-NN method. Rest small IMU errors are estimated in Kalman filter. The compensated results using integrated method combining F-NN and Kalman Filter are shown in Figure 12.

Comparing the result in Figures 11, 12, we can see that the IMU error utilizing effective calibration and integrated compensation approach is eliminated effectively. The compensated error of gyro is within $[-0.05\ 0.05]$ deg/s in Figure 12 (a). The compensated mean error of accelerometer is within 10mg deg/s in Figure 12 (b). The experimental results indicate that the proposed integrated compensation method outperforms the classical method. We guarantee a robust (against temperature variation and rate) sensor performance.

In the future, the fast and simplified algorithms as calibration module of IMU would be developed to make the feasibility further and high efficiency in navigation system based on FPGA and DSP. Moreover, further work addresses the testing methodologies that have been used to effectively evaluate the continually evolving MEMS based IMU over a variety of environments, including acceleration, vibration, shock, and temperature. The effectiveness of the proposed integrated calibration method is investigated further through a kinematic van test using integrated GPS and compensated



(a)



(b)

Figure 12 Compensated MEMS IMU error

low-cost MEMS IMU.

4. Conclusions

This paper has presented a complete calibration procedure for a low cost MEMS IMU with experimental results. A static, rate and thermal calibration procedure was performed using the raw output. The intelligent thermal-compensated method was integrated into a Kalman Filter, which could not only eliminate dominant stabilized bias according to measurement of temperature sensor in static test, but also estimate random error, dynamic time varying bias, etc in rate test. The prototype development board based on FPGA, dual-core processing could satisfy the demands of navigation calculation in IMU in virtue of experimental testing. It costs 10 $\sim$ 15ms to accomplish the computation of INS navigation. Taking the advantage of proposed method, the MEMS IMU errors are compensated effectively. The absolute rate error of the calibrated gyro in the selected application is within 0.04deg/s in entire dynamic thermal and rate range, and the absolute error accelerometer is within 10mg.

References

[1] M. EI Diasty, A. EI Rabbany, and S. Pagiatakis,"Temperature variation effects on stochastic characteristics for low-cost MEMS-based inertial sensor error", In: *Measurement Science and Technology*, vol.18, pp.3321-3328, 2007.

[2] D. Jurman , M. Jankovec, R. Kamnik, M. Topic, "Calibration and data fusion solution for the miniature attitude and heading reference system", In: *Sensors and Actuators*, vol.138, pp.411-420, 2007.

[3] D. Li, R. J. Landry, P. Lavoie, "Low-cost MEMS Sensor-based Attitude Determination System by Integration of Magnetometers and GPS: A Real-Data Test and Performance Evaluation", In: *IEEE/ION Position, Location and Navigation Symposium*, pp.1190-1198, May 2008.

[4] K. Sheard, I. Scaysbrook, D. Cox, "MEMS sensor and integrated navigation technology for precision Guidance",In:*IEEE Position, Location and Navigation Symposium*, pp.1145-1151, 2008.

[5] J. K. Bekkeng, "Calibration of a Novel MEMS Inertial Reference Unit", In: *IEEE Transactions on Instrumentation and Measurement*, vol.58, no.6, pp.1967-1974, 2009.

[6] P. Aggarwal, Z. Syed, X. Niu, N. EI-Sheimy, "A standard testing and calibration procedure for low cost MEMS inertial sensors and units", In: *Journal of navigation*, vol.61, pp.323-335, April 2008.

[7] L Wenger, D. Gebre-Egziabher, "System concepts and performance analysis of multi-sensor navigation systems for UAV applications", In: *2nd AIAA Unmanned Unlimited Systems, Technologies, and Operations - Aerospace, Land, and Sea Conference*, pp.1-11, San Diego, 2003.

[8] Jiancheng Fang, Jianli Li. "Integrated Model and compensation of Thermal Errors of Silicon Microelectromechanical Gyroscope", In: *IEEE Transactions on Instrumentation and Measurement*, vol.58, pp.2923-2930, Sep, 2009.

[9] Haiying Hou. Modeling Inertial Sensors Errors Using Allan Variance, Engineering university of Calgary, Master of Science thesis, 2004.

[10] G. Farid. "Analysis, Modeling and Compensation of Bias Drift in MEMS Inertial Sensors", In: *2009 4th International Conference on Recent Advances in Space Technologies*, pp.591-596, 2009.

[11] P. Aggarwal, Z. Syed, N. El-Sheimy "Thermal calibration of low cost MEMS sensor for land vehicle navigation system", In: *IEEE Vehicular Technology Conference*, pp.2859-2863, 2008.

[12] K. Shcheglov, C. Evans, and R. Gutierrez. "Temperature characteristics of JPL silicon MEMS gyroscope", In: *2000 IEEE Aerospace Conference Proceedings*, Piscataway NJ USA, PP.403-411, 2000.