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A Study on the Compensation Algorithm for Inertial Navigation System

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Abstract

This paper describes a method that how a relatively compensate the position errors in the using of low cost Inertial Measurement Unit (IMU) has been evaluated and compared with the well established method based on a Kalman Filter (KF). The compensation algorithm for IMU has been applied to the problem of integrating information in Inertial Navigation System (INS). The KF is used to estimate and compensate the errors of an INS by using the integrated INS velocity and position, respectively.

First by using Kalman Filter, we try to reduce noise of acceleration data, where two of an acceleration, constant drift and period drift, are considered. With the constant drift, it depends on sensor and it always keeps on constant error. When using double integration for calculates distance and velocity, these kinds of drifts can make increasing velocity and position errors. So, we tried to find these

errors and used constant compensation algorithm for compensation of errors in data.

Second, external environment circumstance is changed ordinarily. Almost of them can be changed on periodic time. The average drift can be obtained during constant periodic time. And use this value, we consider with a factor as a periodic external disturbance which affects to the exact position. We used a repetitive method to reduce the external environment change. We verified the proposed algorithm by simulation results.

Chapter 1. Introduction

1.1 Background and Objective

Over the years, there has been a major upsurge of interest in the integrated global positioning system (GPS) and inertial navigation system (INS) as a cost-effective way of providing accurate and reliable navigation aid for civil and military vehicles (ships, aircraft, land vehicles, and etc) (Britting 1971, Chui and Chen 1987, Farrell and Barth 1998, Loebis et.al. 2004).

The Global Position Systems (GPS) and Inertial Navigation Systems (INS) are widely used for position and attitude determination applications. When combined together, GPS and INS provide many complimentary characteristics that overcome the limitations experienced when using each sensor individually. The primary restriction in the proliferation of such technology into a broader range of applications is the high cost of the inertial sensors. A low cost IMU (Inertial Measurement Units) that can be integrated with GPS are now available for approximately $5000 or less. However, they suffer from large sensor errors such as biases and scale factor errors. Another problem experienced with low cost sensors is that the error sources are not stable and have to be constantly calibrated using GPS updates.

For auto sailing system in the sea, generally a GPS is very useful for measuring the exact position, because of no obstacle between ship and satellite. But, the GPS module suffers a large bound of position error. Also, when the ship is passed through in the sea-pollution area, it requires a precise auto sailing system.

However, for measuring precise position, also the INS device needs a high resolution and high price of GPS module.

To overcome these errors, the phi-angle approach and psi-angle approach (Benson 1975, Bar-Itzhack 1981, 1988) have proposed. But, that solution requires a small attitude error. In many case, the requirement can not satisfied for low cost inertial measurement whose sensitivity is not enough to measure the earth rate. Thus, the INS error models with small angle assumption can not satisfy in given accurate and performance for the navigation system with low cost IMU.

GPS and INS sensors are typically combined using with Kalman filter. The Kalman filter requires a dynamic model to describe the way in which the errors develop over time, and a stochastic model to describe the noise characteristics of each sensor. The standard inertial navigation system error model is generally considered to be sufficient to model the inertial system.

1.2   Inertial navigation system

Generally, the INS includes two modules: alignment module and navigation module. From these modules, any errors in either the alignment module or the navigation module will be integrated and will propagate over time. The performance and the navigation accuracy of the INS are determined by its errors.

IMU (Inertial Measurement Unit) is assumed to include a set of three orthogonal installed accelerometers and three orthogonal installed gyros. The standard IMU is shown in *Fig. 1*. By install their sensors with vehicle body, this kind of INS is called strap-down INS. For implementation, the INS should

overcome to the unbounded growth in the position and the velocity errors due to the integration of inertial measurements that will contain various forms of error.

Also, alignment module and navigation module are included in INS. From the accelerometers and the gyros, the measured data are inputs to the INS. In consideration of installation of accelerometers and gyros, the measured data should be converted to base position in INS. By mis-alignment of accelerometers and gyros, the error of alignment will be integrated in obtaining velocities and positions.
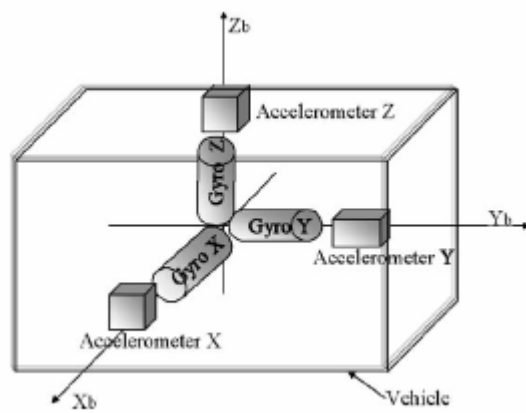
Fig. 1 An IMU installed in a vehicle

In navigation module, there compensates the gravity and non-gravity acceleration sensors, and transforms to the coordinate system. From the transformed data, double integral calculation will be done for obtaining the position. In this case, bias factor, integration error, zeros setting and other environment changes will be integrated together. Also, the signal of acceleration sensor is passed through filter and amplifier. The acceleration signal includes the

infinitesimal drift in steady state. So it makes an immense position error in case that the drift passed by double integral calculation for converting to position.

In this thesis, an INS compensation (Periodic Drift Compensation and Constant Drift Compensation Gain) algorithm for auto sailing system was proposed. A low cost IMU (Inertial Measurement Unit) was used for measuring the acceleration. To develop the compensation algorithm, we used a repetitive method to reduce the external environment changes and verified the proposed algorithm by using experiment results. First, we denote the basic INS algorithm with IMU and show that how to compensate the error of position by using low cost IMU. Second, in considering the ship's characteristic and ocean environments, we consider with a factor as a periodic external disturbance which effects to the exact position. The computer simulations were carried out by using MATLAB.

Chapter 2. The Kalman Filter and Application in INS

2.1   The Kalman filter

It is an extremely effective and versatile procedure for combining noisy sensor outputs to estimate the state of a system with uncertain dynamics. The Kalman filter useful for reduce the noise in follows case:

l   The noise of sensors may include in GPS receivers and inertial sensors (accelerometers and gyroscopes, typically) also there include speed sensors (e.g., wheel speeds of land vehicles, water speed sensors for ships, air speed sensors for aircraft, or Doppler radar), and time sensors (clocks).

l   The system state in question may include the position, velocity, acceleration, attitude, and attitude rate of a vehicle on land, at sea, in the air, or in space, but the system state may include ancillary nuisance variables for modeling correlated noise sources (e.g., GPS Selective Availability timing errors) and time-varying parameters of the sensors, such as infinitive active position system scale factor, output bias, or (for clocks) frequency.

l   Uncertain dynamics includes unpredictable disturbances of the host vehicle, whether caused by a human operator or by the medium (e.g., winds, surface, currents, turns in the road, or terrain changes), but it may also include unpredictable changes in the sensor parameters.

The Kalman filter maintains 2 types of variables

First is estimated state vector: the components of the estimated state vector include the following:

The variables of interest (i.e., we want or need to know, such as position and velocity).

Nuisance variables that are of no intrinsic interest but may be necessary to the estimation process. These nuisance variables may include, for example the selective availability errors of the GPS satellites. We generally do not wish to know their values but may be obliged to calculate them to improve the receiver estimate of position

The Kalman filter state variables for a specific application must include all those system dynamic variables that are measurable by the sensors used in that application. For example, a Kalman filter for a system containing accelerometers and rate components do not have to be those along the sensor input axes, however. The Kalman filter state variables could be the components along locally level earth-fixed coordinates, even though the sensors measure components in vehicle-body-fixed coordinates.

In similar fashion, the Kalman filter state variables for GPS-only navigation must contain the position coordinates of the receiver antenna, but these could be geodetic latitude, longitude, and altitude with respect to a reference sphere, or ECEF Cartesian coordinates, or ECI coordinates, or any equivalent coordinates.

Second is a Covariance Matrix: a Measure of estimation uncertainty. The equations used to propagate the covariance matrix (collectively called the Riccati

equation) model and manage uncertainly taking into account how sensor noise and dynamic uncertainty contribute to uncertainty about the estimated system state.

By maintaining an estimate of its own estimation uncertainty and the relative uncertainty in the various sensor outputs, the Kalman filter is able to combine all sensor information optimally, in the sense that the resulting estimate minimumizes any quadractic loss function of estimation error, including the mean-squared value of any linear combination of the state estimation errors. The Kalman gain is the optimal weighting matrix for combining new sensor data with a prior estimate to obtain a new estimate.

The Kalman filter is a two-step process, the steps of which we call prediction and correction. The filter can start with either step, but we will begin by describing the correction step first. The correction step makes corrections to an estimate, based on new information obtained from sensor measurements.

The derivation begins with background on properties of Gaussian probability distributions and Gaussian likelihood functions, then development of models for noisy sensor outputs and a derivation of the associated maximum-likelihood estimate (MLE) for combining prior estimates with noisy sensor measurements.

The rest of the Kalman filter is the prediction step, in which the estimate and its associated covariance matrix of estimation uncertainty P are propagated from one time epoch to another. This is the part where the dynamics of the underlying physical processes come into play. The state of a dynamic process is a vector of variables that completely specify enough of the initial boundary value conditions for propagating the trajectory of the dynamic process forward in time, and the procedure for propagating that solution forward in time is called *state*

prediction. The model for propagating the covariance matrix of estimation uncertainty is derived from the model used for propagating the state vector.

In this section, the method of using Kalman filter is described. The Constant Drift Compensation and Periodic Drift Compensation method are also reviewed. To apply Kalman filter for estimation, the error model based is used. More details can be seen in B. Boberg and S.L. Wirkander (2002). The state equations can be written in the following form

$$\dot{v}_N = f_N - 2\Omega v_E \sin L + \frac{v_N v_D}{R + h} - \frac{v_E^2 \tan L}{R + h} \tag{1}$$

$$\dot{v}_E = f_E + 2\Omega(v_N \sin L + v_D \cos L) + v_E \frac{v_D + v_N \tan L}{R + h} \tag{2}$$

$$\dot{v}_D = f_D - 2\Omega v_E \cos L - \frac{w_E^2}{R + h} - \frac{v_N^2}{R + h} + g \tag{3}$$

$$\dot{L} = \frac{v_N}{R + h} \tag{4}$$

$$\dot{\lambda} = \frac{v_E}{(R + h)\cos L} \tag{5}$$

$$\dot{h} = -v_D \tag{6}$$

where, v_N, v_E and v_D are the components of the vehicle's velocity vector relative to the earth, L and λ are the latitude and longitude, respectively, h is the

height of the vehicle over the earth's surface, Ω is the earth angular speed, and R is the radius of the earth. The specific force component, f_N, f_D and f_E are considered input signals.

Similarly in B. Boberg and S.L. Wirkander (2002), to compare the two methods we will use the Kalman estimation algorithm, but for the discrete time case to estimate the INS error from an error model based. In this case, we consider the model

$$x(t+1) = Ax(t) + Bu(t) + Bw(t) \tag{7}$$

$$y(t) = Cx(t) + v(t) \tag{8}$$

where t is the time, x and y are the state and the measurement vectors. A, B and C are the system matrices. w and v are discrete white noise.

The block diagram below shows how to generate both true and filtered outputs.
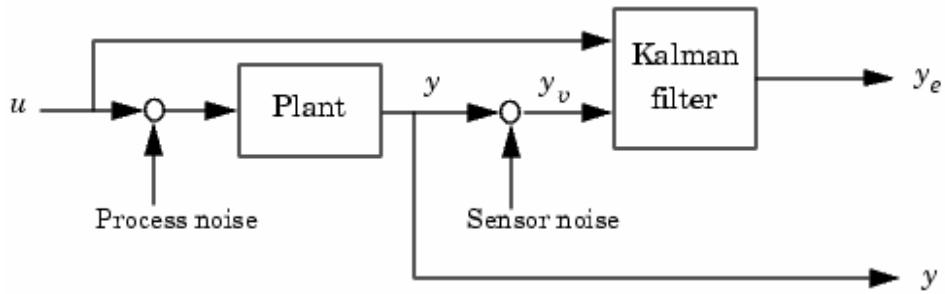

Fig. 2 Block Kalman filter

2.2   Acceleration sensors

All acceleration sensors used in inertial navigation system are generally called *accelerometers*. These kinds of acceleration sensors are used for other purposes which include bubble levels (for measuring the direction of acceleration), gravimeters (for measuring gravity fields), and seismometers (used in seismic prospecting and for sensing earthquakes and under-ground explosions). From now we will show the accelerometer sensors.

Accelerometer Types: Accelerometers used for inertial navigation depend on Newton's second law (in the form $F = ma$) to measure acceleration (a) by measuring force (F), with the scaling constant (m) called *proof mass*. These common origins still allow for a wide range of sensor designs.
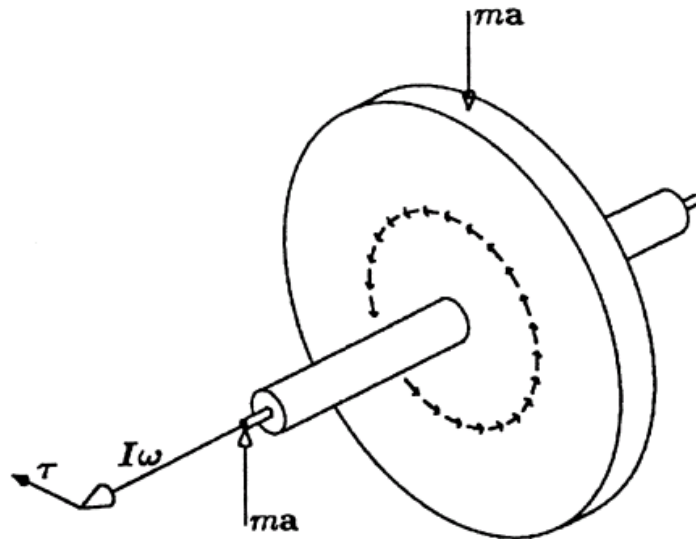

Fig. 3 Precession due to mass unbalance

Gyroscopic Accelerometers: Gyroscopic accelerometers measure acceleration through its influence on the precession rate of a mass-unbalanced gyroscope, as illustrated in *Fig. 3*. If the gyroscope is allowed to process, then the net precession angle change (integral of precession rate) will be proportional to velocity change (integral of acceleration). If the gyroscope is torqued to prevent precession, then the required torque will be proportional to the disturbing acceleration. A pulse-integrating gyroscopic accelerometer (PIGA) uses repeatable torque pulses, so that pulse rate is proportional to acceleration and each pulse is equivalent to a constant change in velocity (the integral of acceleration). Gyroscopic accelerometers are also sensitive to rotation rates, so they are used almost exclusively in gimbaled systems.

Pendulous Accelerometers: Pendulous accelerometers use a hinge to support the proof mass in two dimensions, as illustrated in *Fig. 4a*, so that it is free to move only in the input axis direction, normal to the *paddle* surface. This design requires an external supporting force to keep the proof mass from moving in that direction, and the force required to do it will be proportional to the acceleration that would otherwise be disturbing the proof mass.

Force Rebalance Accelerometers: Electromagnetic accelerometers (EMAs) are pendulous accelerometers using electromagnetic force to keep the paddle from moving. A common design uses a voice coil attached to the paddle and driven in an arrangement similar to the speaker cone drive in permanent magnet speakers, with the magnetic flux through the coils provided by permanent magnets. The coil current is controlled through a feedback servo loop including a paddle position sensor such as a capacitance pickoff. The current in this feedback loop through the voice coil will be proportional to the disturbing acceleration. For pulse-integrating accelerometers, the feedback current is supplied in discrete pulses with very repeatable shapes, so that each pulse is proportional to a fixed change in velocity.

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An up/down counter keeps track of the net pulse count between samples of the digitized accelerometer output.

Integrating Accelerometers: The pulse-feedback electromagnetic accelerometer is an integrating accelerometer, in that each pulse output corresponds to a constant increment in velocity. The *drag cup* accelerometer illustrated in *Fig. 5* is another type of integrating accelerometer. It uses the same physical principles as the drag cup speedometer used for half a century in automobiles, consisting of a rotating bar magnet and conducting envelope (the drag cup) mounted on a common rotation shaft but coupled only through the eddy current drag induced on the drag cup by the relative rotation of the magnet. (The design includes a magnetic circuit return ring outside the drag cup, not shown in this illustration.) The torque on the drag cup is proportional to the relative rotation rate of the magnet. The drag cup accelerometer has a deliberate mass unbalance on the drag cup, such that accelerations of the drag cup orthogonal to the mass unbalance will induce a torque on the drag cup proportional to acceleration. The bar magnet is driven by an electric motor, the speed of which is servoed to keep the drag cup from rotating. The rotation rate of the motor is then proportional to acceleration, and each revolution of the motor corresponds to a fixed velocity change. These devices can be daisy chained to perform successive integrals. Two of them coupled in tandem, with the drag cup of one used to drive the magnet of the other, would theoretically perform double integration, with each motor drive revolution equivalent to a fixed increment of position.

Strain-Sensing Accelerometers: The cantilever beam accelerometer design illustrated in *Fig.4b* senses the strain at the root of the beam resulting from support of the proof mass under acceleration load. The surface strain near the root of the beam will be proportional to the applied acceleration. This type of accelerometer

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can be manufactured relatively inexpensively using MEMS technologies, with an ion-implanted piezoresistor pattern to measure surface strain.
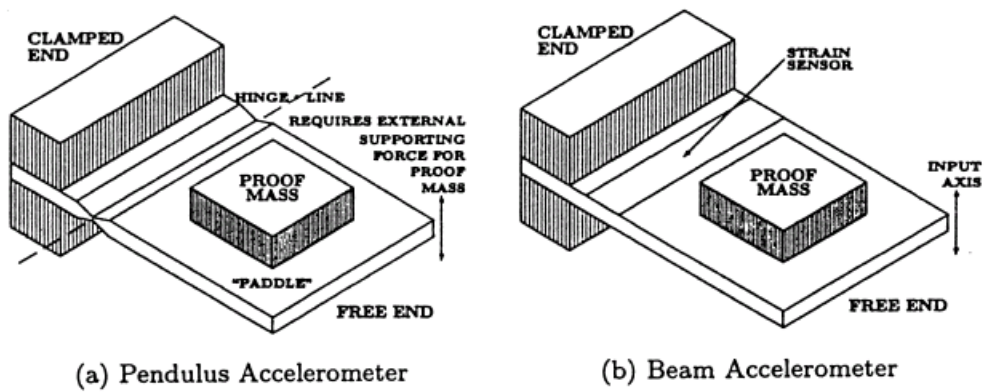

(a) Pendulus Accelerometer   (b) Beam Accelerometer

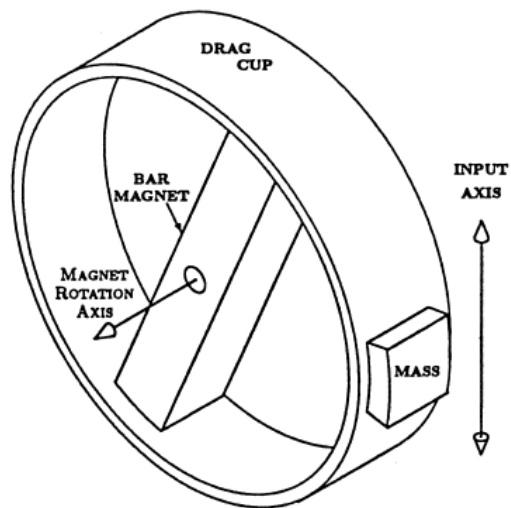*Fig. 4 Single-axis accelerometers*
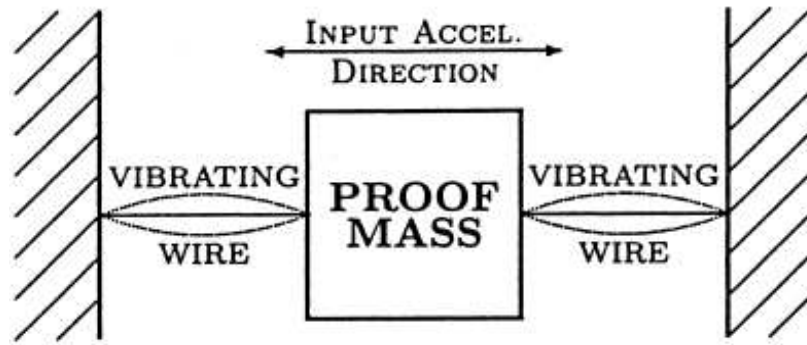

Fig. 5 Drag cup accelerometer

Fig. 6 Single-axis vibrating wires accelerometer.

Vibrating-Wire Accelerometers: The resonant frequencies of vibrating wires (or strings) depend upon the length, density, and elastic constant of the wire and on the square of the tension in the wire. The motions of the wires must be sensed (e.g., by capacitance pickoffs) and forced (e.g., electrostatically or electromagnetically) to be kept in resonance. The wires can then be used as digitizing force sensors, as illustrated in *Fig. 6*. The configuration shown is for a single-axis accelerometer, but the concept can be expanded to a three-axis accelerometer by attaching pairs of opposing wires in three orthogonal directions.

In the *push-pull* configuration shown, any lateral acceleration of the proof mass will cause one wire frequency to increase and the other to decrease. Furthermore, if the preload tensions in the wires are servoed to keep the sum of their frequencies constant, then the difference frequency

$$\omega_{left} - \omega_{right} \, \alpha \, \frac{ma}{\omega_{left} + \omega_{right}} \qquad (9)$$

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Both the difference frequency $\omega_{left} - \omega_{right}$ and the sum frequency $\omega_{left} + \omega_{right}$ (used for preload tension control) can be obtained by mixing and filtering the two wire position signals from the resonance forcing servo loop. Each cycle of the difference frequency then corresponds to a constant delta velocity, making the sensor inherently digital.

Accelerometers cannot measure gravitational acceleration. An accelerometer effectively measures the force acting on its proof mass to make it follow its mounting base, which includes only non-gravitational accelerations applied through physical forces acting on the INS through its host vehicle. Satellites, which are effectively in free fall, experience no sensible accelerations.

Accelerometers have scale factors, which are the ratios of input acceleration units to output signal magnitude units (e.g., meters per second squared per volt). The signal must be rescaled in the navigation computer by multiplying by this scale factor.

2.3   Acceleration problems

Accelerometers cannot measure gravitational acceleration. An accelerometer effectively measures the force acting on its proof mass to make it follow its mounting base, which includes only non-gravitational accelerations applied through physical forces acting on the INS through its host vehicle. Satellites, which are effectively in free fall, experience no sensible accelerations.

Accelerometers have scale factors, which are the ratios of input acceleration units to output signal magnitude units (e.g., meters per second squared per volt). The signal must be rescaled in the navigation computer by multiplying by this scale factor.

Gravitational accelerations must be modeled and calculated in the navigational computer, then added to the sensed acceleration (after error and scale compensation) to obtain the net acceleration of the INS

Accelerometers have *output errors*, including:

l   Unknown constant *offsets*, also called *biases*;

l   Unknown constant *scale factor errors*;

l   Unknown sensor input *axis misalignments*;

l   Unknown *non-constant variations* in bias and scale factor; and

l   Unknown *zero-mean additive noise* on the sensor outputs, including quantization noise and electronic noise. The noise itself is not predictable, but its statistical properties are used in Kalman filtering to estimate drifting scale factor and biases.

2.4   Application in INS

The time-varying Kalman filter is a generalization of the steady-state filter for time-varying systems or LTI systems with non-stationary noise covariance. Given the plant state and measurement equations as in (7), (8) the Kalman filter is designed as in B. Boberg and S.L. Wirkander (2002).

Input signals include white noise and measuring device noise. By using Kalman Filter, we can receive the output-filtered signals. We using double integration for calculating the distance and velocity, these kinds of drifts can make the increasing the position error dramatically. We can use two methods: constant compensation algorithm and periodic compensation algorithm, for reducing errors in velocity and position. That method will show in next chapter.

Chapter 3. Design Method for Drift Compensation Gain

The drift of accelerometer is generated by its circumstance and it can be divided into two cases: constant drift and periodic drift. The constant drift is depended on the circumstance of sensor inside and kept on constant condition. But the outside circumstance will be changed with low frequency, which affected by seasonal, day and night, temperature, and atmospheric pressure etc. When using double integration for calculating the distance, these kinds of drifts can make the increasing the position error dramatically. Also when using ISN module, it's certainly have errors. The errors consist of different combinations of white noise components and constant components. So we try to use constant drift compensation and periodic drift compensation to solve that problem.

3.1 Design method for constant drift compensation gain

The data we get from accelerometer included white noise and measuring device noise. First time, we use Kalman filter for reduces that noise. When we using double integration for calculating the distance and velocity, the position errors can make and increasing. So we try to find the constant drift of accelerometer and compensation that problem

For compensating the constant drift of accelerometer, the following algorithm will be used generally.

Step1: Acquire the acceleration sensor values with drift on x, y and z axes, respectively.

$$\bar{a}_x = a_x + \delta a_x \tag{10}$$

where a_x denotes original acceleration sensor value and δa_x denotes an accelerometer value with drift on x axis, respectively.

Step 2: Calculate the velocity by using numerical integral method.

$$\bar{v}_x(t+1) = \int_t^{t+1} \bar{a}_x(\tau)d\tau + \bar{v}_x(t) \tag{11}$$

Step 3: Compensate the drift for velocity

$$v_x(t+1) = \bar{v}_x(t+1) + d_v \tag{12}$$

Step 4: Calculate the position by using numerical integral method.

$$\bar{x}(t+1) = \int_t^{t+1} \bar{v}_x(\tau)d\tau + \bar{x}(t) \tag{13}$$

Step 5: Compensate the drift of position

$$x(t+1) = \bar{x}(t+1) + d_p \tag{14}$$

In the above algorithm, the drift can be compensated by on-line calculation, thus v_x and x can be obtained respectively, where an accumulated position error will be reduced by small sampling time, but computational error will be increased. To obtain design method for the drift compensation gains d_v and d_p, we will show two methods: constant compensation algorithm and periodic compensation algorithm.

If the drift of accelerometer included into original signal, then the average drift can be obtained during constant periodic time. So the original signal can be estimated by drift compensation method from the measured signal with drift value.

For this, the accelerometer should be installed in steady state and obtain the accelerometer data during constant periodic time. From these data, the velocity drift d_v and position drift d_p are calculated, respectively. At this time, the accelerometer should be leaved from the external circumstance changes with long experimental time. But, the constant drift compensation algorithm is not useful when the circumstance is changed or the type of accelerometer is changed.

In constant compensation algorithm, after using Kalman Filter for reduced noise from accelerometer and measuring device noise, we can calculate, and compensate for velocity and position by velocity drift d_v and position drift d_p.

3.2   Design method for Periodic drift compensation gains

Generally, the external environment circumstance will be changed ordinarily. Almost these kinds of circumstances can be changed on periodic time such as, seasonally, day and night, or tide etc. At the same time, the average drift can be obtained during constant periodic time and used this value, when drift includes into original signal.

On the other hand, in auto pilot system for ship, the navigation module is used GPS system for detecting the position, but actually the GPS has position error and it depends on the weather condition. For compensation of the GPS signal, some time there uses an IMU. In this case, the sea condition such as tide, wind or sea surface condition etc. can affect to navigation ship. Under the general assumption, the ship can be moved by sinusoidal wave where tide or wind affects

to the ship sailing in periodically. From these conditions, we can make a periodic drift compensation algorithm by following procedure.

An INS compensation (Periodic Drift Compensation) algorithm for auto sailing system was proposed. The main procedure to design the periodic drift compensation algorithm can be briefly described as the following

In *Fig. 7*, the parameters α_v and α_p denote the velocity and position errors compensation gains and β_v and β_p denote the periodic compensation gains for velocity and position errors, respectively.

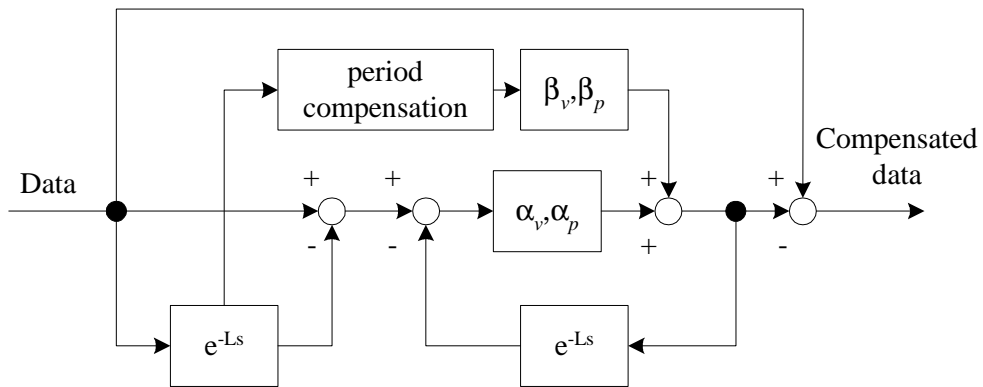***Fig. 7 Block Diagram of Periodic Drift Compensation***

< Procedure for Calculation of Periodic Compensation Gains >

Step 1: Calculate the natural frequency and its magnitude for accelerometer circumstance by *FFT* method.

Step 2: From the *FFT* results, decide the dominant frequency L of accelerometer.

Step 3: Make periodic L data table from decided dominant frequency modes.

Step 4: Initialization of periodic L data table.

Step 5: Calculate the velocity drift compensation gain

$$d_v(t+1) = \beta_v(\max(peak) + \min(peak))/2 \\ + \alpha_v(\bar{v}_y(t+1) - \bar{v}_y(t+1-L) - d_v(t)) \tag{15}$$

where $\max(peak)$ and $\min(peak)$ denote the maximum and minimum value from obtained acceleration sensor data, respectively.

Step 6: Calculate the position drift compensation gain

$$d_p(t+1) = \beta_p(\max(peak) + \min(peak))/2 \\ + \alpha_p(\bar{y}(t+1) - \bar{y}(t+1-L) - d_p(t)) \tag{16}$$

In the above procedure, the step 5 and 6 will be calculated by periodically on the calculation routine. And the calculated values should be saved and used it in next calculation.

Chapter 4. Implementation and Results

4.1 Using Kalman filter and IMU bias

We have considered accelerometer data from acceleration signals. For our experiments, the *Crossbow-CXL10LP3* accelerometer was used. The *Crossbow-CXL10LP3* can measure both dynamic acceleration (e.g., vibration) and static acceleration. The sampling time was 0.01[s], and the data in steady state for 60[s]. Output signals of the accelerometer are analog signals whose voltages are proportional to acceleration in each axis, respectively. The accelerometers output can be measured directly with A/D converter inside the microprocessor. UART of the microprocessor get the accelerometer data and transmits them to computer by serial port. The microprocessor used in data acquisition is ATMEL ATmega128L.

First time, we assumed the accelerometer do not to move. We tried to find the constant drift of accelerometer when environment do not change. From that condition, the data of accelerometer received. But normally the data of accelerometer also included noise from accelerometer (measuring device) and white noise. By using Kalman filter, we can reducing their noise and find the errors of sensor. When using double integration for calculating the distance, these kinds of drifts can make the increasing the position error dramatically. We could find the constant drift and reduced their errors by follow our method which last chapter we showed. With the bias drift problem, these errors would be accumulated and the accuracy is deteriorated as time increases due to integration. The data including acceleration input and white noise are given in *Fig.8*.
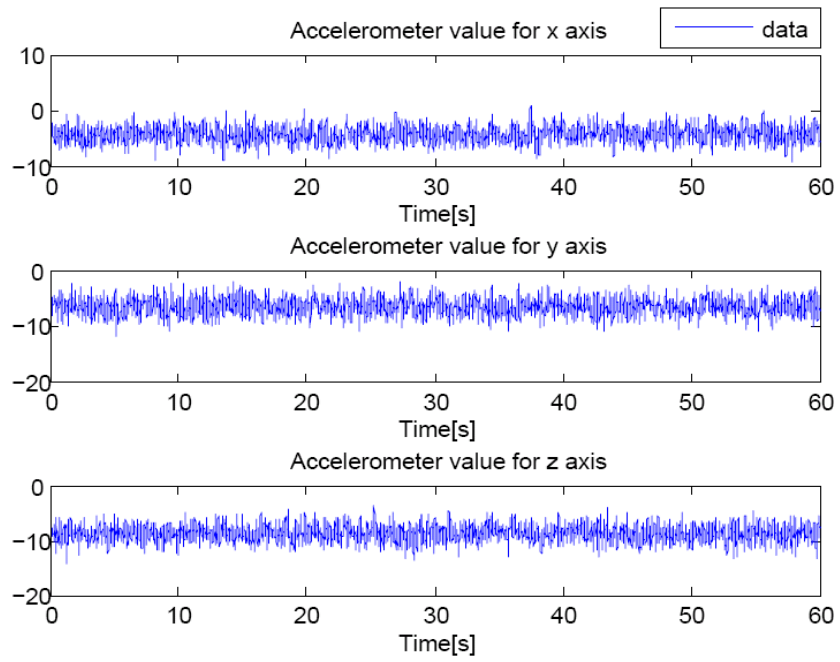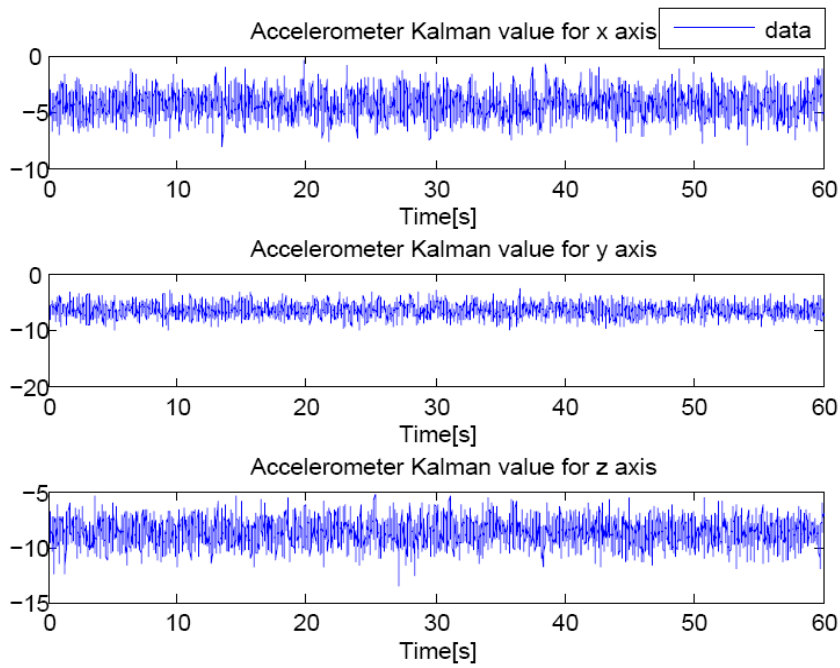
Fig.8 Accelerometer value included noise

Fig.9 Accelerometer value after using Kalman filter

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Applying Kalman Filter, the accelerometer data could reduce white noise and measuring device. Their results are given in *Fig.9.* After using Kalman filter, the distance and the velocity could be calculated by using double integrals. The result of distance and velocity without bias compensation is shown in *Fig.10.* In *Fig.10*, we observe that the errors of distance on x, y and z axes increased so high value. We have to reduce that error by follow our method. We find the constant compensation value for velocity and distance. The results are show as *table 1*.
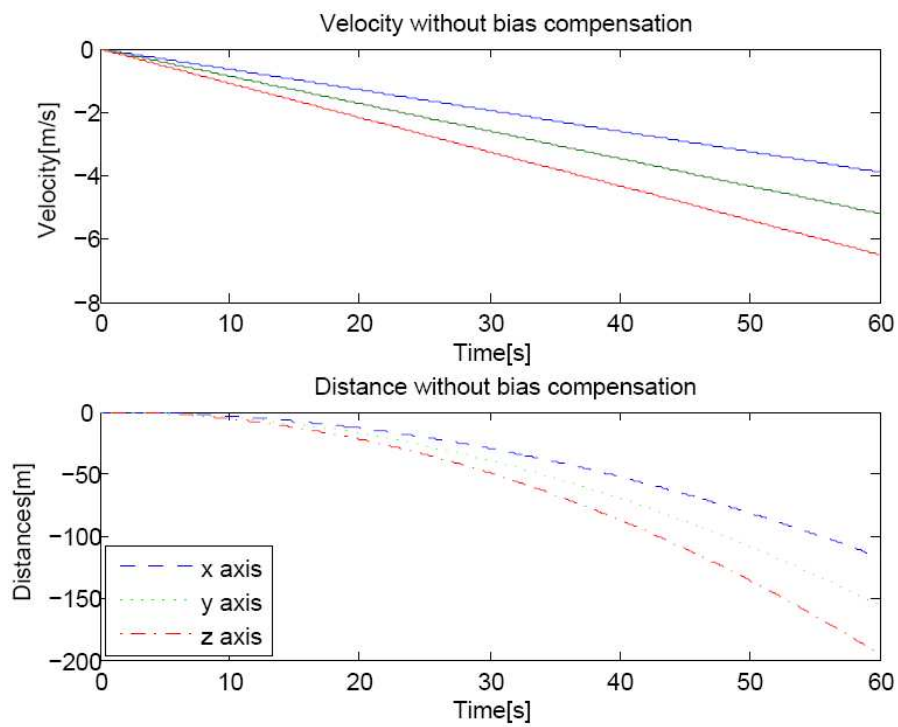

Fig.10 Distance without bias compensation

Table 1 Calculated Bias for 60 [s] on each axes

	x **Axis**	*y* **Axis**	*z* **Axis**
Velocity Bias	*-0.0012955*	*-0.0017321*	*-0.0021636*
Distance Bias	*-0.000081*	*0.000041*	*-0.000024*

By using *Table 1*, we can compensate the velocity and the distances, which calculated by integral method. The compensated distance and velocity data can be received as in *Fig.11*.
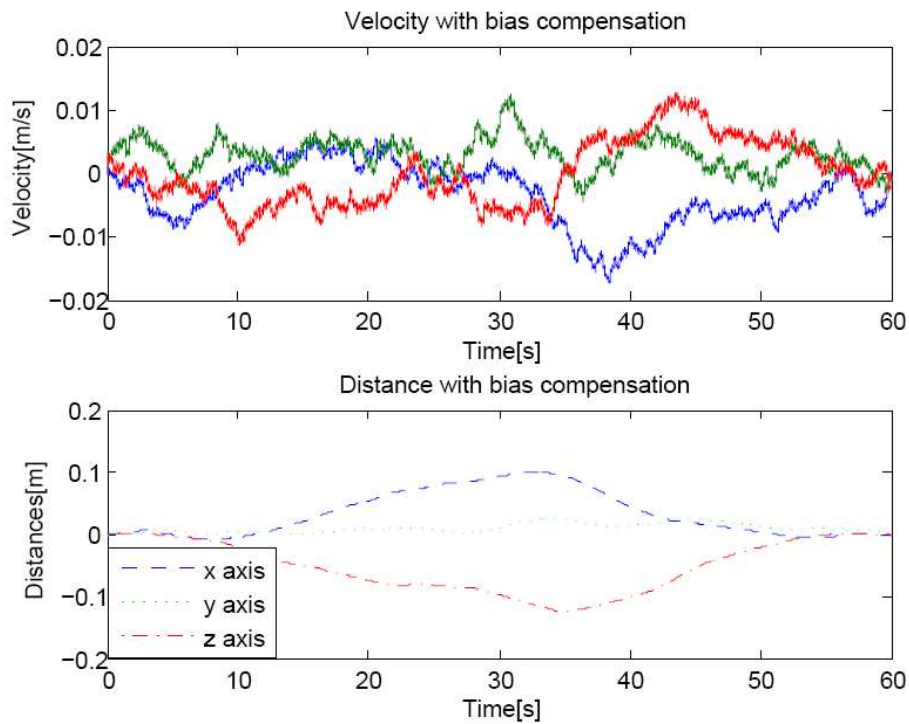

Fig.11 Distance with constant bias compensation

From this result, with the environment do not change, the value of distance and velocity just fluctuate kept within value which we can accept and the deviation is acceptable. We can observe that the constant bias compensation algorithm effects to the accelerometer bias compensation.

4.2   Constant bias compensation

To verify the constant bias compensation, we did an accelerometer test by experiment. In natural environment condition, we never have good condition. The boat can under the influence of wave, wind e.g., so the boat always floating on the waves. For experiment that case, we considered the accelerometer is oscillated on x, y and z axis with sinusoidal. We tried to vibrate amplitude our accelerometer for simulation sinusoidal signal. Certainly the accelerometer data are included white noise and errors from measuring device signals. First, using Kalman filter for reduced white noise and measuring device. With the constant drift compensation method, the velocity and position can be compensated. The results are given from Fig. 12 to Fig. 14 for x, y and z axis. In that fig, accelerometer value for each axis is a value after using Kalman filter.
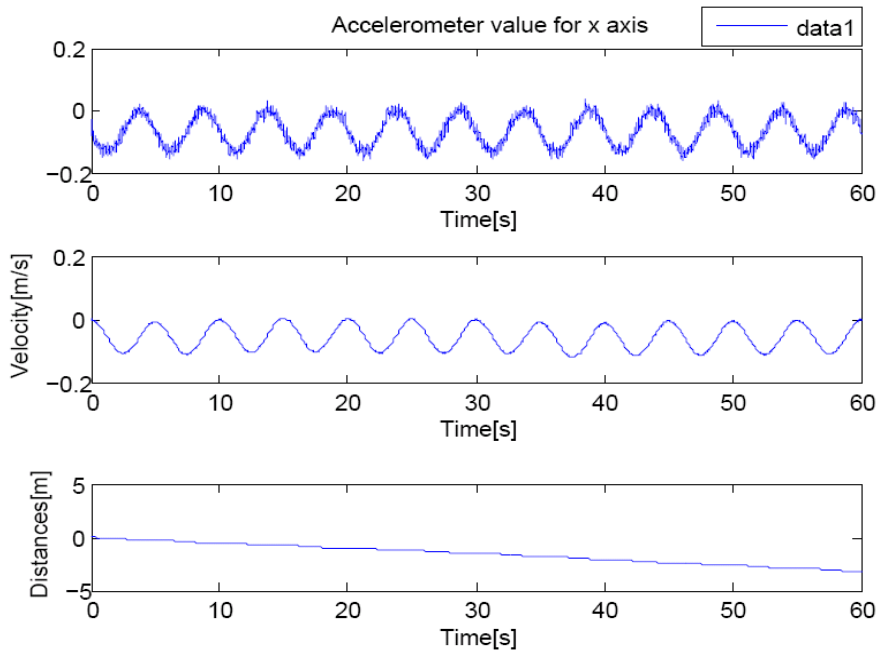
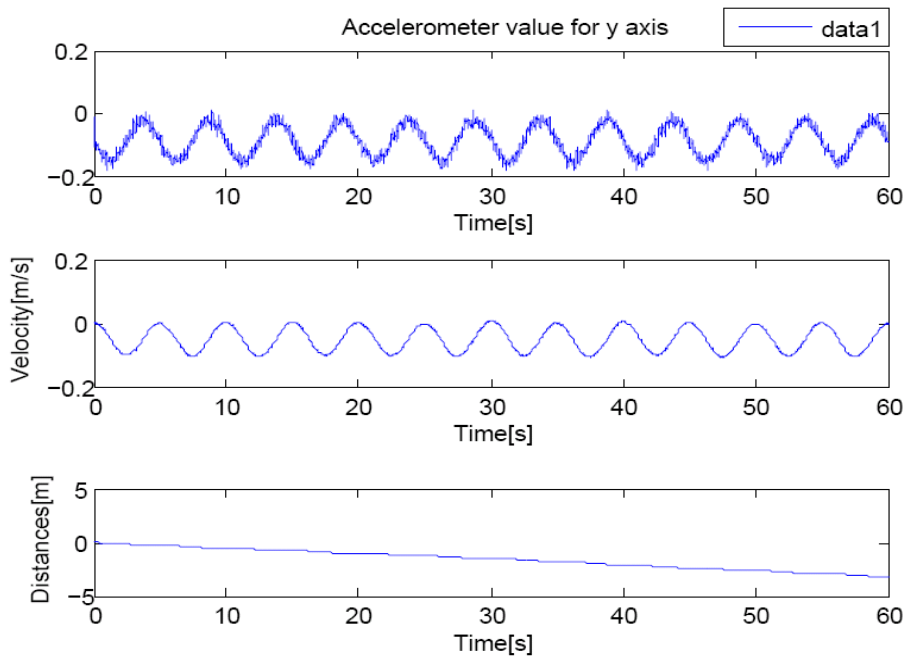*Fig. 12 Constant bias compensated data on x axis*

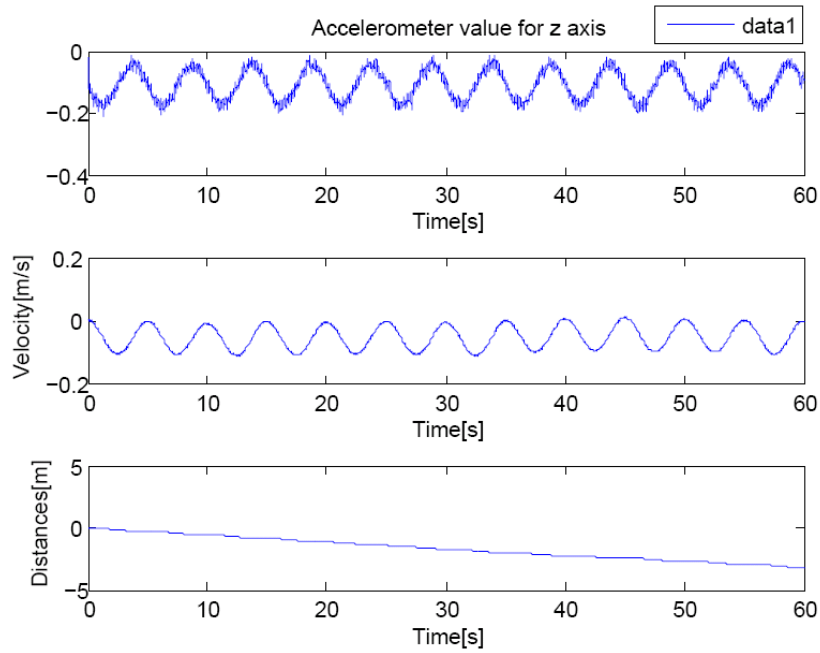*Fig. 13 Constant bias compensated data on y axis*

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Fig. 14 Constant bias compensated data on z axis.

Although using Kalman filter and constant drift compensation method, the distances were increased by external environment changes. When we did the experiments, our vibration amplitudes have just around 0.3 [*m*]. But the distances received after applying constant bias compensation, is 3.16 [*m*] on *x* axis. We can see that error to high. So we tried to use Periodic bias compensation.

4.3   Periodic bias compensation

In this subsection, we used Period bias compensation. First, we verified the environment changes. To do this, we used *FFT method* to check the main frequency term, which affected the accelerometers. The *FFT result* is shown in *Fig.15*
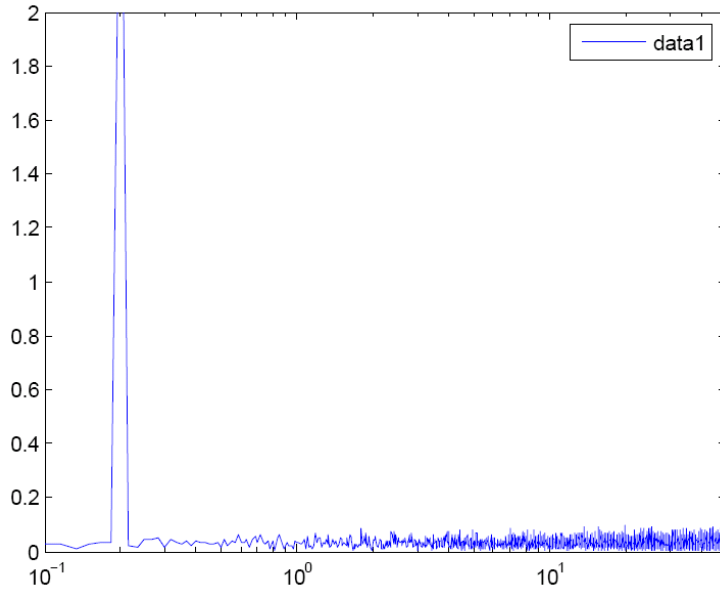
30

Fig.15 FFT results on x axis

In *Fig.15* the main frequency is 0.199967 [*Hz*] and its magnitude is 3.025656. From the frequency, the period is calculated as 5.0008[*s*]. In simulation for periodic bias compensation, we defined the parameters as *Table. 2*.

Table 2: Parameters for periodic bias compensation

	x **Axis**		*y* **Axis**		*z* **Axis**	
	V	*D*	*V*	*D*	*V*	*D*
α	0.5	0.5	0.5	0.1	0.5	0.1
β	6.0	2.0	5.0	1.0	5.0	4

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By using the parameters in *Table 2* and the periodic compensation algorithm, we can get the results in *Fig. 16 - Fig. 18*, where the same accelerometer's data with constant bias compensation method are used.
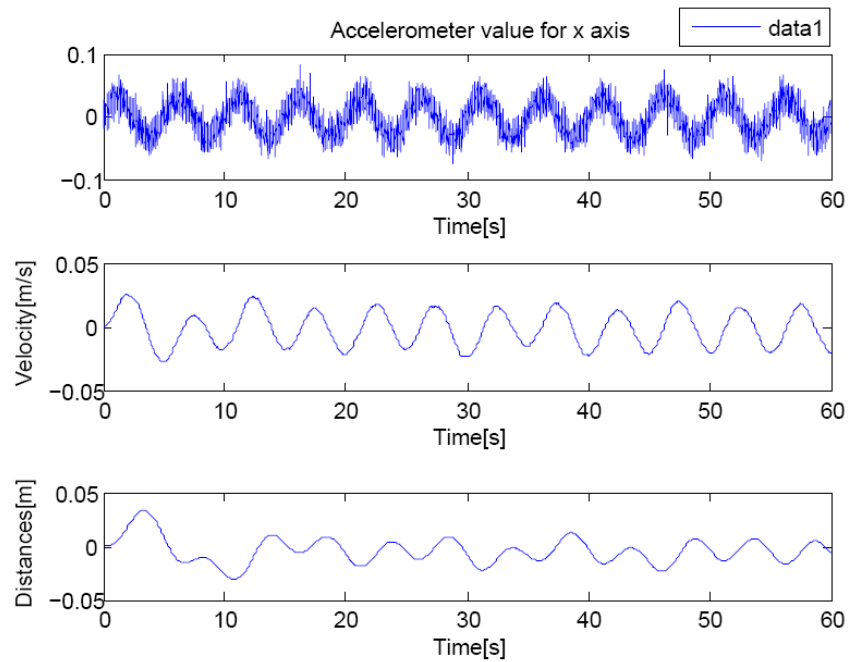

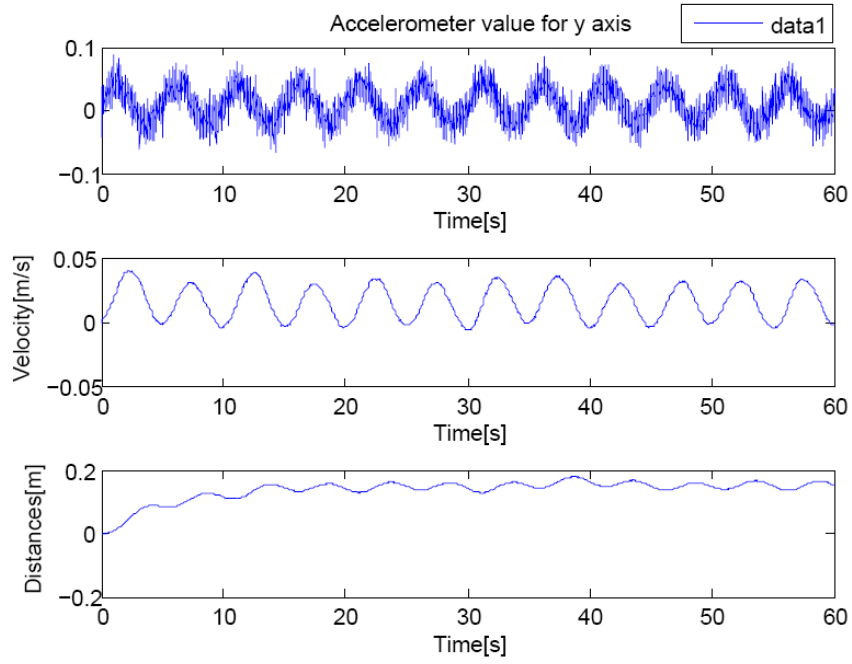*Fig.16 Periodic bias compensated data on x axis*

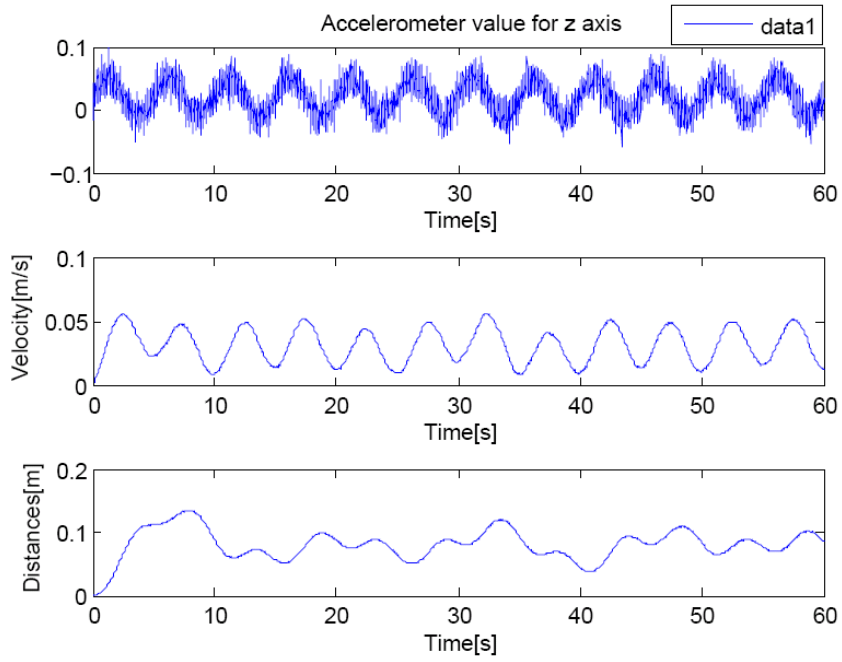*Fig. 17 Periodic bias compensated data on y axis*

Fig. 18 Periodic bias compensated data on z axis.

From *Fig.16* to *Fig.18*, we can see the distance data after using Periodic bias compensation, are reduced when external environment changes. Last time, when we use constant drift compensation method, the distance is 3.16 [m] for x axis. But now as you see in *Fig 16*, the distance just oscillate around 0.05 [m]. So we verify that the above results show is good noise cancellation.

Chapter 5. Conclusions

In this thesis, we applied the method of Kalman filter for estimating the acceleration data and compensate constant bias. In constant drift compensation method, there can only reduce the velocity and distance errors in some extents. The compensated error was still relatively large. This due to the fact that Kalman filter requires error model. With FFT method through periodic bias compensation, we could reduce the error effectively.

In container terminal, they are use AGV to transfer the container. Their AGV included the GPS modules for detected the position of AGV. Sometimes, when AGV move to under Gantry Crane, the GPS signal can not received data into control room. Their Gantry Crane included some noise. That noise bringing the transmission has interrupt or delay data. At that condition, the INS included out method very useful. By our INS solution, we can know exact the position of AGV.

In the future research, we will try to compare the periodic compensation algorithm with numerical double integration of acceleration measurements in noise using rectangular and trapezoidal rules. At that time, the angle sensors might be considered to improve the accuracy of the position for vehicle.

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Vita

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